Adoption of Artificial Intelligence in an Organizational Context: Analysis of the Factors Influencing the Adoption and Decision-Making Process

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Dissertation

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I hereby declare that the submitted thesis is my own work. All quotes, whether word by word or in my own words, have been marked as such.

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Ich erkläre hiermit ehrenwörtlich, dass ich die vorliegende Arbeit selbstständig angefertigt habe. Sämtliche aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Die Arbeit wurde bisher weder einer anderen Prüfungsbehörde vorgelegt noch veröffentlicht.

Verena Eitle

Darmstadt, 12.04.2023

Abstract

The emergence of Artificial Intelligence (AI) shifts the business environment to such an extent that this general-purpose technology (GPT) is prevalent in a wide range of industries, evolves through constant advancements, and stimulates complementary innovations. By implementing AI applications in their business practices, organizations primarily benefit from improved business process automation, valuable cognitive insights, and enhanced cognitive engagements. Despite this great potential, organizations encounter difficulties in adopting AI as they struggle to adjust to corresponding complex organizational changes.

The tendency for organizations to face challenges when implementing AI applications indicates that AI adoption is far from trivial. The complex organizational change generated by AI adoption could emerge from intelligent agents' learning and autonomy capabilities. While AI simulates human intelligence in perception, reasoning, learning, and interaction, organizations' decision-making processes might change as human decision-making power shifts to AI. Furthermore, viewing AI adoption as a multi-stage rather than a single-stage process divides this complex change into the initiation, adoption, and routinization stages. Thus, AI adoption does not necessarily imply that AI applications are fully incorporated into enterprise-wide business practices; they could be at certain adoption stages or only in individual business functions. To address these complex organizational changes, this thesis seeks to examine the dynamics surrounding AI adoption at the organizational level. Based on four empirical research papers, this thesis presents the factors that influence AI adoption and reveals the impact of AI on the decision-making process. These research papers have been published in peer-reviewed conference proceedings.

The first part of this thesis describes the factors that influence AI adoption in organizations. Based on the technology-organization-environment (TOE) framework, the findings of the qualitative study are consistent with previous innovation studies showing that generic factors, such as compatibility, top management, and data protection, affect AI adoption. In addition to the generic factors, the study also reveals that specific factors, such as data quality, ethical guidelines, and collaborative work, are of particular importance in the AI context. However, given these technological, organizational, and environmental factors, national cultural differences may occur as described by Hofstede’s national cultural framework. Factors are validated using a quantitative research design throughout the adoption process to account for the complexity of AI adoption. By considering the initiation, adoption, and routinization stages, differentiating and opposing effects on AI adoption are identified.

The second part of this thesis addresses AI’s impact on the decision-making process in recruiting and marketing and sales. The experimental study shows that AI can ensure procedural justice in the candidate selection process. The findings indicate that the rule of consistency increases when recruiters are assisted by a CV recommender system. In marketing and sales, AI can support the decision-making process to identify promising prospects. By developing classification models in lead-and-opportunity management, the predictive performances of various machine learning algorithms are presented.

This thesis outlines a variety of factors that involve generic and AI-specific considerations, national cultural perspectives, and a multi-stage process view to account for the complex organizational changes AI adoption entails. By focusing on recruiting as well as marketing and sales, it emphasizes AI’s impact on organizations’ decision-making processes.

Abstract (German version)

Die Einführung von Künstlicher Intelligenz (KI) verändert das Geschäftsumfeld derart, dass diese Allzwecktechnologie in einer Vielzahl von Industrien verbreitet ist, sich ständig weiterentwickelt und ergänzende Innovationen vorantreibt. Durch die Implementierung von KI-Anwendungen in ihre Geschäftsabläufe profitieren Unternehmen in erster Linie von einer stärkeren Automatisierung von Geschäftsprozessen, wertvollen kognitiven Erkenntnissen und einem verstärkten kognitiven Engagement. Trotz dieses großen Potenzials stoßen Unternehmen bei der Einführung von KI auf Schwierigkeiten, da sie sich mit dem entsprechend komplexen organisatorischen Wandel auseinandersetzen müssen.

Die Tendenz, dass Unternehmen bei der Implementierung von KI-Anwendungen auf Herausforderungen stoßen, zeigt, dass die Einführung von KI alles andere als trivial ist. Der komplexe organisatorische Wandel, der durch die Einführung von KI ausgelöst wird, könnte sich aus den Lern- und Autonomiefähigkeiten intelligenter Agenten ergeben. Während KI die menschliche Intelligenz in den Bereichen Wahrnehmung, Denken, Lernen und Interaktion simuliert, könnten sich die Entscheidungsfindungsprozesse in Organisationen ändern, wenn die menschliche Entscheidungsgewalt auf KI übergeht. Betrachtet man die Einführung von KI als einen mehrstufigen und nicht als einen einstufigen Prozess, so wird diese komplexe Veränderung in die Phasen der Initiierung, der Einführung und der Routine unterteilt. Die Einführung von KI bedeutet also nicht zwangsläufig, dass KI-Anwendungen vollständig in unternehmensweite Geschäftspraktiken integriert sind; sie könnten sich in bestimmten Phasen oder nur in einzelnen Geschäftsfunktionen befinden. Um dem komplexen organisatorischen Wandel entgegenzuwirken, wird in dieser Arbeit die Dynamik im Zusammenhang mit der Einführung von KI auf der Organisationsebene untersucht. Auf der Grundlage von vier empirischen Forschungsarbeiten werden die Faktoren vorgestellt, die den Einsatz von KI beeinflussen und die Auswirkungen von KI auf den Entscheidungsprozess aufgezeigt. Diese Forschungsarbeiten wurden in von Experten begutachteten Konferenzberichten veröffentlicht.

Der erste Teil dieser Arbeit beschreibt die Faktoren, die die Einführung von KI in Unternehmen beeinflussen. Basierend auf dem Technologie-Organisation-Umwelt-Framework stimmen die Ergebnisse der qualitativen Studie mit früheren Innovationsstudien überein, die zeigen, dass generische Faktoren, wie Kompatibilität, Top-Management und Datenschutz die Einführung von KI beeinflussen. Zusätzlich zu den generischen Faktoren ergibt die Studie auch, dass spezifische Faktoren, wie Datenqualität, ethische Richtlinien und kollaboratives Arbeiten im Kontext von KI von besonderer Bedeutung sind. Angesichts dieser technologischen, organisatorischen und umweltbedingten Faktoren können jedoch nationale kulturelle Unterschiede auftreten, wie sie in Hofstedes nationalem Kultur Framework beschrieben werden. Die Faktoren werden mit Hilfe eines quantitativen Forschungsdesigns entlang des gesamten Einführungsprozesses validiert, um die Komplexität der Einführung von KI zu berücksichtigen. Durch die Betrachtung der Initiierungs-, Einführungs-, und Routinisierungsphasen werden differenzierende und gegenläufige Effekte auf die Einführung von KI identifiziert.

Der zweite Teil dieser Arbeit befasst sich mit den Auswirkungen von KI auf den Entscheidungsprozess in den Bereichen Recruiting sowie Marketing und Vertrieb. Die experimentelle Studie zeigt, dass KI im Bewerberauswahlprozess für Verfahrensgerechtigkeit sorgen kann. Die Ergebnisse deuten darauf hin, dass die Regel der Konsistenz zunimmt, wenn Personalverantwortliche von einem Lebenslaufempfehlungssystem unterstützt werden. In Marketing und Vertrieb kann KI den Entscheidungsprozess unterstützen, um vielversprechende Interessenten zu identifizieren. Durch die Entwicklung von Klassifikationsmodellen im Lead- und Opportunity-Management werden die Vorhersageleistungen verschiedener maschineller Lernalgorithmen vorgestellt.

In dieser Arbeit werden eine Reihe von Faktoren beschrieben, die allgemeine und KI-spezifische Erwägungen, nationale kulturelle Perspektiven und eine mehrstufige Prozessbetrachtung umfassen, um den komplexen organisatorischen Wandel, den die Einführung von KI mit sich bringt, zu berücksichtigen. Durch die Fokussierung auf die Bereiche Recruiting sowie Marketing und Vertrieb werden die Auswirkungen von KI auf die Entscheidungsprozesse von Unternehmen hervorgehoben.

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List of Abbreviations

α	Cronbach’s alpha
Acc.	Accuracy
ADO	Adoption
AI	Artificial intelligence
AIS	Association for information systems
APJ	Asia Pacific Japan
ASA	Attraction-selection-attrition
AUC	Area under the receiving operating curve
AVE	Average variance extracted
B2B	Business-to-business
C	Penalty parameter
CEO	Chief executive officer
C-Level	Chief-level
CMB	Common method bias
CR	Composite reliability
CRM	Customer relationship management
CV	Curriculum vitae
CW	Collaborative work
d	Cohen’s d
df	Degrees of freedom
DOI	Diffusion of innovation
DQ	Data quality
DS	Data sensitivity
DSS	Decision support system
DSR	Design science research
E	Experience
E#	Expert #
ECIS	European Conference on Information Systems
EG	Ethical guidelines

EMEAN	Middle East and Africa North
EMEAS	Middle East and Africa South
EUR	End user readiness
EUT	End user training
EXP	AI expertise
f^2	Effect size
FN	False-negative
FP	False-positive
FR	Financial resources
GC	Greater China
GDP	Gross domestic product
GDPR	General data protection regulation
GER	Germany
GPT	General-purpose technology
H	Hypothesis
HICSS	Hawaii International Conference on System Sciences
HR	Human resources
HRM	Human resource management
ICT	Information and communications technology
ID	Identification
iDSS	Intelligent decision support system
IND	Industries
INI	Initiation
IS	Information system
ISO	International organization for standardization
IT	Information technology
KSA	Knowledge, skills, abilities
LA	Latin America
LDA	Latent dirichlet allocation
MEE	Middle and Eastern Europe
ML	Machine learning
NA	North America
NLP	Natural language processing
OCR	Optical character recognition
ORG	Organizational

P	Performance
p	Probability value
PC	Process compatibility
PCC	Percentage correctly classified
P-E	Person-environment
P-G	Person-group
P-J	Person-job
PLS	Partial least squares
P-O	Person-organization
Prec.	Precision
P-S	Person-supervisor
P-V	Person-vocation
Rank. corr.	Ranking correlation
RBF	Radial basis function
R&D	Research and development
ROUT	Routinization
RQ	Research question
SD	Standard deviation
SEM	Structural equation modelling
Sens.	Sensitivity
Sig.	Significance
Spec.	Specificity
SPSS	Statistical package for the social sciences
SRMR	Standardized root mean square residual
Std. dev.	Standard deviation
SVM	Support vector machine
T	Task
t	T-Test
TMS	Top management support
TN	True-negative
TOE	Technology-organization-environment
TP	True-positive
US	United States
y	Years

1 Introduction

AI is transforming the business environment as organizations strive to leverage AI's potential in nearly every industry and business function. Organizations embrace AI applications primarily because they allow them to optimize business processes, derive new insights from data, and strengthen customer and employee engagements (Davenport and Ronanki, 2018). Despite this great potential, organizations struggle to fully incorporate AI applications into their business landscapes and core business processes (Balakrishnan et al., 2020; Chui et al., 2021). To accelerate the adoption rate of AI applications, this thesis addresses the dynamics of AI adoption at the organizational level.

1.1 Overarching Motivation

In an organizational context, AI is considered to be a pervasive innovation that enables organizations to evolve in the digital age (Davenport, 2018b). In recent discussion, AI has even been envisioned as a GPT which refers to a type of technological innovation that has a significant impact on progress and economic growth, such as the steam engine or electricity (Brynjolfsson and Mcafee, 2017). Bresnahan and Trajtenberg (1995) characterize a GPT by its pervasiveness across industries, its continuous technical improvements, and the development of complementary innovations. According to Brynjolfsson et al. (2017), AI exhibits the features of a GPT as AI applications are used in a variety of industries such as finance (e.g., Sezer et al., 2020; Fu et al., 2021), human resources (e.g., Black and van Esch, 2020; Cheng et al., 2021), supply chain (e.g., Toorajipour et al., 2021), sales (e.g., Syam and Sharma, 2018; Liu et al., 2021), and healthcare (e.g., Buck et al., 2021; Secinaro et al., 2021). Furthermore, AI applications improve over time due to tremendous advances in sophisticated algorithms, low-cost graphics processors, and the availability of large datasets (Collins et al., 2021). Finally, AI applications are also capable of triggering a wave of complementary innovations and services that multiply their impact (Brynjolfsson et al., 2017). According to Russell and Norvig (2021), AI applications are designed as intelligent agents that take percepts from the environment through sensors and execute corresponding actions through actuators. Intelligent agents' learning and autonomy capabilities enable AI applications to learn from previous experiences and apply this knowledge to new environments. Drawing on these capabilities, AI simulates human intelligence in machines using perception, reasoning, learning, and interaction (Russell and Norvig, 2021).

Although organizations benefit greatly from these AI capabilities in business process automation, cognitive insights, and cognitive engagement (Davenport and Ronanki, 2018), they have not yet leveraged AI's full potential. According to a global survey on the state of AI in 2021, only 56% of 1,843 participants reported that their organizations implemented AI applications in at least one business function (Chui et al., 2021). Compared to the previous year, the AI adoption rate increased slightly. In 2020, 50% out of 2,395 organizations adopted AI in at least one business function, while only 16% moved beyond the pilot stage in deep learning as a subset of machine learning (Balakrishnan et al., 2020). These findings show that AI applications may not be deployed enterprise-wide and instead may be implemented only in certain business functions or only reach one stage of the adoption process. Organizations are likely to encounter difficulties in managing the complex changes that AI adoption entails as, for instance, AI's learning and autonomy capabilities have a major impact on the decision-making process (Berente et al., 2021). To ensure there is sufficient organizational readiness to handle such extensive changes, the factors that influence AI adoption need to be identified and examined in more detail.

When organizations implement AI applications, humans are no longer solely responsible for the decision-making process and are instead supported by AI. As a subdomain of decision support systems, intelligent decision support systems (iDSS) assist users in decision-making using their intelligent capabilities (Phillips-Wren, 2013). More precisely, AI techniques facilitate Simon's (1960, 1977) decision-making processes by enhancing the intelligence phase to identify problems, the design phase to provide a range of alternatives, the choice phase to select the most appropriate solution, and the implementation phase to execute operational tasks (Mora et al., 2005). Although the findings of the global survey on the state of AI in 2021 indicate that AI applications are not yet dominant in all business functions, the most common AI use cases occur in service operations, product and service development, marketing and sales, supply chain management, risk, manufacturing, strategy and corporate finance, and human resources (Chui et al., 2021). AI could assist in decision-making processes in business functions such as human resources as well as marketing and sales that are becoming increasingly complicated for humans to manage due to the growing amount of data produced by digitization (Ngai et al., 2009; van Esch et al., 2019). Examining AI's potential to simplify decision-making in the use cases of candidate selection and lead-and-opportunity management is particularly suitable.

Overall, it is important to gain more insight into the dynamics of AI adoption at the organizational level in the digital age. Thus, this thesis contributes to research by elaborating on the factors that affect AI adoption and provides practical guidance to organizations for successful AI adoption.

1.2 Overarching Research Questions

While the implementation of AI applications transforms the business landscape as organizations benefit from business process automation, cognitive insights, and cognitive engagements (Davenport and Ronanki, 2018), organizations continue to encounter difficulties in adopting AI (Chui et al., 2021). Since AI differs from other technologies primarily in its learning and autonomy capabilities (Berente et al., 2021), the adoption of AI entails complex changes at the organizational level (Jöhnk et al., 2021). Instead of focusing only on the technological components, as is common in the diffusion of innovation (DOI) literature (Rogers, 1983), the impact of organizational and environmental components on AI adoption might account for the complex changes required. Therefore, there is an urgent need for research to identify the factors that influence the successful implementation of AI applications based on the TOE framework (Tornatzky and Fleischer, 1990) and the organizational readiness concept (Jöhnk et al., 2021).

Since AI adoption is far from trivial, other considerations need to be taken into account when examining the influencing factors. Leidner and Kayworth (2006), for example, emphasize that national culture has a considerable impact on how groups interact with technologies. To understand how national cultural dynamics influence AI adoption, Hofstede’s (2001) national cultural framework, which is widely accepted in Information Systems (IS) research, should be combined with the TOE framework (Tornatzky and Fleischer, 1990). By intertwining Hofstede’s (2001) national cultural dimensions of power distance, individualism, masculinity, uncertainty avoidance, and long-term orientation with the technological, organizational, and environmental factors, valuable insights can be gained about national cultural differences in relation to AI adoption. Furthermore, complex changes at the organizational level could be caused by innovation adoption being viewed as a multi-stage rather than a single-stage process (Grover and Goslar, 1993). By dividing adoption into initiation, adoption, and implementation stages (Thompson, 1969; Pierce and Delbecq, 1977; Grover and Goslar, 1993; Damanpour and

Schneider, 2006), differentiating and opposing effects of the influencing factors can be detected (Fichman, 2000). The various factors that have an impact on AI adoption at the organizational level are further explored in the first overarching research question:

RQ1: Which factors influence AI adoption at the organizational level?

Due to AI's learning and autonomy capabilities derived from intelligent agents (Berente et al., 2021), the degree of responsibility shifts in the decision-making process. Particularly in the area of recruiting, incorporating AI applications into the candidate selection process helps recruiters to manage the growing amount of digital applicant data (Ngai et al., 2009; van Esch et al., 2019). Since the decision-making process in selecting candidates can be biased by previous work experiences and personal beliefs (Åslund and Skans, 2012; Eckhardt et al., 2014), the use of AI in the form of recommender systems might ensure procedural justice by increasing consistency (Leventhal, 1980; Gilliland, 1993; Greenberg and Colquitt, 2005). Besides this great potential in the candidate selection process, AI could also have a positive impact on the decision-making process in marketing and sales. Particularly in lead-and-opportunity management, AI applications could provide insights into the sales pipeline that would enable salesmen to predict promising prospects (Ngai et al., 2009). By deploying machine learning algorithms in the sales process, the likelihood of winning a sales deal could be predicted and the algorithms could be incorporated into the human decision-making process (D'Haen and Van Den Poel, 2013; Yan et al., 2015). Investigating which machine learning algorithm performs best in predicting the most promising lead or opportunity would therefore be a significant research contribution. Given these opportunities for improvement, the second overarching research question examines AI's augmentation potential in the decision-making process:

RQ2: What impact does AI have on the decision-making process using the examples of candidate selection in recruiting and lead-and-opportunity management in marketing and sales?

In summary, this thesis attempts to make the following contributions to research. First, it identifies and validates the factors that influence AI adoption as both a single-stage and a multi-stage process. Second, it seeks to demonstrate the impact AI can have on the decision-making process in organizations.

1.3 Structure of the Thesis

Based on these two research questions, this thesis comprises four research papers published in peer-reviewed conference proceedings as presented in Table 1. Addressing RQ1, research papers 1.A and 1.B seek to identify the factors that influence AI adoption in organizations. As a starting point, research paper 1.A explores the factors based on the TOE framework using a qualitative research design. In addition to identifying technological, organizational, and environmental factors, the study examines cultural differences in AI adoption. Taking into account Hofstede's (2001) national cultural dimensions of power distance, individualism, masculinity, uncertainty avoidance, and long-term orientation, national cultural differences between Germany and the United States in the implementation of AI applications are presented. Research paper 1.B views AI adoption as a multi-stage rather than a single-stage process. The study aims to validate the organizational readiness factors that influence the particular stages of initiation, adoption, and routinization. In response to RQ2, research papers 2.A and 2.B examine the impact of AI on the decision-making process in recruiting as well as marketing and sales. By focusing on the selection phase in the recruiting process, research paper 2.A is concerned with procedural justice and therefore investigates the extent to which the incorporation of CV recommender systems can increase consistency in candidate selection. In marketing and sales, research paper 2.B analyzes the predictive performances of AI algorithms in lead-and-opportunity management.

RQ1	Research Paper 1.A	Eitle, Verena; Buxmann, Peter (2020): **Cultural Differences in Machine Learning Adoption: An International Comparison between Germany and the United States.** In: European Conference on Information Systems (ECIS), Virtual AIS Conference, VHB-Ranking: B.
	Research Paper 1.B	Eitle, Verena; Zoell, Anne; Buxmann Peter (2022): **Organizational Readiness Concept for AI: A Quantitative Analysis of a Multi-stage Adoption Process from the Perspective of Data Scientists.** In: European Conference on Information Systems (ECIS), Timișoara, Romania, VHB-Ranking: B.
RQ2	Research Paper 2.A	Eitle, Verena; Peters, Felix; Welsch, Andreas; Buxmann, Peter (2021): **The Impact of CV Recommender System on Procedural Justice in Recruiting: An Experiment Candidate Selection.** In: European Conference on Information Systems (ECIS), Marrakesh, Morocco (Virtual AIS Conference), VHB-Ranking: B.
	Research Paper 2.B	Eitle, Verena; Buxmann, Peter (2019): **Business Analytics for Sales Pipeline Management in the Software Industry: A Machine Learning Perspective.** In: Hawaii International Conference on System Sciences (HICSS), Waikoloa Village, Hawaii, VHB-Ranking: C.

Table 1. Overview of publications presented in this thesis

As shown in Table 2, a variety of research designs are represented in the research papers presented in this thesis. As part of qualitative research design, research paper 1.A uses in-depth expert interviews which were conducted using a semi-structured interview guideline. To validate influencing factors, research paper 1.B follows a quantitative research design by applying the partial least squares method for measurement and structural models. The experimental research design of research paper 2.A shows how candidate rankings are created between a control group and a treatment group based on different settings. In research paper 2.B, three different types of models were developed to compare the predictive performances of different AI algorithms in lead-and-opportunity management.

Chapter	**Research Paper**	**Theoretical Background**	**Research Design**
Chapter 3	Research Paper 1.A	TOE Framework	Qualitative Research Design
Chapter 4	Research Paper 1.B	Organizational Readiness Concept	Quantitative Research Design, Structural Equation Modeling
Chapter 5	Research Paper 2.A	Procedural Justice and Recommender Systems	Experimental Research Design
Chapter 6	Research Paper 2.B	Lead-and-Opportunity Management and AI Algorithms	Model Development

Table 2. List of theoretical backgrounds and research designs

All publications[1] included in this thesis are presented in Chapters 3-6. Chapter 2 outlines the overarching theoretical background of artificial intelligence, innovation adoption at the organizational level, and decision-making in organizations. Chapter 7 descibes the overarching contributions and concluding remarks of the thesis.

[1] To ensure consistency of the layout in this thesis, the research papers have been slightly modified from their original versions. Since several co-authors contributed to the research papers, they are written in the first-person plural.

2 Theoretical Background

2.1 Artificial Intelligence

The history of AI began in 1956 when John McCarthy invited 10 researchers to a conference at Dartmouth College “to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves” (Russell and Norvig, 2021, p. 17). As AI research progressed, human-centered and rationalist approaches emerged which included different methods and measurements. While the human-centered approach followed empirical science and focused on predicting human behavior and human performance, the rationalist approach relied on mathematical and engineering techniques to achieve ideal performance. Following the rationalist approach, the premise of an AI application is that a rational agent strives to maximize the performance measure and obtain the best outcome through its performed actions. To achieve the expected performance improvement, the rational agent must be able to learn from the initial knowledge and experiences it gains. The ability to learn allows the rational agent to become independent from the initial knowledge and adapt to a variety of environments. Thus, an intelligent agent is an autonomous entity that perceives its environment using sensors and acts using actuators to achieve its goal through learning (Russell and Norvig, 2021).

Based on the concept of an intelligent agent, AI encompasses any technique that enables machines to simulate human intelligence, such as perceiving, reasoning, learning, and interacting (Russell and Norvig, 2021). These techniques can be categorized into the AI domains of expert systems, machine learning, robotics, natural language processing (NLP), and machine vision (Benbya et al., 2021; Collins et al., 2021). Expert systems were developed to solve complex problems using decision-making capabilities similar to those of humans. As a knowledge-based system, expert systems apply inference rules to extract knowledge from a knowledge basis consisting of accumulated experiences (Russell and Norvig, 2021). The first expert system, Dendral, was developed by Edward Feigenbaum and Joshua Lederberg in 1965 to perform difficult mass spectra analysis of organic molecules (Feigenbaum and Buchanan, 1993).

The domain of machine learning, on the other hand, refers to machines that learn from historical data to derive patterns and predict future outcomes without being explicitly programmed (Murphy, 2012). The learning capability that distinguishes machine learning from other technologies is defined by Tom Mitchell: “A computer program is said to learn from experience

E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E" (Mitchell, 1997, p. 2). In general, there are three machine learning approaches, with different prerequisites and methods of training the machine learning models. Supervised machine learning requires labeled input and output data to learn the mapping between these pairs on the training dataset and to predict the output on the test dataset. While unsupervised machine learning uses unlabeled data to discover hidden patterns and clusters, reinforcement machine learning is based on a reward and punishment system that aims to maximize and minimize them, respectively (Murphy, 2012). Machine learning can also be divided into several subsets. Deep learning, for instance, is based on artificial neural networks that mimic the structure of the human brain through their node layers consisting of an input layer, several hidden layers, and an output layer (Goodfellow et al., 2016). Another subset of machine learning is recommender systems, which are designed to provide users with suggestions related to items or products. Depending on the method by which recommendations are generated, recommender systems are categorized into various types such as content-based, collaborative filtering, and knowledge-based recommender systems (Ricci et al., 2011).

As part of the AI domain, robotics includes physical robots that were originally used in the industrial context with the purpose of automation. While industrial robots are primarily suited for hazardous or repetitive tasks, such as in the automotive industry, service robots are mainly used in human-oriented environments (Sprenger and Mettler, 2015). According to ISO 8373:2012 (International Organization for Standardization), service robots are defined as robots that (semi) autonomously perform useful tasks for humans or equipment. These tasks can be for personal use, including transportation and physical support, and for professional use, including inspection and surveillance (ISO, 2021).

NLP is another AI domain that enables machines to understand and process human language. Whether NLP is used for information extraction by pulling valuable textual information from natural language texts, machine translation by recognizing multiple languages, or for text generation in the form of data-to-text, text-to-text, and dialog-to-text, NLP enables machines to determine the meaning of text or voice data (Chowdhury, 2005; Eisenstein, 2018).

Besides human language, AI also extracts information from digital images, videos, and other visual inputs, which is known as computer vision. This AI domain is needed in particular for applications such as optical character recognition (OCR), which converts images of written text into machine-encoded text, or machine inspection as part of quality assurance (Szeliski, 2010).

An intelligent agent's capability to simulate human intelligence enables organizations to optimize their business practices. According to Davenport and Ronanki (2018), AI applications are well-suited to enhance business process automation for highly repetitive and mundane tasks. Coupling robotic process automation with AI technologies can significantly increase workflow efficiency by rapidly analyzing and aggregating large datasets (Chugh et al., 2022). Organizations can also leverage AI applications to gain cognitive insights by recognizing patterns and interpreting their meanings. For instance, machine learning can be applied to predict customer purchase preferences, detect credit fraud, or target personal digital ads (Awoyemi et al., 2017; Davenport and Ronanki, 2018). In addition, organizations also benefit from AI in terms of cognitive engagement by facilitating interaction with employees and customers. In particular, NLP can be used to provide service support or to implement an intelligent bot for conversions or to answer questions (Davenport and Ronanki, 2018; Adamopoulou and Moussiades, 2020). Despite the considerable gains in efficiency, these optimization potentials have a significant effect on the organizations' decision-making processes because they are no longer exclusively the human's responsibility but are augmented by AI. However, Berente et al. (2021) emphasize the risk of inscrutability since the procedures and outcomes of AI applications may become opaque to certain end users because of intelligent agents' learning and autonomy capabilities (Berente et al., 2021; Russell and Norvig, 2021). Taking these insights into account, organizations that implement AI applications into their business practices as expert systems, machine learning, robotics, NLP, or machine vision primarily benefit from automated business processes, cognitive insights, and cognitive engagements.

2.2 Innovation Adoption in Organizations

Research on innovation adoption is closely related to the DOI literature stream, which defines diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 1983, p. 5). While communication channels refer to the exchange of information and the members of a social system comprise individuals, informal groups, and organizations, the element of time is of great importance for the innovation diffusion process as it determines the rate of adoption.

According to Rogers (1983), the rate of adoption is measured by the time it takes certain members of a system to adopt an innovation. Rather than treating the innovation decision as a single stage of adoption or non-adoption (e.g., Zhu et al., 2003; Borgman et al., 2013; Gutierrez et al., 2015), innovation adoption should be viewed as a multi-stage process (Grover and Goslar, 1993). The number and duration of each adoption stage varies depending on the multi-stage process framework. Initially, a three-stage process consisting of the initiation, adoption, and implementation stages gained acceptance in research on innovation adoption (Thompson, 1969; Pierce and Delbecq, 1977; Grover and Goslar, 1993). More precisely, the initiation stage includes the identification of use cases and their technical assessments, the adoption stage encompasses resource allocation, and the implementation stage concerns actual development. The DOI framework by Rogers (1983) distinguishes between the innovation processes of individuals and organizations. Individuals go through the stages of knowledge gathering, persuasion, decision, implementation, and confirmation when deciding whether to adopt an innovation. However, at the organizational level, the innovation process is divided into two stages: the initiation stage, comprising agenda-setting and the matching substages; and the implementation stage, comprising the redefining, clarifying, and routinizing substages (Rogers, 1983). Meyer and Goes' (1988) assimilation process contains the three main decision-making stages of knowledge-awareness, evaluation-choice, and adoption-implementation with nine detailed substages. With respect to IT implementations, Cooper and Zmud (1990) expanded the original three-stage process to a six-stage process by outlining the stages of initiation, adoption, adaption, acceptance, routinization, and infusion. The initiation stage involves scanning the problem and the corresponding IT solution, and the adoption stage includes decision-making on resource allocation for the IT solution's implementation. The subsequent adaption stage, which comprises the development and implementation of the IT solution, is followed by the acceptance stage, in which the actual use takes place. Once the routinization stage is reached, in which individuals are encouraged to fully use the IT solution, the process ends with the infusion stage, which ultimately reflects efficiency gains (Cooper and Zmud, 1990). However, to reduce complexity, the condensed three-stage process consisting of the initiation, adoption, and routinization stages (Thompson, 1969; Pierce and Delbecq, 1977; Grover and Goslar, 1993) has been used primarily in innovation adoption studies in IS research (e.g., Damanpour and Schneider, 2006; Zhu, Kraemer, et al., 2006; Wu and Chuang, 2010; Chong and Chan, 2012; Martins et al., 2016).

Furthermore, Rogers (1983) emphasized that an innovation's rate of adoption can be influenced by five perceived attributes. According to the DOI framework, these attributes are relative advantage, which reflects an innovation's superiority compared to a previous idea; compatibility, which expresses its consistency with existing values and experiences; complexity, which reflects the perceived degree of challenge experienced in actual use; trialability, which allows users to test it in a limited setting; and observability, which represents its visibility to others (Rogers, 1983). With its particular focus on the organizational context, the TOE framework developed by Tornatzky and Fleischer (1990) is the most widely accepted framework for innovation adoption in organizations. While the five attributes of the DOI framework mainly outline the technological perspective, the TOE framework additionally considers the organizational and environmental perspectives to account for the high degree of complexity associated with innovation (Zhu, Kraemer, et al., 2006; Baker, 2012; Martins et al., 2016). To capture all the factors that may influence the innovation adoption in an organization, the TOE framework by Tornatzky and Fleischer (1990) encompasses the technological, organizational, and environmental contexts. The technological context refers to the evaluation of internal innovations that are already present in an organization and external innovations that are being considered for adoption. According to the DOI framework, the technological context comprises the factors of relative advantage, compatibility, and complexity (e.g., Rogers, 1983; Tornatzky and Fleischer, 1990; Tung and Rieck, 2005; Gangwar et al., 2015; Martins et al., 2016; W. Xu et al., 2017). The organizational context describes the structure and processes of an organization that can affect the success of innovation adoption (Tornatzky and Fleischer, 1990). Especially, organizational factors such as human or financial resources (e.g., Zhu et al., 2004; Gangwar et al., 2015; Gutierrez et al., 2015; W. Xu et al., 2017), top management (e.g., W. Xu et al., 2017; Chandra and Kumar, 2018), and company size (e.g., Thong, 1999; Zhu, Kraemer, et al., 2006; W. Xu et al., 2017) can positively influence the rate of adoption. The environmental context refers to external factors that an organization has to contend with when adopting an innovation (Tornatzky and Fleischer, 1990) such as legal regulations (e.g., Zhu, Kraemer, et al., 2006; Karunagaran et al., 2016) or competitive pressure (Lin and Lin, 2008; Karunagaran et al., 2016). Given its holistic view, the TOE framework has been widely used in studies on innovation adoption in areas such as enterprise resource planning (e.g., W. Xu et al., 2017), radio frequency identification (e.g., Chong and Chan, 2012), e-business (e.g., Zhu, Kraemer, et al., 2006; Chandra and Kumar, 2018), and cloud computing (e.g., Martins et al., 2016).

Since innovation adoption entails profound and complex changes, the change management literature emphasizes the need for organizational readiness (Weiner et al., 2008; Weiner, 2009; Lokuge et al., 2018). Lokuge et al. (2018) describe organizational readiness as a state in which organizations are prepared to perform certain activities. According to Weiner (2009), in addition to structural preparedness in human, financial, and technological resources, psychological preparedness is a crucial factor in implementing change. It reflects a state when organizational members feel committed to and confident in their collective ability to accomplish the upcoming change. As part of organizational commitment, change variance defines the extent to which organizational members collectively appreciate the change. On the other hand, change efficacy represents organizational members' shared belief in their collective capabilities to execute the activities associated with change (Weiner, 2009). To accommodate the complex changes associated with AI's learning and autonomy capabilities, Jöhnk et al. (2021) proposed an organizational readiness framework dedicated to AI that comprises the categories of strategic alignment, resources, knowledge, culture, and data.

2.3 Decision-Making in Organizations

Decision-making in an organizational context includes searching for occasions to make a decision, looking for possible courses of action, and choosing among those courses of action (Simon, 1960). Simon (1960, 1977) describes the decision-making process with the three and later four phases of intelligence, design, choice, and implementation. The intelligence phase includes identifying a problem and collecting decision-relevant information. In the design phase, the variables and their relationships are defined to build the decision model. In the choice phase, the actual decision is made by selecting and evaluating existing alternatives. The impact of the decision's success or failure is assessed in the final implementation phase (Simon, 1960, 1977). However, since humans have difficulty processing information relevant to decision-making due to their limited cognitive capacities, imperfect knowledge, and time constraints, the term "bounded rationality" was introduced (Simon, 1957). To cope with complex decision-making environments, decision support systems (DSS) assist users to solve semi-structured or unstructured tasks (Keen, 1980). The framework, by Gorry and Morton (1971), distinguishes between structured decisions that do not require decision support because they already have existing procedures and routines; semi-structured decisions that rely on DSS's analytical methods in combination with human judgement; and unstructured decisions that depend on the decision maker's expertise alone because there is no general decision procedure available. While DSS covers a wide range of subdomains, such as group and collaborative DSS, intelligent DSS (iDSS) refers to systems that incorporate AI techniques (Phillips-Wren, 2013). Mora et al. (2005) proposed a framework that assigns the intelligent capabilities of an iDSS to Simon's (1960, 1977) decision-making process. By using AI in the intelligence phase, data collection and problem identification can be performed jointly and automatically to determine the problem scheme. In the design phase, the intelligent capabilities enable organizations to automatically detect problematic decisional situations. During the choice phase, AI is applied to facilitate the selection of multiple alternatives in conjunction with explanatory features. In the implementation phase, intelligent capabilities support the execution of subsequent operational tasks (Mora et al., 2005). Thus, decision-making is no longer the sole responsibility of humans but can be augmented by AI by using iDSS.

3 Research Paper 1.A: Cultural Differences in Machine Learning Adoption

Title

Cultural Differences in Machine Learning Adoption: An International Comparison Between Germany and the United States

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Abstract

Taking the lead in artificial intelligence (AI) forms part of the national agenda of several countries. Despite the investment volume of other countries, Germany and the United States are superior in implementing AI applications due to their high number of early adopters. Therefore, one area of interest refers to the adoption of machine learning, as a subfield of AI, from a cultural and organizational perspective. Through qualitative research, this study explores how culture affects the technological, organizational, and environmental (TOE) determinants of machine learning adoption by conducting a comparative case study between Germany and the United States. Based on Hofstede's cultural dimensions and the TOE framework, the results of 21 expert interviews show that distinct cultural characteristics impact the TOE determinants. For instance, the varying extent of uncertainty avoidance results in different technological and environmental approaches. Germany tends to take preparatory actions for data management, while the low index of the United States is reflected in the absence of data protection regulations. By combining the TOE framework with a national culture construct, our study identifies cultural characteristics that influence machine learning adoption and, thus, could serve as a guideline for future cultural research and managerial decisions for machine learning adoption.

Keywords

Machine Learning Adoption, Cultural Influence, Cultural Dimensions, TOE Framework

3.1 Introduction

The race to become the leader of artificial intelligence (AI), stimulated by the aggressive adoption of this technology, is in full force. The first indicator refers to the maturity level of embracing digital technologies. According to McKinsey, the United States and China assume the leading role in digitalization since the digital and AI parts of the ICT sector cover 3.3% of GDP in the United States and 2.2% of GDP in China, while in Europe 1.7% of GDP accounts for digitalization. The investment volume is a further indicator as the American and Chinese AI R&D budgets are significantly larger than in Germany (German Federal Ministry for Economic Affairs and Climate Action, 2018; Groth et al., 2019). However, from the adoption perspective, a recent global AI study conducted by Deloitte shows that 24% of the AI early adopters in the United States are considered highly mature due to their large number of productive AI implementations, followed by 22% in Germany and only 11% in China (Loucks et al., 2019). Despite the massive differences in financial resources, Germany and United States assume a superior role in the adoption of mature AI applications. This fact leads to the assumption that besides the economic factors, organizational factors play an essential role for the adoption of AI applications.

Thus, from an information systems (IS) perspective, researchers have slowly started to examine measures and factors that influence the AI adoption rate from an organizational context. Pumplun et al. (2019) explicitly explored the organizational readiness factors for implementing AI technology by using the technology-organization-environment model (TOE), proposed by Tornatzky and Fleischer (1990). In contrast to this general approach, Kruse et al. (2019) focused particularly on the finance industry to identify drivers and inhibitors of AI adoption among finance service providers. Despite the fact that the organizational factors have come into focus in the race of AI, adoption rates across countries still vary significantly. Due to this tendency, the fact that culture is seen as a critical variable which influences how groups interact with IT, as Leidner and Kayworth (2006) proposed, becomes increasingly relevant in the context of AI. By examining the relationship between culture and AI, insights can be gained how countries differ in their approaches of implementing AI. Despite the fact that the United States and Germany are western countries and are considered early adopters of AI, their approaches of how to implement AI might differ due to their cultural differences. Prim et al. (2017) has classified Germany and the United States in two distinct clusters – planning and competing – with regard to their innovation capabilities, based on Hofstede’s (2001) cultural dimensions of power distance, uncertainty avoidance, individualism, masculinity, and long-term orientation. For instance, in terms of power distance, both countries have similar low-medium indices, indicating an equal distribution of power. However, there is a large gap in long-term orientation as Germany focuses on strategic long-term goals, while the United States emphasizes short-term financial success. As described above, it is widely recognized that the United States and Germany are superior in successfully implementing AI applications, whereas their cultural and organizational distinctions concerning AI adoption remain, to our knowledge, unexplored. Therefore, this study aims to examine the cultural differences associated with the unique factors of machine learning adoption, as a subfield of AI, within the technological, organizational, and environmental context between Germany and the United States. By using Hofstede's (2001) cultural dimensions in conjunction with the TOE model as the conceptual frameworks, we thus investigate the following research question: *How does culture influence the technological, organizational, and environmental determinants of machine learning adoption in Germany and the United States?*

As highlighted before, this study focuses on machine learning rather than on AI since the latter implies the broader study of intelligent agents that aim to maximize the chances of success by perceiving their environment and taking the best actions. Due to the fact that the intelligent agent can be any machine that mimics cognitive functions through learning abilities (Russell and Norvig, 2010), this study narrows its research focus on machine learning applications, as a subfield of AI. To be more precise, the term machine learning describes a concept that enables computers to learn based on large historical datasets rather than being explicitly programmed (Samuel, 1959) and is defined as "[a] computer program [that] is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E" (Mitchell, 1997, p. 2). The remainder of this paper is structured as follows: First, the theoretical background of the cultural dimensions and the TOE framework is described. After outlining the methodology of the exploratory case study, the results and the discussion are presented in detail. The final section outlines the contributions, limitations and proposes opportunities for future research.

3.2 Theoretical Background

3.2.1 Cultural Influence based on Hofstede's Dimensions

Even though the use and diffusion of technology is not limited to national boundaries, innovation adoption frameworks are not universally applicable in a cross-cultural context. Since cultural differences might influence the adoption rate of innovations, researchers emphasize the importance to connect these frameworks with national culture constructs (Keil et al., 2000;

McCoy et al., 2005; Martinsons and Davison, 2007). The existing literature on societal culture contains a variety of definitions including the definition by Kroeber and Kluckhohn (1952) whom describe culture from an anthropological point of view as a pattern of beliefs. According to the definition by Trompenaars and Hampden-Turner (1997), culture represents the common approach of a group of individuals to overcome problems and dilemmas whereby, Hofstede (2001) defines culture as “the collective programming of the mind that distinguishes the members of one group or category of people from another” (Hofstede, 2001, p. 9).

In addition to the definition, Hofstede (2001) proposed the following four main dimensions to highlight cultural differences: 1) power distance, 2) individualism 3) masculinity, 4) uncertainty avoidance. Besides this original set of dimensions, long-term orientation was subsequently added as the fifth dimension (Hofstede, 2001). A definition for each cultural dimension is provided in Table 3.

Cultural Dimensions	Definition
Power Distance	Extent to which less-powerful individuals accept the unequal distribution of power. In organizational terms, power distance is reflected by the interpersonal power between a superior and its subordinate and centralized decision structures.
Individualism	Degree to which individuals place their own needs above the sense of belonging to a group. In case that individuals are given greater autonomy within an organizational environment, they take their own responsibility.
Masculinity	Extent to which male characteristics such as assertiveness and material values dominate society. In contrast, female civilizations emphasize cooperation and generosity. Masculinity in organizations is expressed through competition and performance pressure.
Uncertainty Avoidance	Degree of tolerance for an ambiguous or unpredictable situation. In an organizational environment, uncertainty avoidance is, for instance, reflected in compliance with regulations.
Long-Term Orientation	Extent of encouraging the future by supporting perseverance and pragmatic approaches. Long-term oriented organizations believe in visions and promote experiments, while short-term oriented organizations emphasize on immediate results on a monthly, quarterly or annual basis.

Table 3. Hofstede’s (2001) cultural dimensions

By taking these cultural dimensions into account, the indices published by Hofstede (2001) reflect the preferences of certain affairs in different cultures. Table 4. presents the main cultural differences between Germany and the United States that have been identified by previous innovation studies.

Cultural Dimensions	Cultural Differences	References
Power Distance	**Germany: 35 – medium-low** A decentralized and consultative style prevails since the subordinate is able to participate in decisions due to his expertise.	(Hofstede, 2001; Prim et al., 2017)
	United States: 40 – medium-low Despite hierarchical structures inequalities are minimized since the subordinate is able to express and share his opinion freely.	(Griffith et al., 2000; Lee et al., 2013; Prim et al., 2017)
Individualism	**Germany: 67 – medium-high** Taking responsibility and working independently is considered as a prerequisite.	(Hofstede, 2001)
	United States: 91 – high Seeking information on their own, displaying strong initiatives and making independent decisions is common practice.	(Griffith et al., 2000; Dinev et al., 2009; Lee et al., 2013)
Masculinity	**Germany: 66 – medium-high** A strong sense of determination and assertiveness is required in order to achieve the expected performance.	(Hofstede, 2001)
	United States: 62 – medium-high The focus is on competition and ambition as rewards depend on performance and success.	(Srite and Karahanna, 2006; Dinev et al., 2009; Alshare et al., 2011)
Uncertainty Avoidance	**Germany: 65 – medium-high** The reduction of uncertainty and risks through formal laws, specific rules and precise procedures is preferred.	(Hofstede, 2001; Lee et al., 2013)
	United States: 46 – medium-low The willingness to accept higher risks promotes the emergence of new ideas and innovative products.	(Srite and Karahanna, 2006; Lee et al., 2013; Prim et al., 2017)
Long-Term Orientation	**Germany: 83 – high** The focus lies on long-term success and sustainability of the organization rather than on short-term achievements.	(Hofstede, 2001; Prim et al., 2017)
	United States: 26 – low The urge for short-term financial success in the form of profit and loss statements strives for immediate results.	(Hofstede, 2001; Prim et al., 2017)

Table 4. Cultural differences between Germany and the United States

3.2.2 Innovation Adoption based on TOE Framework

The origins of innovation adoption theory date back to 1962 when Rogers (1983) introduced the diffusion of innovation framework describing that the attributes of relative advantage, compatibility, complexity, trialability, and observability influence the acceptance rate of innovations. Since innovation adoption is a highly complex construct, further facets must be considered in addition to the technological and organizational view. In order to take external factors into account, the technology-environment-organization model (TOE), proposed by Tornatzky and Fleischer (1990), is ideally suited to examine the adoption of innovations on a firm-level (Oliveira and Martins, 2011). The **technological context** comprises the assessment of the internally available technologies compared to the new external innovations (Tornatzky and Fleischer, 1990). A strong indicator refers to *relative advantage* which determines the degree of superiority of an innovation over existing practices in regard to economic or social factors (Rogers, 1983). Previous studies have identified a positive association between relative advantage and innovation adoption in terms of efficiency increase (Tung and Rieck, 2005; Chandra and Kumar, 2018), cost reduction (Tung and Rieck, 2005; Borgman et al., 2013), and the achievement of competitive advantage (Tung and Rieck, 2005; W. Xu et al., 2017). Moreover, *compatibility* reflects the perception of whether an innovation is compatible with rooted values and customer-centric needs (Rogers, 1983). The assumption that firms are more willing to adopt innovations if there is a high level of compatibility with existing processes (Venkatesh and Bala, 2012; Gangwar et al., 2015; W. Xu et al., 2017; Pumplun et al., 2019) and existing technologies (Zhu, Dong, et al., 2006; Gangwar et al., 2015; W. Xu et al., 2017) has been positively supported. In addition, the availability of tools which are compatible with existing competences also contribute to the adoption of innovations (Rana et al., 2014). A further dimension of the technological context relates to *complexity* which affects the adoption rate by the perceived difficulty in understanding and using the innovation (Rogers, 1983). Since complexity is associated with a higher uncertainty of a successful implementation, the factor has a negative effect on adoption (Low et al., 2011; W. Xu et al., 2017). The **organizational context** encompasses the structures and processes of an enterprise that either challenge or drive the adoption of innovations (Tornatzky and Fleischer, 1990). The literature indicates that the availability of technological, human, and financial *resources* within an organization contributes to the likelihood of adopting innovations. Technological resources comprise, for example, the accessibility of data and bandwidth requirements (Gangwar et al., 2015; Pumplun et al., 2019), while from a human resource perspective the recruitment of competent talents and the knowledge base of non-IT employees and top management are considered as crucial factors (Thong, 1999; Gangwar et al., 2015; Gutierrez et al., 2015; Pumplun et al., 2019). In addition, it is necessary to provide sufficient financial resources to make adequate investments (Zhu et al., 2004; W. Xu et al., 2017). Furthermore, *top management* is regarded as a decisive driver for innovation adoption as the management level in particular contributes to the creation of a supportive atmosphere. As innovations are usually associated with refinement and complexity, efforts to spread a long-term vision, strengthen values and commit resources are essential to promote internal support while eliminating resistance (Borgman et al., 2013; W. Xu et al., 2017; Chandra and Kumar, 2018; Yoo and Kim, 2018). In addition, *company size* is considered as an important indicator since the assumption that larger organizations tend to adopt innovations more easily is justified by the higher availability of resources, more investments and the greater willingness to take risks (Thong, 1999; Zhu et al., 2004; Zhu, Dong, et al., 2006). According to Pumplun (2019) the choice between traditional and rigid organizational structures versus flexible set-ups in the form of central hubs might also have a great impact on the adoption of innovations. The **environmental context** describes the external circumstances to which a company is exposed in the conduct of its business (Tornatzky and Fleischer, 1990). *Legal regulations* are regarded as a influencing factor since data protection regulations, for example, are perceived controversially by organizations and users (Zhu, Dong, et al., 2006; Karunagaran et al., 2016; Yoo and Kim, 2018). Another environmental factor that influences the adoption rate is the *competitive pressure* that a company faces from its competitors (Lin and Lin, 2008; Karunagaran et al., 2016). As proposed by Porter and Millar (1985), innovations strengthen a company's competitive role by changing the industry structure and creating competitive advantages. Besides the competition, organizations also have to deal with the pressure arising from their *trading partners* which might have a positive effect on innovation adoption (Zhu, Dong, et al., 2006; Lin and Lin, 2008).

3.3 Methodology

Beyond the organizational context of existing literature, this study aims to examine the nascent phenomenon of machine learning adoption from a cultural perspective which has, to our knowledge, not yet been explored. In order to discover which cultural differences occur when implementing machine learning applications and to investigate more closely how cultural characteristics influence the technological, organizational, and environmental determinants, we believe that an explorative approach is the appropriate research design (Eisenhardt, 1989; Miles and Huberman, 1994). According to Yin (2014), a case study design is recommended when the study focuses on a "how" research question and the contemporary phenomenon is embedded in a real-life context. In addition, the case study design allows us to explore the perspectives of persons who are directly involved in the event. Based on Yin's (2014) argument that a case study is either explorative, descriptive or explanatory in nature, an explorative case study seems to be the appropriate method due to its inductive factor. In general, some sort of theory is used as a guidance to develop or extent a conceptual framework that might be validated in a future study (Sarker et al., 2018). Due to this reason, this study was designed as an exploratory case study since we are seeking to examine how cultural characteristics, expressed through Hofstede's (2001) cultural dimensions, influence the technological, organizational, and environmental determinants. This explorative approach allows us to extend the TOE framework for machine learning with cultural dimensions which should also be validated in further empirical studies. In order investigate the cultural differences, the comparative case study reporting type has been chosen as it enables the identification of differences across two case studies. Due to the assumption of cross-cultural contracting results, we refer to the theoretical replication when selecting the case studies (Yin, 2014). For our study, we chose Germany and the United States as the respective case studies because even though their machine learning applications are highly mature, they differ in their cultural characteristics. Thus, we aim to investigate how the cultural differences between the two countries influence the approaches of adopting machine learning applications from a technological, organizational, and environmental perspective.

ID	**Country**	**Position**	**ID**	**Country**	**Position**
E1	GER	Lead of Digitalization	E11	US	IT Senior Manager
E2	GER	Head of Data Science	E12	US	Founder
E3	GER	Coordinator of Big Data	E13	US	Technical Product Manager
E4	GER	Lead of Center for AI	E14	US	Senior Manager of Data Science
E5	GER	Team Lead of Data Science	E15	US	Lead of Data Science
E6	GER	Head of Data Architecture & Data Science	E16	US	Deputy State Chief Data Officer
E7	GER	Method and Process Manager	E17	US	Program Lead of Analytics
E8	GER	IT Project Manager	E18	US	Process Control Manager
E9	GER	Director of Data Science	E19	US	Software Engineer
E10	GER	IT Senior Manager	E20	US	Director of Data Architecture
			E21	US	Technical Project Manager

Table 5. Participant overview of the comparative case study

Due to the selection of Germany and the United States as the respective case studies, we have defined the geographical location of the headquarters, or the machine learning related department, of the organization as the main selection criterion. In addition, we paid attention that the participants are either citizens or residents of these countries. Since the explorative approach also requires that only people that participate in the process of machine learning adoption are included in the sample, we ensured that the experts are part of and have a leading position in a machine learning related department. Considering these selection criteria, the German sample consisted of ten participants, of which five experts were heads of the data science team, followed by the digitalization and IT department as shown in Table 5. The American sample consisted of eleven experts, whereas the breadth of positions was more diverse as they ranged from technical project managers to heads of data science, analytics and data architecture teams. The principal method of data collection was in-depth expert interviews which were conducted through a semi-structured interview guideline consisting of initial questions, the main section of the technological, organizational, and environmental determinants, and closing questions.

The data collection of the 21 in-depth expert interviews took place between May and August 2019 in the form of telephone interviews. A saturation of answers was noticed at 21 interviews as proposed by Eisenhardt (1989), indicating a valid dataset. The 17.5 hours of recorded expert interviews were transcribed after mutual agreement and analysed with the qualitative data analysis software MAXQDA. Taking the coding scheme into account, a two coding cycle has been applied as proposed by Saldaña (2009). The first coding cycle consisted of structural and descriptive coding in order to summarize an interview section, combined with magnitude coding that enabled the comparison between the German and the American samples based on the intensity level. In addition, value coding was used to detect the cultural differences based on the experts' values and beliefs. After combining codes by applying pattern coding within the second coding cycle, the codes of both samples were analysed through the group comparison and the code-relation-browser in MAXQDA (Saldaña, 2009). In order to ensure rigor and trustworthiness, the coding was critically discussed and reviewed by multiple IS researchers.

3.4 Results

3.4.1 Machine Learning Adoption based on Hofstede's Dimensions

The most relevant similarities and differences within Hofstede's (2001) cultural dimensions between Germany and the United States will be highlighted in Table 6. and explained below. The extent of the **power distance** reflects the involvement of the less powerful members, which was highlighted in the German sample in regard to the initiation of machine learning use cases. Six experts mentioned that the business units have the decision-making power to initiate machine learning use cases as the following example shows: "*The actual use cases arise from the respective business units"(E4)*. The strong engagement by the business units can be explained by their deep expert knowledge as described as follows: “*The concrete machine learning use cases typically arise from the business units because they are so specific that we do not even know that there may be a problem”(E2).*

POWER DISTANCE				**UNCERTAINTY AVOIDANCE**			
GER		**US**		**GER**		**US**	
Business unit	6	Top management	6	High preparation requirements	6	High preparation requirements	1
Top management for approval	4			Rigorous selection process	3	Rigorous selection process	1
IT team	3			Weak cloud adoption	3	High cloud adoption	4
Data science team	1			Standardization	3	IP protection	2
Digitalization team	1			Strong data privacy regulations	3	Weak data privacy regulations	7
				Legal topics	3		
				Ethical topics	1		
MASCULINITY				**LONG-TERM ORIENTATION**			
Competition	5	Competition	7	Strategic focus	4	Monetary benefit	5
Status in recruitment	2	Status in recruitment	3	Differentiating competency	2	Tradition-oriented	2
Status as leader	2			Future driver	2		
Number represents # of experts who have mentioned the content							

Table 6. Differences between Germany and the United States in respect to Hofstede's (2001) dimensions

The involvement of top management has been mentioned by four participants only in the context of strategic support and prioritization as expert 5 highlights: “*Top management might come in when such a topic has already been identified. Then, the top management […] gives it a high priority”(E5).* In contrast, in the United States a top management-driven selection process of machine learning initiatives has been observed in the statements of six experts as illustrated in the following example: *“In almost all of our cases in the last two years, the CEO and people on the C-level have been involved in the initial discussion and they were driving those initiatives down to the business unit”(E12).* Therefore, a top-down management style dominates in American organizations when determining the machine learning use case which was also stated by expert 14: *“There was definitely a very top-down management style […]”(E14).*

In relation to **masculinity** five German experts have commented that competition is perceived as a fierce factor for the adoption of machine learning because "*you always read what others do and especially in the area of machine learning it is very motivating"(E6)*. In addition, Germany is a status-driven country that aims to assume a leading role as described by expert 4: *"The decisive players on the market are concerned with the topic. We believe that we have a very good position in the industrial context and play a leading role [...]"(E4).* Masculinity is also expressed through the dominance in talent acquisition as highlighted in the following example: *"In fact, it is noticeable that the market for real AI experts is scarce and the competition among the key players is really big. We have a very rigorous selection process, which is very time-consuming on our part, but ensures that the quality level and fit to the team can be maintained"(E4)*. The United States reacts relatively similar in terms of masculinity since the high level of competitive pressure has been mentioned by seven participants as *"there is definitely an arm race for AI and machine learning right now"(E21)* and *"we know that the Silicon Valley giants already have that technology"(E13)*. However, a tendency of falling behind the leader in machine learning has also been noticed through statements such as *"We are expanding our machine learning because some of these places were already a little further ahead than we were in the United States"(E18).* In terms of talent acquisition, the connection to universities is viewed as an advantage as stated by expert 16: *"We have a very close relationship [...] and are therefore in their talent pipeline to pick the best graduate"(E16)*.

The extent of **uncertainty avoidance** in the German sample was mainly reflected by the need for preparatory activities prior to the start of machine learning projects. A frequently cited example refers to the preparation of data as *"our data structures and databases have not been designed for AI in recent years and therefore, you first have to clean them up before you can carry out such an AI project"(E8).* In addition, Germany tends to follow a relative rigorous and strict selection process of machine learning use cases to pursue only the promising machine learning projects that ultimately lead to success as stated by expert 5: *"[...] we should concentrate even more on the so-called fail fast. This allows us to quickly find out at the beginning what is not working and not to waste time on projects that are of no use at the end"(E5)*. Besides the need for technical standardization, Germany faces some major challenges in the acceptance of cloud systems since data protection and data transfer in particular are critical factors in operating machine learning models in the cloud, because "*the cloud risk process means that before you enter information into the cloud, you have to go through a risk assessment process in order to clarify how high the risk is that we are taking when transferring the data into the cloud"(E7).* In relation to the General Data Protection

Regulation (GDPR), which was passed in 2018 within the European Union, the predominant way of thinking was that *"we first want to create a basis and to regulate topics like GDPR and do not follow the approach of others who deal with it in parallel and get into a data scandal"(E1).* In addition to fulfilling legal requirements, the ethical implications are also considered highly important as illustrated by the following example: *"Our machine learning application respects human autonomy, prevents all kinds of damage, protects individual freedom, strives for interpretability, does not discriminate, assumes social responsibility and is designed to be externally auditable"(E9)*. In contrast, the United States is very advanced in deploying cloud systems as the statement of expert 11 describes the trend of American companies to accept cloud technology as follows: *"I think there has been a big change since now we are much more open towards cloud storage solutions"(E11)*. In terms of regulations, expressions such as *"The US is actually a little bit behind Europe in terms of how they think about machine learning as needing regulations"(E15)* demonstrates that the United States has not passed a central data protection law prohibiting the disclosure and misuse of personal data as strict as in the European Union. Even though the absence of data privacy regulations might not be a showstopper for machine learning, there are major concerns about the intellectual property protection since "*We do not want competitors to be able to see the data that we are collecting and what the results are"(E11).*

With respect to **long-term orientation** the implementation of machine learning in German organizations is regarded as a strategic focus and thus paves the way to a leading position in this field as described by expert 6: *"We have a corporate strategy and part of it is that we want to be the digital leader in the industry."(E6).* In addition, two German experts perceive machine learning to be a competency that enables them to differentiate themselves from their competitors by stating that, for example, the *"[...] final goal is to be a data-driven company [...]and the implementation of machine learning as the driving force for the strategic orientation"(E4).* Especially, from a long-term perspective, machine learning is regarded as a future driver and the leading technology in Germany for the near future since "*[...] machine learning will be one of the core methods for maintaining sustainability. We assume that within 10 years all of our products have either machine learning in the development process or are actually incorporated in the functionality"(E4)*. In contrast to Germany's long-term-oriented mindset, the United States is characterized by its strong focus on short-term performance goals. Five participants highlighted the monetary benefit that can be achieved through the use of machine learning by stating: "*Honestly it is about monetary and time saving"(E18)* and *"They see the opportunity to increase profit and reduce costs"(E11).* Since the short-term financial success of machine learning is closely monitored in the United States and *"some of the concepts have been proven that you can actually derive some monetary benefit from it. I think the support of the management level is definitely increasing […]"(E11).*

It must be noted that no insights have been found in regard to individualism since the implementation of machine learning is not influenced through the bond of individuals.

3.4.2 Machine Learning Adoption based on TOE Framework

Due to the unique approaches in adopting machine learning applications, the crucial technological, organizational, and environmental determinants will be presented in Table 7. and elaborated below. With regard to the **technological context**, the *relative advantage* of implementing machine learning refer to superiority, cost reduction and efficiency increase in both countries but differ in their specifications. In Germany, superiority is mainly driven by a strategic and future-oriented motivation as well as growth potential through the adoption of machine learning as indicated by expert 3: *"We are hoping for more growth opportunities"(E3)*, while in the United States machine learning is used to *"establish a further competitive advantage"(E12).*

Technology								
RELATIVE ADVANTAGE			**COMPATIBILITY**			**COMPLEXITY**		
	GER	**US**		**GER**	**US**		**GER**	**US**
Motives			**Integration**			**Employee Reaction**		
Superiority	6	4	Process integration	2	2	Pushers	7	5
Cost reduction	6	7	System integration	6	9	Skeptics	8	8
Efficiency	8	8	Feedback loop	4	3	**Interpretability**		
Data Analytics Purposes			**Tools**			In place	4	8
Human vs machine	6	8	Open- source libraries	4	6	Planned	2	0
Pattern recognition	4	2	Commercial tools	6	4	Research topics	1	0
Organization								
RESOURCES			**TOP MANAGEMENT**			**FIRM SIZE**		
Data Management			**Top Management Interest**			**Large Firm Size**		
Centralization: good	7	1	Future competence	5	1	More investment	4	4
Ownership: good	5	3	Value add	5	2	More know-how	1	3
Access/transfer: good	5	8	**Machine Learning Strategy**			High data volume	2	2
Quantity: good	8	7	Strategy: yes	7	9	Better recruitment	1	0

Quality: poor	8	9	Strategy: no	3	0	More risk averse	4	0
Talent Acquisition			**Top Management Participation**			Pressure on vendor	0	2
Recruitment: good	5	2	Participation: high	0	6	Change difficult	0	1
Recruitment: poor	4	7	Participation: low	4	0	**Small Firm Size**		
Non-IT Knowledge			**Top Management Knowledge**			Less bureaucracy	0	1
Rating scale: >5	5	1	Knowledge: good	6	7	Vision by CEO	0	2
Rating scale: 2-4	7	8	Knowledge: low	2	1	No impact	3	2
Rating scale: <1	5	2				**ORG. STRUCTURE**		
Financial Resources						**Centralized**		
Support: enough	9	6				Data scientist team	6	5
Support: not enough	0	4				Analytics team	2	4
						Decentralized		
						In business units	5	2
Environment								
REGULATIONS			**COMPETITION**			**TRADING PARTNERS**		
Data Protection Regulation			**Competition Type**			**Vendor Selection Criteria**		
Sensitive data: yes	2	4	Direct	3	6	Support	2	1
Sensitive data: no	4	2	Indirect	5	2	Expertise	1	0
GDPR: compliant	4	1				Accuracy	1	1
GDPR: not existing	0	6				Costs	1	0
Number represents # of experts who have mentioned the content								

Table 7. Differences between Germany and the United States in respect to the TOE framework

Furthermore, both countries aim to reduce their costs through the use of machine learning by reducing efforts and optimizing processes, as well as to enhance efficiency by handling larger amount of data, reducing error rates, and an increase in speed compared to humans. Another relative advantage relates to the purpose of data analysis, as the majority of the two samples consider the augmentation of human activities through machine learning capabilities to be a significant advantage as they aim to *“relieve people of the slightly stupid tasks that machines can do better anyway”(E5).* Fewer experts see the advantages in facilitating pattern recognition. In terms of *compatibility*, the majority of the two samples assessed integration into existing systems as mandatory, whereby four German and three American experts additionally described a feedback loop as essential for the training of machine learning models with real-time data. With regard to the availability of tools, it was striking that German organizations mainly rely on open source libraries such as TensorFlow, SciPy, and Scikit-learn, while the United States show a clear preference for commercially available machine learning tools. *Complexity* was mainly expressed through the anticipated employee reaction which encountered an even distribution between pushers and skeptics in both countries. Machine learning is particularly appreciated by employees when it simplifies human tasks by taking over manual work, as described by expert 13: *"Most of them were excited to have it because it really decreases their workload"(E13)*. On the other side, machine learning is also rejected by employees due to the immense fear of being replaced and the lack of trust and knowledge, especially among older generations who did not grow up as digital natives. To reduce complexity, eight American experts stated that they have already incorporated interpretability capabilities as it increases user acceptance when they *"know how the algorithm functions"(E13)*, while three German experts mentioned that they are only in the planning or research phase.

Within the **organizational context**, major differences were identified in the allocation of *resources*. From the perspective of technological resource, the handling of data management plays a decisive role when implementing machine learning applications. Seven German experts believe that efforts on data centralization have a positive impact on machine learning adoption since *"the aim of an enterprise data lake is to have the most important data all in one rather than at different places"(E9)*. In addition, data ownership as well as data access and transfer have been assessed as being well advanced by both countries. In terms of the data transfer, the United States clearly benefits from its high affinity towards cloud computing for processing and storing data. In addition, the majority of the two samples indicated that their chosen data type generates sufficient data volume. The greatest issue, however, lies in data quality as mentioned by eight German and nine American experts. Data quality problems are mainly caused by data incompletion *"in terms of missing values"(E19)* and by capturing incorrect data as described by expert 12: *"It is not a very high quality, it is not very clean because there is a lot of sensor noise"(E12).* When considering human resources, the experience in talent acquisition was perceived differently since five German experts shared the opinion that there are enough competent machine learning talents on the market, whereas American organizations are facing a lack of specialized applicants. Potential reasons for the poor hiring rate relates to the shortage of qualified people and the fierce competition between the high-tech big players in the recruitment of data scientists as expert 20 describes: *"It seems like that all the young and* *energetic data scientists are not interested in the oil and gas industry as much as in the blooming tech industry such as Facebook and Uber"(E20).* Nevertheless, American organizations tend to seek proximity to universities to attract new graduates, whereby a lower seniority level is considered as a downside. With regard to the non-IT staff, the majority of the two samples rated their machine learning knowledge between 2-4. In order to deepen their knowledge, both samples offer dedicated machine learning or digitalization trainings for their employees, which are supplemented by a more informal exchange of experiences in Germany. As part of the resources, the financial support has been positively assessed by nine German experts, while four American experts claimed that they did not have sufficient financial support. In terms of top management commitment, the majority of the German experts share the view that the top management adopts machine learning primarily because *"they really expect added value from it"(E6)* and aim to establish a future competence. From a strategic perspective, seven German and nine American participants claimed that a dedicated strategy for machine learning is in place by stating that *"yes, it is anchored in our strategy that AI and machine learning are important and that certain measures have to be implemented"(E9)*. As far as top management participation is concerned, the United States has experienced a more active involvement, while in Germany it is described as more supportive. The knowledge of the top management is described as solid, but at a high-level, in both samples. Taking the *firm size* into account, the advantages of larger firms in terms of investment, personnel, provisioning of data and risks management have been shared by both countries. The majority of both samples has set up a centralized data science team to promote machine learning projects as part of their organizational structure.

Within the **environmental context**, different approaches to the data protection regulations can be observed as the United States particulary relies on sensitive data to train its machine learning models while German experts claimed to dispense sensitive data. Even though Germany uses mainly insensitive data, four experts stated that one of their biggest concern is the compliance with GDPR as the following examples shows: *"GDPR is definitely a topic. […] GDPR is absolutely meaningful and good"(E4)*. In contrast, the United States, despite the fact that it uses sensitive data, has not passed an equivalent data protection law as described by expert 16: *"We do not have GDPR, only California in the US has something similar to that today"(E16)*. A further external factor that can influence the machine learning adoption rate refers to competition. In Germany, indirect competition is mostly present due to pressure to increase efficiency and reduce costs as expert 2 points out: *"I see it rather that competitive pressure generally causes cost pressure, which makes one think about possibilities such as machine* *learning […]"(E2)*. The majority of the American sample, however, is exposed to direct competition since the organizations face pressure from their competitors who are more advanced in implementing machine learning. Both samples select their vendors based on support availability, the level of expertise, the prediction accuracy and the corresponding costs when choosing trading partners.

3.5 Discussion

In terms of the conceptual framework, our study reveals that certain machine learning characteristics have been identified which should be additionally complemented to the TOE model. In accordance with the literature review, our qualitative research shows that the following technological, organizational, and environmental determinants, derived from previous innovation studies (2006; Venkatesh and Bala, 2012; W. Xu et al., 2017; Chandra and Kumar, 2018) are of great importance for machine learning adoption: relative advantage (motives), compatibility (integration), complexity (understanding), resources (talent acquisition, non-IT knowledge, financial resources), top management (interest, strategy, participation, knowledge), firm size, regulations, competition, and trading partners. However, based on our findings, we have identified additional machine learning related factors within these determinants as well as distinct specifications which will be elaborated in the following. Besides considering efficiency improvement and cost reduction as the only *relative advantages* of the technological context, the implementation of machine learning applications enables organizations also to achieve superiority through strategic positioning and growth potential. Furthermore, the purpose from a data analytics point of view can also contribute to the adoption rate since either the augmentation of human capabilities or pattern recognition is considered a priority. The *compatibility* determinant should also be extended by a feedback loop integration as this capability allows machine learning models to be automatically trained with a consistent flow of real-time data. As suggested by Rana et al. (2014), our study shows that the choice of machine learning tools in the sense of open-source libraries or commercial products can also have an impact on the likelihood of adopting machine learning applications. Since machine learning applications usually act as a black box, interpretation capabilities reduce the level of *complexity* and allow users to better understand the results which consequently increases the adoption rate. As highlighted by Pumplun (2019), data is regarded as one of the most essential *resources* from an organizational perspective when dealing with machine learning applications. This study agreed that the success of a machine learning implementation depends on the data management as data centralization, ownership, access, and transfer as well as quantity and quality are crucial components of machine learning applications. Moreover, our study shows that the *organizational structure* of a centralized or decentralized data science team can have an effect on the adoption rate which was also suggested by Pumplun (2019). Since data is regarded as one of the major resources in machine learning applications, the impact of data protection regulations must be explicitly assessed within the environmental context (Kruse et al., 2019; Pumplun et al., 2019).

By considering Hofstede's (2001) cultural dimensions, our study is able to highlight the cultural differences between Germany and the United States which affect the distinct approaches of machine learning adoption in regards to the technological, organizational, and environmental context as shown in Figure 1. In terms of power distance, our study shows that the extent of this cultural dimension has a direct effect on the participation of top management in the initiation of machine learning use cases. Due to the medium-low power distance index of 35, a low participation of top management in German organizations can be observed since business units on the lower hierarchical levels are strongly involved in strategic decisions on which machine learning use cases should be initiated, while top management only acts as a supporting role. In contrast, the preference of the United States for structures and precise specifications from top management, as indicated by the medium-low power distance index of 40, is fully reflected in our findings.

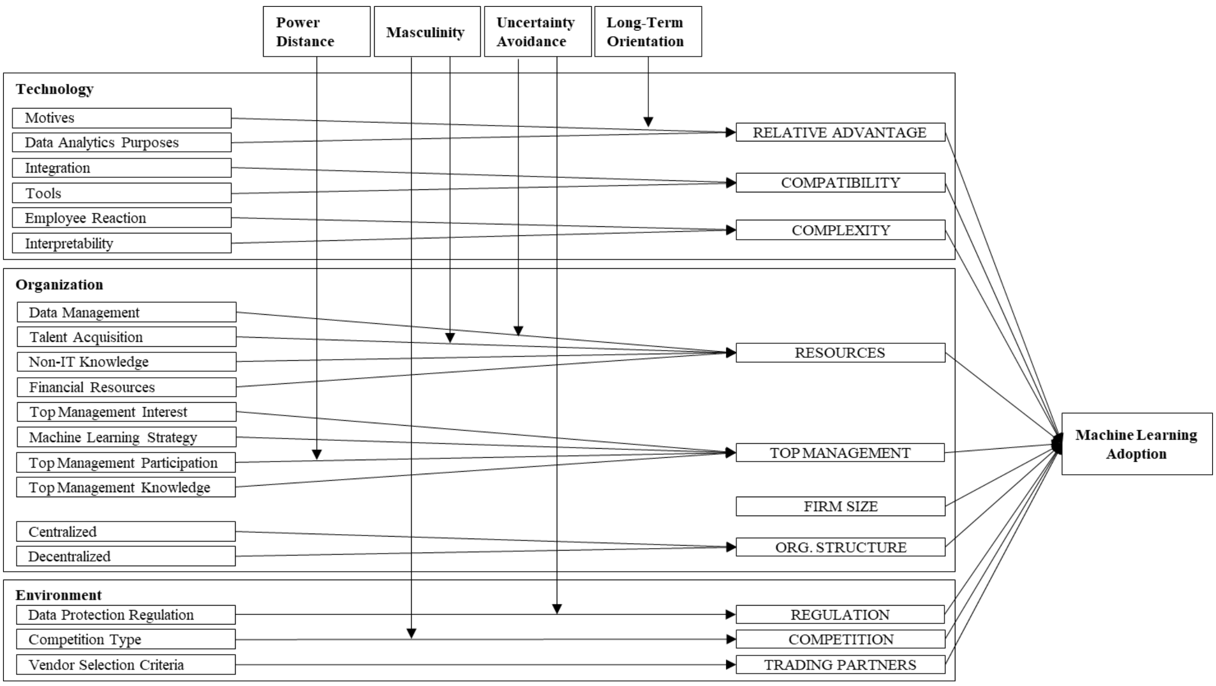

Figure 1. Cultural impact on the TOE framework for machine learning adoption

Despite the fact that the difference between the power distance indices is only 5 points, our study demonstrates that American organizations rely more strongly on the strategic decisions of top management, while the lower hierarchical levels are hardly assigned any decision-making power. Based on these results, it can be stated that due to the extent of power distance, the degree of top management participation and the distribution of decision-making powers across the hierarchical structures varies across these countries and thus influences machine learning adoption in a different way.

Furthermore, we have identified masculine characteristics in the course of implementing machine learning applications that reinforce competitive pressure. With a medium-high masculinity index of 66, German organizations tend to primarily count on machine learning applications to counteract indirect pressure of efficiency increase and cost reduction. In addition, masculinity has also been noted in the area of talent acquisition since German organizations believe to assume a dominant position in attracting and recruiting machine learning experts. Unlike Germany, the assertive and competitive behavior of the United States, with a medium-high masculinity index of 62, was mainly reflected in the direct competition of machine learning advancements between other organizations in the industry. Instead of assuming a dominant role in recruitment, American organizations face a fierce competition in talent acquisition in the field of machine learning. In line with similar masculinity indices in both countries, the study reveals that the masculine behavior influences the degree of competition and talent acquisition in Germany and the United States, while differences in regard to the competition types remain.

In terms of uncertainty avoidance, our study demonstrates that the gap of indices is also reflected in the way these countries handle data management and comply with regulations which are regarded as crucial factors for machine learning. With a medium-high index of 65, Germany has a tendency to avoid uncertainty by taking a set of preparatory actions in data management before implementing machine learning. In case that requirements for data management are assessed as inadequate, German organizations tend to discontinue machine learning projects rather than to risk anticipated failures. The same behavior occurs in the environmental context of regulations, as Germany is amongst the countries with the highest priority in data protection and therefore pays particular attention of being compliant with GDPR even though sensitive data is hardly used in any machine learning models. The approach of the United States, indicated by a medium-low index of 46, contradicts this strong degree of uncertainty avoidance and encourages the emergence of new ideas and innovations. This tendency was also observed in our qualitative research, as the high maturity rate of cloud systems in the United States has a positive effect on machine learning adoption. To be more precise, the United States is relatively advanced in the deployment of cloud systems for data storage and transfer and has minimal concerns about the risks of data protection in cloud-based systems, which strengthens data management. The same behavior is evident in the enforcement of effective data protection rules as the United States has not yet passed a central law against the misuse of personal data and currently pays minimal attention to regulations or restrictions. Thus, the great gap of uncertainty avoidance indices has been reflected in the different approaches of data management and regulations of the two countries.

Furthermore, our study reveals that the large discrepancies in the indices of long-term orientation between both countries have a great impact on the motives for implementing machine learning applications in organizations. The future orientation and highly pragmatic attitude of Germany, expressed by the high index of 83, reinforces the tendency to focus on long-term motives of achieving superiority. To be more precise, German organizations perceive machine learning as a strategic and future-oriented technology that has the potential to gain momentum in multiple areas. By taking a leading role in machine learning at an early stage, they believe they can differentiate themselves from other competitors and thus benefit from the strategic orientation and growth potential. In addition, the high extent of long-term orientation has a great effect on the interest of top management, as the management level relies on the implementation of machine learning to build future competencies. In the United States an urge for short-term financial success was observed, expressed by the low index of 26. Rather than focusing on long-term goals, the main motives of American organizations to implement machine learning applications are cost reduction and profit improvement.

Summarizing these qualitative results, it can be concluded that cultural differences, expressed through Hofstede’s (2001) cultural dimensions, exist in the way that Germany and the United States implement machine learning applications in a different way without judging which approach performs better. This qualitative study has examined the cultural impact on machine learning and indicated that power distance, masculinity, uncertainty avoidance, and long-term orientation influence the determinants of relative advantage, resources, top management, regulations, and competition.

3.6 Contributions, Limitations, and Future Research

The comparative case study between Germany and the United States with regard to machine learning adoption from a cultural and organizational perspective makes several contributions to research and practice. First, this study extends the TOE framework with machine learning specific factors and specifications. Second, by incorporating Hofstede's (2001) cultural dimension, as a national culture construct onto the TOE framework, this study advances the machine learning adoption research with cultural implications. In particular, this study determines distinct cultural characteristics of Germany and the United States that have an impact on relative advantage, resources, top management, regulations and competition. Third, these findings help practitioners of multinational companies to promote the progress of machine learning adoption by taking the distinct cultural and organizational factors into account when implementing machine learning applications.

Even though this study provides added value for academia, we are aware of certain limitations which can be addressed in future research. Since the case study design focuses solely on western countries, the results are restricted in terms of generalizability and may therefore not be representative for other cultures. In addition, even though the selection of the participants was based on their citizenship or residency, their cultural backgrounds in terms of their beliefs, value, and ethics could also have an impact on their perceptions of machine learning adoption. Due to these limitations, future research could expand the case study design by including Asian and emerging countries. Furthermore, we encourage researchers to validate the impact of the identified cultural dimensions on the technological, organizational, and environmental determinants through a quantitative study in order to obtain further cultural and organizational insights on a larger scale.

4 Research Paper 1.B: Organizational Readiness Concept for AI

Title

Organizational Readiness Concept for AI: A Quantitative Analysis of a Multi-stage Adoption Process from the Perspective of Data Scientists

Authors

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Abstract

Artificial intelligence (AI) is reshaping the business world in ways that enable organizations to create business value and reinvent their business models. Despite the great potential, organizations have difficulties in moving beyond the pilot stage and fully adopting AI applications. To better understand how organizations can implement AI into their core practices, we examine the impact of organizational readiness factors along the adoption process of AI through a quantitative research design. By integrating the organizational readiness factors into the multi-stage adoption process of AI, we unpack the interdependencies between these two literature streams. Due to the multi-faceted nature of organizations, we investigate the differentiating and opposing effects of the organizational readiness factors on the initiation, adoption, and routinization stages of AI.

Keywords

Artificial Intelligence, Organizational Readiness, Adoption Process

4.1 Introduction

The race to adopt AI in organizations is in its full swing as it provides organizations the opportunity to generate new business value and disrupt their business models (Brynjolfsson and Mcafee, 2017). In particular, by implementing AI, organizations are able to turn their data into value (Davenport, 2018a), develop new products and services (Davenport and Ronanki, 2018; Ransbotham et al., 2019), and improve operational efficiency through data-driven decision-making (Brynjolfsson et al., 2011). Due to its disruptive potential, AI has been deployed in various industries and sectors, including finance (e.g., Fu et al., 2021), healthcare (e.g., Hofmann et al., 2019), and human resources (e.g., Black and van Esch, 2020). Given the business impact, AI is considered one of the most promising innovations to remain competitive in the digital age (Seddon et al., 2017; Dremel et al., 2020; May et al., 2020). However, while 50% of the 2,395 participants in a global survey on the state of AI in 2020 stated that their organizations have adopted AI applications in business processes or products, only 16% have implemented AI beyond the pilot stage (Balakrishnan et al., 2020). These findings imply that organizations are still struggling to pass the pilot stage in which AI applications are implemented only in ad hoc pilots rather than being rolled out into enterprise-wide programs. Therefore, the adoption rate of AI does not necessarily reflect that AI applications are fully embedded in core practices. The tendency of not moving beyond the pilot stage indicates that AI poses new challenges to organizations compared to other technologies. Based on the concept of intelligent agents (Russell and Norvig, 2021), AI applications are able to self-learn and make autonomous decisions (Berente et al., 2021). As these given capabilities increase the degree of inscrutability (Berente et al., 2021), associated changes at the task level ultimately affect the human decision-making process. While decisions are no longer made exclusively by humans but are augmented by AI, human-machine collaboration becomes increasingly important for organizations. In order to fulfil new requirements posed by innovations, literature particularly emphasizes to promote organizational readiness (Weiner, 2009; Lokuge et al., 2018; Nguyen et al., 2019). Weiner (2009) argues that organizational readiness is an essential precursor for successful implementations of complex changes as an organization’s change commitment and change efficacy directly influence adoption rates. Despite its great importance, organizational readiness has not yet been extensively empirically studied in research (Weiner, 2009; Lokuge et al., 2018) and, particularly in relation to AI, very little is known about the organizational readiness factors that influence the adoption process of AI. Since only qualitative studies provided theoretical groundwork on the organizational readiness factors for AI (e.g., Kruse et al., 2019; Pumplun et al., 2019; Eitle and Buxmann, 2020), we aim to respond to the research call by Jöhnk et al. (2021) to validate the organizational readiness concept for AI. Furthermore, the indication that adoption rates do not necessarily reflect the full implementation of AI applications demonstrates that the decision-making process for AI adoption is far from trivial. Recent studies tend to treat the adoption of AI applications as a single stage of adoption or non-adoption (Kruse et al., 2019; Pumplun et al., 2019; Eitle and Buxmann, 2020), rather than viewing it as a multi-stage adoption process (Cooper and Zmud, 1990). This binary approach is too short-sighted from a theoretical point of view as the limitation to an one-time adoption decision does not reflect whether an innovation is fully incorporated into the organization and its work routines (Fichman, 2000; Zhu, Kraemer, et al., 2006). The extensions to a multi-stage approach can provide profound insights into the influencing factors along the entire adoption process. Since most organizations fail in moving beyond the pilot stage, there is an urgent need for research to investigate the differentiating and opposing effects of the organizational readiness factors on the initiation, adoption, and routinization stages of AI (Cooper and Zmud, 1990). While the initiation stage involves initial assessments, the adoption stage refers to activities for implementing AI applications. The routinization stage deals with the incorporation of AI applications into work routines (e.g., Zhu, Kraemer, et al., 2006; Martins et al., 2016). To provide guidance to research and practice, our study seeks to take the entire adoption process into account and provide empirical evidence on the influence of the organizational readiness factors on the adoption stages of AI. Hence, we answer the following research question:

RQ: What organizational readiness factors affect the adoption process of AI and how do they differ across the initiation, adoption, and routinization stages?

In total, 250 respondents participated in our online survey that examines the impact of organizational readiness factors on the adoption process of AI. To the best of our knowledge, we are among the first researchers who address the research call by Jöhnk et al. (2021) to validate the organizational readiness concept for AI using a quantitative research design. As a practical guidance for managers, we recommend, for example, that functional teams should be directly involved in the initiation stage of AI.

4.2 Theoretical Background

4.2.1 Artificial Intelligence

Previous research has not reached a consensus on a uniform definition of AI. In our study, the notion of AI is associated with the concept of an intelligent agent “that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators" (Russell and Norvig, 2021, p. 54). By this definition, AI is not a single application, but rather an agent function that has the ability to learn and act autonomously in a dedicated context. Thus, an AI application performs cognitive functions that can be associated with human thinking, such as self-learning and decision-making (Rai et al., 2009; Berente et al., 2021). Given these unique capabilities, AI comprises machine learning, robotic process automation, and rule-based expert systems (Benbya et al., 2021; Collins et al., 2021). Since the spectrum of application scenarios at the organizational level and across industries is relatively broad, AI is regarded as a general-purpose technology (GPT) that requires purpose-specific considerations (Brynjolfsson et al., 2017; Jöhnk et al., 2021). Due to the unique AI capabilities of self-learning and autonomous decision-making, the sole human responsibility for certain tasks shifts to a human-machine collaboration (Sturm et al., 2021). This change in responsibility leads to an increased level of inscrutability (Berente et al., 2021) which requires context-specific considerations (Jöhnk et al., 2021).

4.2.2 Organizational Readiness for Change

To emphasize the distinction between our study and previous research on organizational readiness, adoption process, and AI adoption, we conducted a literature review as shown in Table 8.

			Alsheibani et al., (2018)	Alsheibani et al., (2019)	Anton et al., (2020)	Eitle & Buxmann, (2020)	Fukas et al., (2021)	Hamm & Klesel (2021)	Holmström, (2021)	Jöhnk et al., (2021)	Kruse et al., (2019)	Laut et al., (2021)	Pumplun et al., (2019)	Pumplun et al., (2021)	Radhakrishnan & Gupta (2021)	Stecher et al., (2020)
Framework or theory		TOE framework	x			x					x	x	x	x		
		Readiness								x						
		Scorecard							x							
		Maturity models		x			x									
		Resource-based														x
Methodology	**Qualitative**	Literature review						x							x	
		Interviews				x				x	x		x	x		
		Design science		x			x									
		Case study													x	
		Comparative										x				

		Mix-method			x											
	SEM															x

Table 8. Literature review

As outlined in the literature review, a variety of different frameworks can be used to study AI adoption, indicating that there is no one-size-fits-all theory. However, since the well-established TOE framework by Tornatzky and Fleischer (1990) only considers generic factors, Jöhnk et al. (2021) argue that the organizational readiness concept is particularly suited to address the purpose and context-specific factors of AI. In light of this consideration, we use the organizational readiness concept for our subject of study. To be more precise on the theoretical foundation, the organizational readiness concept has been applied in Information Systems (IS) literature primarily to examine the degree to which organizations are prepared to adopt new technologies (Lokuge et al., 2018; Nguyen et al., 2019; Jöhnk et al., 2021). Drawing from organizational change literature, organizational readiness reflects a state in which an organization is structurally and psychologically prepared for the upcoming change (Weiner et al., 2008; Weiner, 2009; Lokuge et al., 2018). Rather than focusing solely on structural readiness in terms of human, financial, and material resources, Weiner (2009) suggests that the psychological state (e.g., willing and able) should be considered primarily. According to his research, the concept of organizational readiness is determined by the shared commitment of organizational members to implement change as well as by change efficacy which refers to the shared belief in existing capabilities (Weiner et al., 2008; Weiner, 2009; Lokuge et al., 2018). To be more precise, organizational commitment is reflected in change variance which specifies how organizational members collectively value the change, while change efficacy refers to the assessment of available human, financial, and material resources. The study by Nguyen et al. (2019) suggests considering both structural and psychological perspectives when examining organizational readiness factors by assessing digital assets, digital capabilities, and digital commitment. The combination of both readiness states is proposed primarily because the multi-faceted nature of organizational assets is too complex to measure their assessment solely as part of change efficacy. Since previous studies on organizational readiness (Weiner et al., 2008; Weiner, 2009; Nguyen et al., 2019) provide inconsistent organizational readiness factors, there is a strong need for empirical research to discuss the influencing factors from a theoretical perspective and validate the organizational readiness concept. Particularly in the context of AI, organizations need to be structurally and psychologically prepared for the major changes imposed by the unique AI capabilities of self-learning and autonomous decision-making (Berente et al., 2021). These significant changes can create uncertainties for organizations that can prevent them from moving beyond the initiation stage. Consequently, the organizational readiness concept is particularly appropriate for assessing the organizational state of preparation to leverage the potential of AI.

4.2.3 Adoption Process

Research on AI adoption belongs to the diffusion of innovation literature stream (Meyer and Goes, 1988; Cooper and Zmud, 1990; Rogers, 1995) which assumes that the adoption of an innovation occurs over time rather than in an immediate act. Instead of following a multi-stage adoption process approach, a relatively large number of empirical studies on innovation adoption (Zhu et al., 2003; Tung and Rieck, 2005; Venkatesh and Bala, 2012; Borgman et al., 2013; Gutierrez et al., 2015) consider the adoption decision as a single stage of either adoption or non-adoption. Limiting the adoption decision to only one stage makes it nearly impossible to empirically assess differentiating and opposing effects along the entire adoption process (Damanpour and Schneider, 2006; Zhu, Kraemer, et al., 2006). Since the implementation of innovation can be dynamic und volatile throughout the adoption process, influencing factors might affect only certain adoption process stages or even exhibit opposing effects (Fichman, 2000). For this purpose, Cooper and Zmud (1990) proposed initially a six-stage adoption process model that comprises the initiation, adoption, adaption, acceptance, routinization, and infusion stages. To be more precise, while the initiation stage formulates the problem statement, the adoption stage refers to decisions regarding resource allocation. The adaption stage includes the development and implementation of the innovation, followed by the acceptance stage in which the actual usage is in focus. While the routinization stage involves incorporating the innovation into work routines, the resulting efficiency gains are reflected in the infusion stage (Cooper and Zmud, 1990). In IS literature, however, the three-stage adoption process model consisting of the initiation, adoption, and routinization stages has gained acceptance in place of the detailed six adoption process stages (e.g., Zhu, Kraemer, et al., 2006; Wu and Chuang, 2010; Martins et al., 2016). To follow the widely recognized multi-stage adoption process, we applied the three adoption process stages to the context of AI primarily because the changes regarding the dynamic and volatile environment and the responsibilities imposed by AI applications affect the overall AI adoption process. Organizations need to prepare for these changes to move beyond the pilot stage and successfully implement AI. Particularly the AI capabilities of self-learning and autonomous decision-making determine the influencing factors for AI which, however, may have differentiating or opposing effects on each adoption process stage. To be more precise, we define the adoption process stages of AI as follows: (1) the *initiation* stage addresses the identification of AI use cases and the technical assessment of AI applications, (2) the *adoption* stage involves the decision-making on the allocation of technological, human, and financial resources as well as on the execution of implementation activities, (3) the *routinization* stage refers to the incorporation of AI applications into the work routines of end users (Cooper and Zmud, 1990; Zhu, Kraemer, et al., 2006; Wu and Chuang, 2010; Chong and Chan, 2012; Martins et al., 2016). Since most organizations fail in passing the pilot stage of AI implementations, our study seeks to examine the differentiating and opposing effects of the organizational readiness factors on the initiation, adoption, and routinization stage of AI.

4.3 Hypotheses

The holistic organizational readiness concept for AI with the corresponding hypotheses as well as the assignment of the influencing factors to the five categories of Jöhnk (2021) are shown in Figure 2.

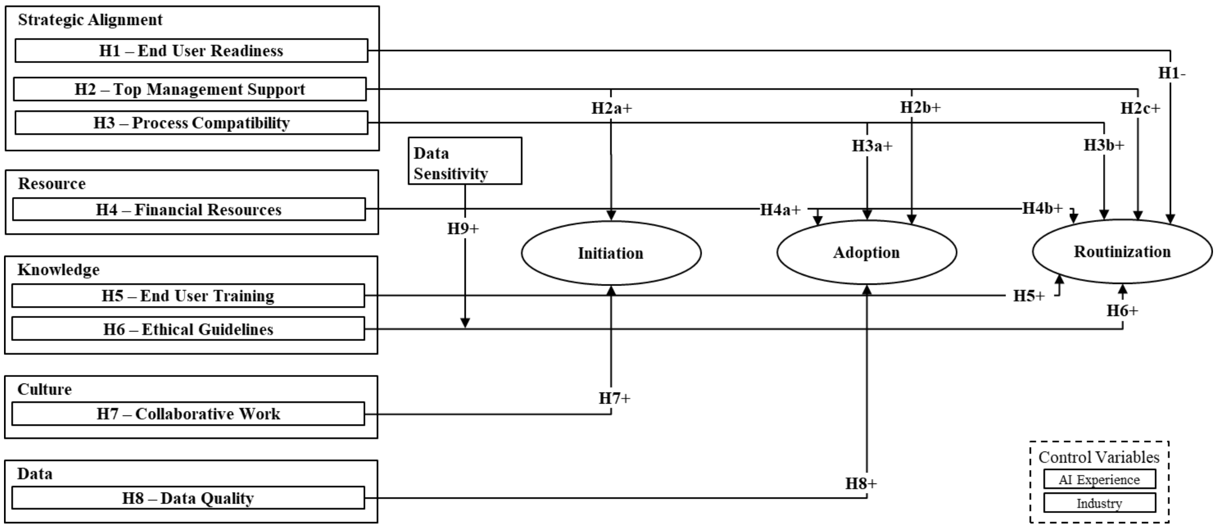

Figure 2. Research model

Strategic Alignment: *End user readiness (EUR)* describes the willingness and acceptance of end users to use AI applications (Pumplun et al., 2019). If end users perceive AI as an advancement, they might show a higher level of commitment to incorporate AI applications into their work routines. According to the literature on change management, end user readiness is a crucial organizational readiness factor as the more end users value change, the more likely they are to embrace it (Weiner, 2009; Nguyen et al., 2019). In the context of AI, end user readiness is particularly important as AI applications are capable of self-learning and autonomous decision-making (Berente et al., 2021). Since the shift in responsibility changes the decision-making process of humans, end users ultimately become more dependent from AI applications in the routinization stage. Therefore, end users must be able to understand and interpret the outcomes of AI applications to properly incorporate them into their decision-making process (Berente et al., 2021). In case that end users are not able to comply with these requirements in the routinization stage of AI, the human-machine collaboration is at risk. Thus, we propose the following hypothesis:

Hypothesis 1: *Lack of end user readiness is negatively related to the routinization stage of AI.*

Since the executive leadership is in the position to promote mechanisms to address new challenges and requirements posed by AI, *top management support (TMS)* is particularly important (Lokuge et al., 2018; Nguyen et al., 2019; Jöhnk et al., 2021). The study by Martins et al. (2016) revealed that top management support positively influences the initiation stage. According to innovation adoption literature, clearly-communicated messages from top management serve as a starting point for driving innovations by providing guidance and building trust among teams in the initiation stage (Gallivan, 2001; Rai et al., 2009; Berente et al., 2021). Particularly in the case of AI, articulating long-term visions and establishing strategic plans can establish an environment in which AI use cases and technical requirements can be properly evaluated (Lokuge et al., 2018; Nguyen et al., 2019; Jöhnk et al., 2021). According to the adoption stage, previous studies have also indicated that a high degree of top management positively supports the decision-making process for allocating financial, technological, and human resources (Chong and Chan, 2012; Martins et al., 2016; Pumplun et al., 2019). Empowering the legitimacy for technology use among end users and setting performance control mechanisms (Liang et al., 2007; Rai et al., 2009) can strengthen the routinization stage. In the context of AI, the legitimacy of top management is important as tasks previously performed by humans may now be augmented by AI (Berente et al., 2021). Since the change in responsibility affects work routines, control mechanisms may increase the acceptance of end users. Thus, we pose the following hypotheses:

Hypothesis 2a: *Top management support is positively related to the initiation stage of AI.*

Hypothesis 2b: *Top management support is positively related to the adoption stage of AI.*

Hypothesis 2c: *Top management support is positively related to the routinization stage of AI.*

According to innovation adoption literature, compatibility is considered an essential prerequisite which reflects the extent to which an innovation is consistent with prior experiences and practices of the organization (Rogers, 1995; W. Xu et al., 2017). Rather than looking at compatibility in general, we follow the recommendation by Jöhnk et al. (2021) and Lokuge et al. (2018) to focus on *process compatibility (PC)* as an organizational readiness factor primarily because AI implementations can lead to substantial changes in business processes. Due to the fact that organizations have often deeply rooted processes in place that have proven successful in the past (W. Xu et al., 2017), changing these rigid processes is a challenge for organizations in the adoption stage (Venkatesh and Bala, 2012). Since the given AI capabilities of self-learning and autonomous decision-making can alter existing business processes (Berente et al., 2021), decision-makers may regard these changes as an obstacle in the adoption stage. However, instead of insisting on rigid structures, reinventing compatible business processes can be seen as an opportunity to increase organizational efficiency and productivity (Brynjolfsson and Mitchell, 2017). To leverage this potential, Kruse et al. (2019) emphasized the need to acquire AI-related process competences. Considering the end user perspective in the routinization stage, the study by Venkatesh and Bala (2012) showed that the likelihood of rejection increases when new processes are not fully integrated into work routines. Thus, business processes should be designed to be compatible to ensure a smooth integration of AI into end users' work routines. Considering these findings, we believe that compatible business processes positively influences the adoption and routinization stages:

Hypothesis 3a: *Process compatibility is positively related to the adoption stage of AI.*

Hypothesis 3b: *Process compatibility is positively related to the routinization stage of AI.*

Financial Resources: Drawing from innovation adoption literature, the commitment of *financial resources (FR)* is regarded as a major prerequisite for a successful implementation of technologies (Zhu, Kraemer, et al., 2006; W. Xu et al., 2017). Adopting a new innovation requires large financial investments in resources for hiring employees, providing adequate infrastructure, and ensuring business process integration (W. Xu et al., 2017). In the case of AI, decision-makers must consider potential uncertainties related to the development, training, and performance of AI models when providing financial resources (Zhang et al., 2020). Especially in the adoption stage, the allocation of sufficient financial resources represents a crucial organizational readiness factor since data scientists need to be hired, hardware and software need to be deployed, and relevant business processes need to be re-designed (Pumplun et al., 2019; Jöhnk et al., 2021). With respect to the routinization stage, the study by Zhu and Kraemer (2005) revealed that financial resources increase the use of innovations by end users. To fulfil the requirement that end users are able to interpret the outcomes of AI applications and incorporate them into their work routines, organizations need to invest in end user training. Thus, we propose the following hypotheses:

Hypothesis 4a: *Financial resources are positively related to the adoption stage of AI.*

Hypothesis 4b: *Financial resources are positively related to the routinization stage of AI.*

Knowledge: Since end user skills and knowledge are essential to realize digital change, *end user training (EUT)* is important for the organizational readiness concept (Nguyen et al., 2019). According to the study by Gutierrez et al. (2015), offering end user training enables organizations to incorporate innovations into the work routines. Providing end users with adequate training on how to use and interact with an innovation can both reduce their anxiety and ambiguity (Schillewaert et al., 2005) and increase their efficiency in using the innovation (Gutierrez et al., 2015; W. Xu et al., 2017). In the context of AI, the offering of end user training is considered an important organizational readiness factor in the routinization stage primarily due to the new capabilities of self-learning and autonomous decision-making. The associated higher level of inscrutability makes it difficult for end users to understand and interpret the results correctly (Berente et al., 2021). While end users do not only need to incorporate the outcomes of AI applications into their decision-making process, they also need to understand the difference in how to interact with autonomous and self-learning AI applications (Jöhnk et al., 2021). By enabling end users to evaluate non-intuitive algorithmic recommendations and properly interact with AI applications, providing AI-specific end user trainings could increase their acceptance level in the routinization stage. Thus, we pose the following hypothesis:

Hypothesis 5: *End user training is positively related to the routinization stage of AI.*

The influence of *ethical guidelines (EG)* when incorporating innovations into end users' work routines has been overlooked in organizational readiness literature. So far organizations have mainly deterministic IS in place that do not contain self-learning capabilities. However, when AI is deployed, end users may face ambiguous outcomes of AI in their decision-making. As AI applications might pose a risk for biased learning and unethical outcomes (Awad et al., 2018), ethical guidelines should be considered an essential organizational readiness factor in the context of AI. The qualitative studies on AI adoption by Eitle and Buxmann (2020), Jöhnk et al. (2021), Kruse et al. (2019), and Pumplun et al. (2019) emphasized that establishing ethical guidelines may increase the trust of end users in AI applications by decreasing the risk of moral dilemmas and unethical outcomes (Awad et al., 2018). Thus, end users may be more encouraged to incorporate AI applications into their work routines if they are aware that ethical guidelines monitor the behaviour of AI. Hence, we pose the following hypothesis:

Hypothesis 6: *Ethical guidelines are positively related to the routinization stage of AI.*

Culture: According to the study of Cao et al. (2010), *collaborative work (CW)* is considered a source of competitive advantage as a close collaboration among stakeholders in terms of frequency and direction can influence the success of innovations. Particularly in the initiation stage of a project, a joint knowledge creation between stakeholders contributes to a better understanding of the problem statement and the requirements. Instead of working in traditional structures and silos, AI implementations rely on integrating different perspectives to evaluate AI use cases and to assess specific technical and functional requirements (Jöhnk et al., 2021). According to the qualitative studies by Kruse et al. (2019), Pumplun et al. (2019), and Eitle and Buxmann (2020), establishing an innovative collaborative work model in which data science and functional teams work together can help initiating AI projects. A strong interaction and communication between these teams can accelerate innovation cycles by fostering ideas and prototyping. Since the evaluation of AI use cases requires both the problem statement by functional teams and the technical assessment of the AI models by data science teams, we pose the following hypothesis:

Hypothesis 7: *Collaborative work between data science and functional teams is positively related to the initiation stage of AI.*

Data: According to the study of Weill and Vitale (1999), *data quality (DQ)* represents a technical quality that has a substantial impact on the performance of IS. Previous research on innovation adoption indicated that data quality positively influences the adoption rate of technologies (e.g., Cruz-Jesus et al., 2019). Especially with respect to the self-learning capabilities of AI applications, the organizational readiness factor of data quality is considered a crucial requirement to train AI models on large datasets. Particularly in the adoption stage, this premise implies that higher quality of training data in terms of accuracy, reliability, and consistency will lead to higher prediction accuracy (Pumplun et al., 2019; Jöhnk et al., 2021). However, since training data is prone to data quality issues due to decentralized data sources (Eitle and Buxmann, 2020), obtaining high-quality data is challenging for organizations (Davenport and Ronanki, 2018; Pumplun et al., 2019). Considering these findings, we assume that improving data quality can increase the organizational readiness for AI:

Hypothesis 8: *Data quality is positively related to the adoption stage of AI.*

To address a sub-aspect of the complex ethical debate on AI (Awad et al., 2018), we address *data sensitivity (DS)* in relation to ethical issues. In IS literature, it is widely discussed that data sensitivity is perceived as risky when processing personal information (e.g., Kehr et al., 2015). Since the risk of loss increases as the information becomes more sensitive, organizations must ensure sufficient protection when incorporating AI applications into work routines. In the field of human resources (HR), for example, numerous personal data are processed and evaluated as part of the application process (Black and van Esch, 2020). As this data contains sensitive information such as gender, age, and personal preferences, a misuse and disclosure of this data in AI applications can lead to severe consequences for organizations. The case of Amazon can be used as prime example for gender discrimination in the application process as their AI-based HR software favoured men over women (Dastin, 2018). This example illustrates that the misuse of sensitive data in AI applications can lead to ethical dilemmas in the routinization stage. By assuming that a higher level of data sensitivity will encourage organizations to establish more ethical guidelines for AI, we propose a moderator effect:

Hypothesis 9: *The more sensitive the data, the more ethical guidelines will be established in the routinization stage of AI.*

4.4 Methodology

As presented in Table 8., we conducted a literature review to distinguish our study from previous research on organizational readiness, adoption process, and AI adoption. Following the recommendations by Webster and Watson (2002), we used the search string “Artificial Intelligence” AND “organizational readiness” OR “adoption” OR “readiness” in the AIS electronic library database to identify relevant literature. For data collection, the survey-based approach in the form of a questionnaire was used to obtain a large sample set for the data analysis and to reduce the common method bias (CMB) by reaching many participants from different organizations. Considering the data analysis, a quantitative research design was applied to validate the impact of the influencing factors on the adoption process of AI.

4.4.1 Conceptual Research Design

Regarding the conceptual research design, we followed the established guidelines for instrument development (i.e., item creation, scale identification, and instrument validation) proposed by Moore and Benbasat (1991) and MacKenzie et al. (2011). As shown in Figure 3., the conceptual research design comprises item creation and scale development (referred to as part 1) as well as instrument validation (referred to as part 2). In part 1, we defined the conceptualization and the nature of constructs. By reviewing prior research and related constructs, we identified the constructs and items through a deductive approach. Based on this selection, we developed an a-priori model (e.g., Burton-Jones and Straub, 2006) for organizational readiness for AI which consists of eight reflective constructs and one moderator variable. The items were selected from literature and will be presented in the next section.

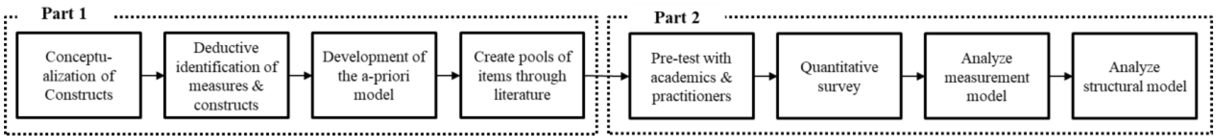

Figure 3. Conceptual research design

4.4.2 Measurements

The development of the applied constructs and items was derived from research on organizational readiness, adoption process, and AI adoption. Modifications in wordings were made to adapt to the AI context. To ensure the validity and reliability of the constructs, we used multi-item measurements based on a seven-point Likert scale ranging from “1 strongly disagree” to “7 strongly agree”. With respect to part 2, we conducted a pre-test with 12 academics and practitioners who worked in the field of AI to validate and adjust the items. Based on their feedback, we improved the terminology of AI by refining expressions and words. The dependent variables of our study reflect the adoption process stages of initiation, adoption, and routinization in the context of AI. The participants assigned themselves to one of the following adoption process stages: (0) no intention to implement AI, (1) intention to implement AI, (2) adoption of AI, and (3) incorporation of AI. Table 19. provides an overview of the selected items of the dependent, independent, and the moderator variables. To rule out unexpected effects, we controlled for the industry and the number of years of AI experience.

4.4.3 Data Collection and Data Analysis

Regarding the data collection process, we contacted 2,153 data scientists via LinkedIn along with a brief explanation of the research scope and invited them to participate in our study. Out of this total number, 1,351 contacts clicked on our survey and 257 participants completed the questionnaire, yielding a completion quote of 19 %. This total count does not include the respondents who assigned themselves to (0) no intention. After sorting out 7 participants who failed the attention check, our sample size is n=250. It distributes among the adoption process stages as follows: initiation n=51, adoption n=98, routinization n=101. The distribution regarding the control variables of industry and AI experience is shown in Table 9. Our results indicate that no CMB is found in the data (Podsakoff et al., 2003).

Industries (IND)	Automotive	Consulting	E-Commerce	Energy	Finance	IT	Logistics	Manu-facturing	Marketing	Healthcare	Other	**AI experience (EXP)**	
												<1 y	4.4 %
												1-2 y	25.2%
												3-5 y	30.4%
												>5 y	40%
in %	7.2	3.6	11.6	5.2	10.8	25.2	3.6	7.6	4.0	8.8	12.4		

Table 9. Description of the sample set

With respect to the data analysis, we used the partial least squares (PLS) method for analyzing the measurement and the structural model using SmartPLSv3 (Fornell and Larcker, 1981). While this statistical method is widely used in IS research (Chin, 1998), the method is particularly well-suited for our study as it is recommended for complex structural models and allows us to simultaneously test relationships between various independent and multiple dependent variables (Gefen et al., 2000; J. Hair et al., 2006; Gaskin and Lowry, 2014).

4.5 Results

Literature proposes the Standardized Root Mean Square Residual (SRMR) as a model fit index that calculates the difference between observed correlations and the model's implied correlations matrix (Hu and Bentler, 1999; J. F. Hair et al., 2016). We tested the model fit and obtained the value of .048 which is below the threshold of .08 proposed by Hu and Bentler (1999). To provide first insights into the descriptive statistics of the variables, we present the means and standard deviations in Table 10.

Constructs	**EUR**	**TMS**	**PC**	**FR**	**EUT**	**EG**	**CW**	**DQ**	**DS**	**INI**	**ADO**	**ROUT**
Mean	4.078	4.560	5.530	5.770	4.151	5.367	5.657	4.588	6.787	5.427	5.960	5.218
SD	1.592	1.554	1.251	1.319	1.649	1.572	1.073	1.286	1.347	1.144	1.054	1.400

Table 10. Means and standard deviations

4.5.1 Measurement Model

In order to validate the measurement model, we investigated the convergent and discriminant validity according to Hair et al. (2006). To ensure convergent validity, we assessed the criteria of item loadings, the composite reliability (CR), Cronbach's Alpha (α), and the average variance extracted (AVE). To ensure that the item loadings exceed the threshold of .7, we analyzed and removed the items below the threshold recursively until all items had a reliability of at least .7 (J. Hair et al., 2006). After removing the two items EUR3 and PC1, all item loadings were higher than the threshold of .7 (Nunnally, 1967; Chin, 1998) except of TMS4. Based on the recommendation of Hair et al. (2016), we decided to keep this item since the corresponding construct already exceeds the AVE threshold of .7. Our study fulfils the criteria of the CR and Cronbach's α exceeding the threshold of .7 (J. F. Hair et al., 2016) as well as AVE exceeding the threshold of .5 (Fornell and Larcker, 1981) as presented in Table 11. Discriminant validity shows the extent to which the measurements of the constructs differ and is examined using the Fornell–Larcker criterion (Fornell and Larcker, 1981). As shown in Table 12., the square root of AVE for each construct was greater than the correlation values of the construct with other constructs. In summary, the data analysis of the measurement model demonstrates that our study fulfils the criteria for convergent and discriminant validity.

	EUR	**TMS**	**PC**	**FR**	**EUT**	**EG**	**CW**	**DQ**	**DS**
Factor loadings	.858-.958	.687-.951	.908-.911	.941-.955	.913-.941	.920-950	.751-.889	.753-.921	.752-.923
CR	.905	.917	.906	.947	.950	.954	.921	.908	.941
Cronbach'α	.806	.886	.792	.888	.924	.929	.893	.868	.933
AVE	.827	.738	.827	.899	.865	.872	.699	.712	.729

Table 11. Assessment of convergent validity

	EUR	**TMS**	**PC**	**FR**	**EUT**	**EG**	**CW**	**DQ**	**DS**
EUR	**.909**								
TMS	-.099	**.859**							
PC	-.120	.354	**.909**						
FR	-.178	.177	.285	**.948**					
EUT	-.158	.590	.336	.239	**.930**				
EG	-.021	.205	.185	.320	.211	**.934**			
CW	-.160	.343	.185	.353	.312	.160	**.836**		
DQ	.027	.204	.210	.092	.173	.180	.117	**.844**	
DS	-.002	-.183	-.040	.057	-.088	.062	.125	-.035	**.854**

Table 12. Assessment of discriminant validity based on the Fornell-Larcker criterion

4.5.2 Structural Model

In the following Table 13., we present the results of the structural model analysis, including the estimated path coefficients with asterisks indicating significant paths. The R^2 value describes how much variance of the dependent variables is explained by the independent variables of our research model. The data analysis revealed that the R^2 value of the three dependent variables (initiation, adoption, and routinization) were 4.8%, 9.4%, and 18.3% which are considered acceptable results. To measure the effect size (J. Cohen, 1992), we examined the f^2 values which reflect the influence of the independent variables on the dependent variables. Our results revealed low and medium effect sizes on the initiation (f^2 =.05), adoption (f^2 =.10), and routinization (f^2 =.22) stages of AI (J. Cohen, 1992, p. 157).

Constructs	EUR	TMS	PC	FR	EUT	EG	CW	DQ	EXP	IND
Initiation	-	.004	-	-	-	-	.203**	-	-.072	.056
Adoption	-	.257***	-.090	.079	-	-	-	.105*	-.051	.079
Routinization	-.103**	-.164**	.227***	.102*	.120*	.093*	-	-	.067	-.081

*p < .10, ** p < .05, *** p < .001

Table 13. Results of the structural model

In terms of strategic alignment, our results revealed that the lack of end user readiness is significantly negatively related to routinization. Furthermore, while top management support has a significant positive path coefficient to adoption, the significant negative impact on routinization is contrary to our assumption. The path coefficient from top management support to initiation, however, is not significant. Even though the path coefficient of process compatibility to adoption is not significant, it has a significant positive path coefficient to routinization. Thus, while the hypotheses H1, H2b, and H3b within the strategic alignment category are supported, H2c is partially supported. H2a and H3a are not supported. Furthermore, our results show that financial resources have no significant path coefficient to adoption but a significant positive path coefficient to routinization. Therefore, while H4b is supported, H4a is not supported. Considering the category of knowledge, end user training has a significant positive path coefficient to routinization and ethical guidelines have a significant positive path coefficient to routinization. According to these results, H5 and H6 are supported. As part of the category of culture, collaborative work between data science and functional teams is significantly positively related to the initiation stage, supporting H7. Since data quality has a significant positive path coefficient to adoption, H8 is also supported. Our results revealed a significant positive influence of the moderator variable data sensitivity (.127, $p < .10$). According to Hair et al. (2016), our moderator effect has a medium effect size of .026 on the path coefficient between ethical guidelines and routinization and therefore supports H9.

4.6 Discussion and Implications

4.6.1 Interpretation of Results

Strategic Alignment: According to our results, *the lack of end user readiness* has a significant negative impact on the routinization stage of AI (H1). This finding indicates that end users who perceive AI applications as difficult to operate tend to resist incorporating them into their work routines. Since AI applications are able to self-learn and make autonomous decisions (Berente et al., 2021), end users might have difficulties in interpreting the outputs correctly. When the degree of inscrutability and the lack of transparency (Berente et al., 2021) prevents end users from understanding decisions made by AI applications, they are more likely to reject them. Therefore, we suggest increasing the level of understanding among end users to strengthen the human-machine collaboration in the routinization stage. Furthermore, we found a significant positive path coefficient between *top management support* and the adoption stage of AI (H2b). Our results confirm the findings of previous innovation adoption studies (e.g., Martins et al., 2016) that top management support influences the adoption decision by providing sufficient financial, technological, and human resources. Contrary to our assumption, we found a significant negative path coefficient between top management support and the routinization stage of AI (H2c). According to this finding, it seems that there is no explicit need for top management to encourage end users to use AI applications through performance control mechanisms if end users regard them as advancements. With respect to the routinization stage, our results also show a positive significant influence of *process compatibility* (H3b). This finding indicates that process compatibility tends to convince end users to incorporate AI applications into their work routines. An explanation could be that end users who do not experience any interruptions in their work routines, are more likely to use AI applications. Thus, we encourage organizations to design compatible business processes.

Financial Resources: Moreover, our results show that financial resources are significantly positively related to the routinization stage (H4b). This finding suggests that financial investments are primarily needed to provide dedicated AI end user training in the routinization stage of AI.

Knowledge: In line with previous studies (W. Xu et al., 2017), we found that *end user training* has a significant positive impact on the routinization stage of AI (H5). This finding indicates that organizations should provide dedicated AI end user training which helps end users to operate AI applications more efficiently. A plausible explanation could be that end users should be able to understand the overarching statistical concept since AI applications are based on probability theory. In particular, in the case of ambiguous outcomes, end users must be able to recognize them and act appropriately (Jussupow et al., 2021). Furthermore, as proposed by previous qualitative studies on AI adoption (e.g., Jöhnk et al., 2021) we found a significant positive path coefficient between *ethical guidelines* and the routinization stage of AI (H6). Thus, our results confirm that end users are more likely to incorporate AI applications if ethical guidelines are in place that reduce the risk for biased learning and unethical outcomes. Thus, we encourage organizations to establish ethical guidelines when implementing AI applications.

Culture: Our results confirm the assumption by Eitle and Buxmann (2020), Kruse et al. (2019), and Pumplun et al. (2019) that *collaborative work* between data science and functional teams has a significant positive impact on the initiation stage of AI (H7). This finding indicates that close interaction and communication between these teams facilitates the identification of AI use cases and the technical assessment of AI applications. While functional teams have dedicated knowledge about the problem statement and the requirements, data science teams have the expertise to develop AI models.

Data: Our results show that data quality is significantly positively related to the adoption stage (H8). This finding is in line with previous qualitative studies on AI adoption (Pumplun et al., 2019; Eitle and Buxmann, 2020; Jöhnk et al., 2021) that suggest that higher data quality can lead to more successful AI implementations due to the increased prediction performance. Thus, our study proposes that organizations should pay particular attention to providing high-quality data for AI model development.

Moderator Data Sensitivity: Based on our results, we found a significant moderator effect of data sensitivity on the path coefficient between ethical guidelines and the routinization stage of AI (H9). To mitigate the risk of ethical dilemmas, this finding suggests that the more sensitive the data is, the more ethical guidelines should be established in the routinization stage.

4.6.2 Theoretical Contributions

Although AI is considered one of the most promising innovations (Brynjolfsson and Mcafee, 2017), the majority of organizations are not able to move beyond the pilot stage (Balakrishnan et al., 2020). This tendency indicates that current research lacks insights into organizational readiness factors and their impact on the adoption process of AI (Jöhnk et al., 2021). By examining what and how organizational readiness factors influence the initiation, adoption, and routinization stages of AI, we answer the research question and contribute to theory as follows: **First**, to investigate what organizational readiness factors affect the adoption process stages of AI, we established a research model that combines the literature streams on organizational readiness and adoption process. While previous studies have typically viewed these literature streams as independent from each other (e.g., Zhu, Kraemer, et al., 2006; Lokuge et al., 2018), we sought to unfold these interdependencies in the context of AI. By intertwining these literature streams into a holistic organizational readiness concept for AI, we were able to identify what influencing factors are essential for managing the complex change of implementing AI applications. Our results showed that organizational readiness is not only a precursor limited to the initiation stage but also has a significant impact on the adoption and the routinization stages. Thus, our study provides empirical groundwork for the research on organizational readiness and the adoption process of AI. **Second**, rather than considering adoption as a single stage, we used a multi-stage adoption process approach which explicitly distinguishes between the three adoption process stages initiation, adoption, and routinization (Gallivan, 2001; Damanpour and Schneider, 2006). As emphasized by Fichman (2000), this process-oriented approach allows us to detect differentiating and opposing effects of the organizational readiness factors on the dedicated adoption process stages of AI. Top management support is an excellent example of demonstrating how organizational readiness can vary along the adoption process of AI. While top management support has no significant influence on the initiation stage, it has a significant positive effect on the adoption stage, but a significant negative influence on the routinization stage of AI. **Third**, our study contributes to theory by responding to the research call by Jöhnk et al. (Jöhnk et al., 2021) to quantitively validate the findings related to the organizational readiness concept for AI. To the best of our knowledge, we are among the first researchers who evaluate the influence of organizational readiness factors on the adoption process of AI using a quantitative research design.

4.6.3 Practical Contributions

Our study provides organizations practical guidance on AI adoption and helps managers to identify relevant organizational readiness factors that can influence each adoption process stage of AI. For instance, when *initiating* an AI implementation, managers should promote the collaboration between data science and functional teams. With respect to the *adoption stage* of AI, top management should ensure an adequate allocation of technological, human, and financial resources for the implementation of AI applications. Taking the *routinization stage* of AI into account, our study showed that the degree of process compatibility influences the willingness of end users to incorporate AI applications into their work routines. Since end users appreciate a high level of process compatibility, our findings suggest that managers should focus on integrating the AI application into the existing process landscape.

4.7 Conclusion, Limitations, and Future Research

By examining the influence of organizational readiness factors on the distinct adoption process stages of AI, our study contributes to research on organizational readiness and adoption process of AI. Despite these contributions, our study is subject to some limitations. By selecting data scientists as the primary target audience, we limited the sample set to a small niche. Even though our sample set contains different industries, our findings cannot be generalized to all organizations. Future studies may seek to increase the sample size to extend the findings of this study. Second, a mix-method research design could provide additional findings compared to a quantitative data analysis. Third, since we observed a moderator effect of data sensitivity, we suggest an in-depth analysis of this moderator and its implications.

5 Research Paper 2.A: The impact of CV Recommender Systems on Procedural Justice in Recruiting

Title

The impact of CV Recommender Systems on Procedural Justice in Recruiting: An Experiment in Candidate Selection

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Abstract

Due to the increasing amount of digitally available applicant information recruiters have difficulties to manage applications through manual recruiting practices. Using CV recommender systems in the selection phase supports recruiters in identifying the most suitable candidates by computing the similarity between a candidate's profile and job requirements. While recent research has mainly focused on technical improvements, we seek to gain more insights about human-algorithm interactions in recruiting. Our study aims to examine what impact the use of a CV recommender system has on procedural justice in the selection process. Through an experimental set-up with 74 recruiters from 22 multinational companies, our study shows that the incorporation of a CV recommender system helps recruiters to ensure the rule of consistency and bias suppression in the selection phase. Thus, our quantitative results indicate that CV recommender systems can have an impact on procedural justice in candidate selection.

Keywords

Candidate Selection, CV Recommender Systems, Procedural Justice

5.1 Introduction

Advancements in information systems and social developments have significantly influenced the way of working in the field of human resource management (HRM). In recent years, organizations have shifted their priorities towards HRM as they perceive their workforce as one of their most important assets. The increasing demand for qualified talents might also result in a war for talents as the shortage of talents is considered one of the most worrying concerns among CIOs and IT executives in 2019 (Kappelman et al., 2020). To attract, select, and retain these talents, recruiting has become a strategic priority in organizations. Black and van Esch (2020) argue that digitization has made a major contribution to further developments in recruiting and emphasize the following eras of e-recruitment. Digital Recruiting 1.0 and 2.0 enable organizations to post job openings on digital job boards on the internet and social network platforms such as LinkedIn. Organizations have the opportunity to narrow down their target group of potential candidates and to contact them directly with concrete job postings (Black and van Esch, 2020). By searching through many digital job postings with a few simple clicks, potential candidates are able to submit multiple applications with less effort. As a result, the increase of incoming applications has made the manual recruiting process more difficult for organizations as recruiters have to manually process digitally available applicant information. While coping with this large amount of applications, recruiters also need to ensure fairness in the selection process as their decision has a major impact on the applicants future (Arvey and Renz, 1992; Gilliland, 1993). However, procedural justice along the decision-making process in the selection phase is often impeded by recruiters' previous work experiences, own beliefs or personal biases (Åslund and Skans, 2012; Eckhardt et al., 2014).

To cope with the increasing amount of data and to ensure fairness, different types of artificial intelligence (AI) technologies have been integrated into the recruiting process (Strohmeier and Piazza, 2015; van Esch et al., 2019) which Black and van Esch (2020) describe as Digital Recruiting 3.0. In particular, the development of Curriculum Vitae (CV) recommender systems is an essential research area in the selection phase of recruiting. These systems are typically applied in the selection phase of the recruiting process (Schneider, 1981) to estimate the person-job (P-J) fit (Caldwell and O Reilly, 1990; Edwards, 1991; Wilk and Sackett, 1996; Kristof-Brown, 2000). By computing the similarity between the details of a candidate's profile and the given job requirements, CV recommender systems can support recruiters in identifying the most suitable candidates. While the performance level is constantly increasing due to technical improvements (e.g., Malinowski et al., 2006; Lu et al., 2013; Bansal et al., 2017), little is known about the socio-technical context of the interaction between human recruiters and CV recommender systems (Green and Chen, 2019b). Since the final decision in candidate selection still remains in the power of recruiters, further insights about the human-algorithm interactions are essential in order to investigate the effect on procedural justice. Therefore, our study aims to examine what impact the use of a CV recommender system has on procedural justice in the selection process. As a research design, we have chosen an experimental set-up in which 74 recruiters from 22 large multinational companies were given the instruction to create top-10 rankings of candidates for two fictional job postings. By randomly assigning the participants to either the control group which represents the non-CV recommender system supported settings or to the treatment group in which recruiters received a matching score generated by a CV recommender system, we were able to investigate our research question. Our study contributes to research and practice in the field of recruiting by providing quantitative findings that CV recommender systems tend to ensure procedural justice as recruiters are able to rank candidates in a more consistent manner and are more likely to assess a candidate's knowledge, skills, and abilities when relying on the CV recommender system.

The rest of this paper is structured as follows: Section 2 outlines the theoretical background of recommender system in recruiting with a focus on CV recommender systems and elaborates on procedural justice in candidate selection. After describing the research design in the form of an experimental set-up in section 3, we present the results of the quantitative study in section 4. The discussion, the contributions to research and practice as well as the limitations and opportunities for future research are outlined in section 5, followed by the conclusion in section 6.

5.2 Theoretical Background

5.2.1 Overview of Recommender Systems

Over the last couple of years, the overload of information with which people need to cope on a daily basis has resulted in complex decision-making environments. The fact that humans have difficulties making decisions due to their limited cognitive resources and time constraints in evaluating and processing available information was coined by Simon (1955) as the phenomenon of bounded rationality. In order to help people deal with the overwhelming amount of data and to support them in the intelligence, design, choice, and implementation phase of complex decision-making processes (Simon, 1977), recommender systems have been developed. By generating personalized suggestions, recommender systems offer only a small number of selection options and eliminate irrelevant and excessive information (Burke, 2002;

Adomavicius and Tuzhilin, 2005). To be more precise, the primary use of recommender systems is to predict elements that a user is likely to evaluate as positively according to his or her underlying preferences (Ricci et al., 2011). In general, recommender systems can be classified into the following categories: Content-based, collaborative filtering, and knowledge-based recommender systems (Burke, 2002; Ricci et al., 2011; Aggarwal, 2016). Content-based recommender systems recommend items to users that are similar to those that they have historically favored or expressed interest in. In order to retrieve a user's preferences, tastes, and desires, the recommender system uses long-term user profiles with user attributes that have been accumulated over time. By matching these user attributes to item attributes, new items will be recommended to the user (Adomavicius and Tuzhilin, 2005; Pazzani and Billsus, 2007; Aggarwal, 2016). Since content-knowledge is mainly derived from unstructured or semi-structured data, item descriptions are composed of a set of textual features that can be acquired by various information retrieval or information extraction methods with the help of statistical, machine learning, or natural language processing techniques (Lops et al., 2011). In contrast, collaborative filtering recommender systems generate item recommendations based on the similarity towards other users' preferences (Adomavicius and Tuzhilin, 2005; Schafer et al., 2007; Aggarwal, 2016). This type of recommender system has to cope with a so-called cold-start issue as a new user has to first rate several items or a new item has to receive a couple of ratings before a user similarity can be determined (Ramezani et al., 2008; Bobadilla et al., 2013). Recommendations generated through knowledge-based recommender systems are derived from specific domain knowledge which have to be acquired through interviews or other knowledge discovery techniques (Aggarwal, 2016). A common form of knowledge representation are ontologies which display relations among attributes, objects, and item features. The main downside of this recommender system lies in the high efforts of knowledge acquisition (Ramezani et al., 2008).

5.2.2 Recommender Systems in Recruiting

According to the attraction-selection-attrition (ASA) framework by Schneider (1981), organizations tend to achieve a certain degree of homogeneity among their employees by identifying candidates during the recruiting phases of attraction, selection, and attrition who have similar characteristics and behaviors as the organization. The empirical study by Judge and Cable (1997) revealed that in the attraction phase, potential candidates search for suitable job postings and organizational cultures based on their own personality, preferences, and field of interest. Particularly in the attraction phase, there is a tendency of organizations to achieve a certain degree of homogeneity by seeking to recruit candidates with similar attributes and behaviors which is also described by the term "right types" (Schneider, 1981). In the selection phase, organizations seek to select candidates who possess specific competencies and skills required for the job position. By narrowing the applicant pool using pre-selection techniques and face-to-face interviews, companies are able to select a homogeneous group of candidates with specific skills (Schneider, 1981; Bretz et al., 1989). During the attrition phase, there is a tendency for employees who do not fit into the organization to eventually leave, while employees who embrace the organizational culture strive to retain their jobs and pursue their careers over time (Schneider, 1981; Chatman, 1991). By retaining the "right types" in the organization who share similar characteristics and behaviors, companies can increase the homogeneity among their workforce (Schneider, 1981). Since the increase in digital job and applicant data particularly impedes the screening and assessment activities of recruiters (Black and van Esch, 2020), the following sections mainly refer to the selection phase in recruiting.

The main task in the selection phase is the matching of potential candidates and job postings, which is an essential subject of the person-job (P-J) fit and person-organization (P-O) fit literature (Rynes and Gerhart, 1990; Adkins et al., 1994; Wilk and Sackett, 1996; Judge and Cable, 1997). The overarching research relates to the fit between a person and the environment, which has been a pervasive component in major research areas including personality theory, occupational psychology, personnel selection, and social psychology (Schneider, 2001). According to the person-environment fit concept (P-E), behavior is influenced by the congruence between personal and situational variables and not just by one of the elements alone. To be more precise, the compatibility between personal variables including abilities, needs, and values as well as environmental variables such as organizational culture, task demands, and job attributes leads to either positive or negative outcomes (Muchinsky and Monahan, 1987; Ostroff, 1993; Kristof-Brown, 2000; Schneider, 2001). Besides the P-J and P-O fit, the comprehensive P-E fit concept comprises further sub-categories including the person-vocation (P-V) fit, the person-group (P-G) fit, and the person-supervisor (P-S) fit (Sekiguchi, 2004; Kristof-Brown et al., 2005).

In the recruiting literature, the concepts of P-J and P-O fit predominate the selection phase of Schneider's (1981) ASA framework since the primary objective is to match individuals and jobs. The operationalization of the P-J fit by Edwards (1991) refers to the demands-ability fit and the needs-supplies fit. To be more precise, the demands-ability fit determines the extent to which an employee's knowledge, skills, and abilities, the so-called KSA’s, meet the requirements of a job. These KSA's comprise, for example, work experience, technical skills, problem-solving skills, academic experience, and leadership skills (Kristof-Brown, 2000). The needs-supplies fit, on the other hand, addresses whether needs, wishes, or preferences of an employee are satisfied by the jobs' characteristics and attributes (Edwards, 1991; Kristof, 1996; Sekiguchi, 2004). However, since candidates tend to select the vacant job positions according to their own needs and preferences (Judge and Cable, 1997), the primary task of recruiters is to identify candidates with the required KSA's. The study by Caldwell and O'Reilly (1990) showed that the match between the KSA's of a candidate and the job requirements positively influences an employee's job performance and ultimately job satisfaction. Furthermore, Wilk and Sackett (1996) reported that the match between an employee's skills and the complexity of the job even allows the employee to move up in the job hierarchy in the future. These empirical results indicate that the demands-ability fit is crucial for assessing the P-J fit (Kristof-Brown, 2000). With regard to the operationalization of the P-O fit, Chatman (1991) argues that the congruence between candidates' values as well as organizational norms and values can have a positive impact on the selection phase since this match increases the likelihood that a candidate identifies himself with the organizational culture. An experiment conducted by Kristof-Brown (2000) revealed that recruiters explicitly distinguish between the P-J fit and the P-O fit when selecting applicants. When assessing the first group of applicants, recruiters tend to follow the P-J fit as they primarily consider the KSA's as their main selection criteria. In the subsequent evaluation rounds of the recruiting process, the emphasis is on the P-O fit since the match between personal values and organizational values is given higher priority (Rynes and Gerhart, 1990; Kristof-Brown, 2000).

With the advancements of Digital Recruiting 1.0 and 2.0 (Black and van Esch, 2020), which allow organizations to post their job openings on digital job boards and professional and social networking platforms like LinkedIn, the amount of digital candidate data has increased significantly. Since the selection phase involves a high proportion of manual tasks, managing the large volume of digital applications can be time-consuming and costly for organizations (Eckhardt et al., 2014; Strohmeier and Piazza, 2015). While different types of artificial intelligence (AI) technologies can be integrated throughout the recruiting process (Strohmeier and Piazza, 2015; van Esch et al., 2019), the emergence of recommender systems have particularly simplified the manual tasks of recruiters in the selection phase. The study by Faerber et al. (2003) has compared the prediction performance of a content-based recommender system, a collaborative filtering recommender system, and a hybrid approach in the field of CV recommendations. According to their findings the content-based approach yields the best results in matching a candidate's profile and the job requirements. Based on the P-J fit, Malinowksi et al. (2006) have developed a CV recommender system that follows the demands-ability fit approach (Edwards, 1991) by recommending candidates whose CVs most closely match the specific job requirements. In order to address the needs-supplies fit approach (Edwards, 1991) by matching a candidate's preference with the job attributes, the authors additionally developed a job recommender system. Based on a latent aspect model both recommender systems are able to compute the similarity between the candidate’s profile and the job requirements. Since the predictive quality of the two recommender systems was the main subject of the study, the computer-generated recommendations were compared with the original list of jobs selected by the study participants and the original list of top candidates. The results showed that the predictions of the CV and the job recommender systems largely corresponded to human choices, which indicate a high prediction quality and promising system performance. Moreover, the content-based recommender system proposed by Lu et al. (2013) is designed as a hybrid model that integrates a CV and a job recommender system in one system. The profile-based similarity of the candidate’s details and the job posting was computed by using latent semantic analysis (LSA) tools. In addition, the recommender system is capable of not only including a candidate's profile and the job requirements, but also processing user interactions. In an experiment, the participants were able to indicate their preferences through the interaction features "posted", "applied", "favorited", "liked", and "visited". The study by Almalis et al. (2016) extents the research of content-based CV recommender systems in a way that the match between human KSA’s and job attributes is based on different value ranges, such as specific values, a range with lower limit, a range with upper limit, and a range with both lower and upper limit. In other words, the proposed CV recommender system is able to differentiate between job requirements that refer to ranges of values such as “candidates must be at least 40 years old” or “between 18-40 years old”. The proposal of a further hybrid content-based recommender system by Bansal (2017) facilitates the matching of candidates profiles and job postings from the perspective of recruiters and job seekers in an integrated system. Instead of using words as textual features, the researcher focused on topic features by applying the topic modelling algorithm Latent Dirichlet Allocation (LDA). Since this unsupervised machine learning technique allows to detect latent topics that are hidden in the text corpus, low-frequency terms can become quite significant as they are linked to other high-frequency terms.

As shown, current research in the selection phase focuses mainly on enhancing the prediction performance of CV recommender systems by evolving algorithms and improving technical features (Faerber et al., 2003; Malinowski et al., 2006; Lu et al., 2013; Almalis et al., 2016;

Bansal et al., 2017). However, instead of optimizing computational performance, Green and Chen (2019a) emphasize that attention in research should rather shift towards a socio-technical context to explore how human-algorithm interactions can be improved. According to their algorithm-in-the-loop framework, algorithmic aid can help to improve the decision-making process by incorporating algorithms which inform and advise humans in their decision-making while the final decision still remains with humans. Although the study of human-algorithm interaction is developing slowly in areas such as web journalism (Christin, 2017), forecasting 90, and criminal justice (Green and Chen, 2019a; Grgic-Hlaca et al., 2019), research has not yet sufficiently taken into account the socio-technical context in the field of recruiting (Green and Chen, 2019b; Grgic-Hlaca et al., 2019).

5.2.3 Procedural Justice in Candidate Selection

Despite the fact that key performance indicators in the recruiting process are largely standardized, the selection process for candidates often differs among recruiters. Previous work experience, individual attitudes, and personal preferences lead to a variety of different behaviour patterns among recruiters which can significantly influence the selection of suitable candidates (Eckhardt et al., 2014). Furthermore, the existence of conscious or unconscious cognitive bias among recruiters might also contribute to the likelihood of inconsistent decision-making processes in the selection phase (Åslund and Skans, 2012; Black and van Esch, 2020). These diverse set of behaviour patterns among recruiters increase the risk of unfairness in the selection phase and can ultimately compromise a candidate’s chance of being selected.

In order to examine fairness in the decision-making process during the selection phase, the literature on organizational justice (Greenberg and Colquitt, 2005) must be taken into account which primarily addresses employees' reactions regarding unfairness and inequity in an organizational context and distinguishes between distributive and procedural justice. Distributive justice describes the degree to which an employee perceives the distribution of outcomes such as payments and rewards as fair in the sense of equity (Adams, 1965; R. L. Cohen, 1987) and equality (Deutsch, 1975). When considering the equity principles which determine the distribution of resources according to the contributions of employees, the foundation of distributive justice refers to Adam’s (1965) equity theory. In contrast, procedural justice refers to the perceived fairness in the actual decision-making process that ultimately determines the outcome (Greenberg and Colquitt, 2005). In order to ensure that the procedure can be assessed as fair, Leventhal (1980) defined the following six rules for procedural justice: consistency, unbiased suppression, accuracy, correctability, representativeness, and ethicality.

Since fairness in the candidate selection process depends on procedural justice, Gilliland (1993) and Arvey and Renz (1992) have defined specific procedural rules for the selection phase. In this context, the rule of consistency should be emphasized as Leventhal (1980) and Gilliland (1993) recommend a certain degree of uniformity in the selection procedure since all candidates should have the chance to receive the same decision-making process regardless of demographics, personality, or background. Arvey and Renz (1992) point out that consistency in candidate selection is only given when the content of the selection system, the scoring, and the interpretation of scores are standardized across all applicants. In addition, the rule of bias suppression by Leventhal (1980) is also crucial to ensure procedural justice in the selection phase as it determines that recruiters should not make decisions based on their own self-interest or be influenced by their own beliefs and opinions (Leventhal, 1980). To ensure objectivity rather than risking subjectivity, Arvey and Renz (1992) suggests to apply quantifiable methods which take certain criteria into account rather than relying on the recruiters' instincts and experiences. The suppression of personal bias is also addressed in the propriety of questions as improper questioning and prejudicial statements impede the level of fairness in the selection phase (Gilliland, 1993).

By examining procedural justice in e-recruiting tools, the findings of Thielsch et al. (2012) show that applicants expect a higher level of objectivity when using an e-recruiting tool compared to traditional manual recruiting practices. In addition, the qualitative study by Ochmann and Laumer (2019) proposes that the implementation of AI-based instruments could contribute even more to increase the level of fairness by increasing objectivity during the selection phase. While traditional selection methods have been perceived as unfair due to the risk of personal bias on part of the recruiters, the qualitative findings suggest that AI technologies could assist in the decision-making process by focusing solely on the candidates' skills and thus increasing objectivity. It should be noted, however, that the level of user reliance in a technology is also considered a critical factor in achieving procedural justice, as the final selection decision still remains in the power of recruiters. Reliance towards a technology depends primarily on user acceptance and the degree of influence that the user allows in their judgment (Arnold and Sutton, 1998; Madhavan and Wiegmann, 2007). Following the study by Ötting and Maier (2018) which empirically examined the impact of human and AI-based intelligent systems on procedural justice in a generic work-life situation, we aim to gain empirical insights into procedural justice in the selection process.

Based on the outlined literature on candidate selection (e.g., Schneider, 1987; Caldwell and O Reilly, 1990; Edwards, 1991; Wilk and Sackett, 1996), CV recommender systems (e.g., Malinowski et al., 2006; Almalis et al., 2016; Bansal et al., 2017), and procedural justice (Arvey and Renz, 1992; Gilliland, 1993; Greenberg and Colquitt, 2005), we believe that incorporating a CV recommender system in the selection phase could increase procedural justice by helping recruiters to ensure consistency and objectivity in their decision-making process. Under the premise that recruiters rely on a CV recommender system and take the generated suggestions into account, we anticipate that the top-10 rankings of recruiters who incorporate a CV recommender system into their decision-making process will be more consistent and similar than the top-10 rankings of those who rely solely on their own judgement without using a CV recommender system. Furthermore, we would like to gain further insights into the demands-ability approach in the context of the P-J fit (Edwards, 1991; Kristof-Brown, 2000) when incorporating a CV recommender system in the decision-making process of recruiters. As outlined above, CV recommender systems are based on the demands-ability fit as they compute the similarity between the applicant's KSA's and the respective job requirements (Faerber et al., 2003; Malinowski et al., 2006; Lu et al., 2013; Almalis et al., 2016; Bansal et al., 2017). Since the suggestions generated by CV recommender systems are based on the KSA's of candidates and are not exposed to subjective discrimination or personal bias by recruiters, we anticipate that the CVs of the top-10 ranked candidates which were selected with the help of a CV recommender system possess stronger KSA's than those ranked on the basis of the recruiters' sole judgment.

5.3 Methodology

Since the aim of our study is to examine what impact the use of a CV recommender system has on procedural justice in the selection process, we conduct an true experimental research with a posttest-only control group that enables us to determine cause-effect relationships (Campbell and Stanley, 1963; Gay et al., 2012). The research design of the experiment is illustrated in Figure 4. and is described in detail in the following section.

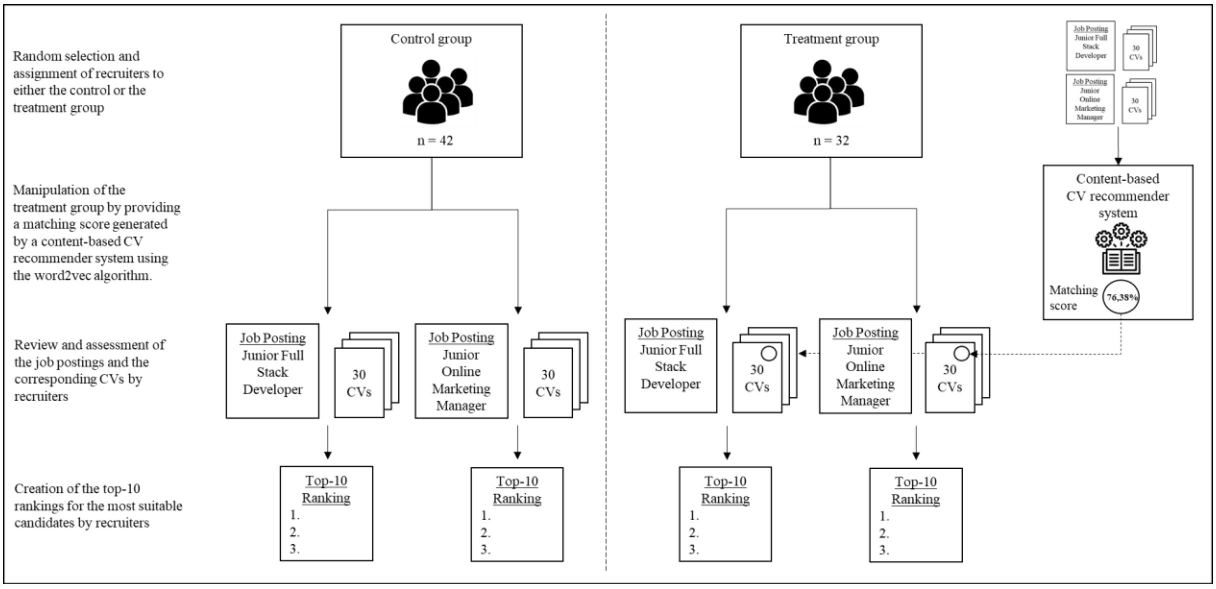

Figure 4. Experimental research design

In order to establish a realistic experimental set-up for a decision-making process in the selection phase, we have involved professional recruiters rather than non-professional study participants. Through a cooperation with a national association for employer branding, talent marketing, and recruiting, we were able to randomly select recruiters who were willing to participate in our experiment. The random selection method is recommended primarily because it ensures external validity by increasing the degree to which the study results can be generalized to other groups (Campbell and Stanley, 1963; Kirk, 2013; Dean et al., 2017). By following a between-subject design, we have also applied the randomization method when assigning participants to either the control or the treatment group. Random assignment is particularly needed to ensure internal validity as it reduces systematic bias between the treatment and the control group by distributing participants equally among these groups (Campbell and Stanley, 1963; Kirk, 2013; Mikolov et al., 2013). The manipulation of the independent variable refers to a matching score generated by a CV recommender system and distinguishes the groups as follows: The control group represents the non-CV recommender system supported setting in which the participants have received CVs without any suggestions generated by a CV recommender system. The treatment group represents the CV recommender system supported setting in which the participants have received the same CVs but to which a matching score generated by the applied CV recommender system has been added in the upper right corner.

Following the current research on recommender systems in the field of candidate selection (Faerber et al., 2003; Malinowski et al., 2006; Lu et al., 2013; Almalis et al., 2016; Bansal et al., 2017), we have decided to also use a content-based CV recommender system that supports recruiters in the selection phase to identify suitable candidates. As we seek to examine the effect of CV recommender systems on procedural justice rather than improving the performance level through technical advancements, we decided to use an existing CV recommender system developed by a global enterprise software provider with sufficient training data. The underlying machine learning technique refers to the word2vec algorithm by Mikolov et al. (2013) which represents a neural network model with a single hidden layer. In the case of the applied CV recommender system, data cleansing activities such as functional removal, lower case, and plural removal are performed on the input document in an initial step. After this prerequisite is fulfilled, the input document is tokenized into corresponding bigrams and trigrams. By using the word2vec algorithm, each token is assigned to a word embedding which ultimately represents a vector space. In order to remove irrelevant tokens and to generate interpretable token clusters, the tokens in the form of word embeddings are assigned to certain branches of a formerly created skill tree. As the final goal is to compare a CV and a job posting, the word embeddings are combined into document-level embeddings to compute the cosine similarity between the document vectors. The output of the selected content-based CV recommender system is a matching score which is expressed as a floating-point number between 0.0 and 1.0. The higher the value of the matching score, the closer the similarity between the CV and the job profile, and the higher the rank of the CV in a list of suitable candidates.

In regard to the experimental set-up, we created two fictional job posting based on examples from the participating companies: one for a Junior Full Stack Developer and one for a Junior Online Marketing Manager. We focused on junior positions as these positions oftentimes receive large numbers of applications and are thus more attractive for the implementation of a CV recommender system. As a second step, we collected a diverse set of 30 CVs for each job posting from computer science, information systems, business, and marketing students of higher education institutions. During the experiment, the participants received the task description through a survey tool in which the two job postings as well as the corresponding CVs were available in the form of PDF documents. Based on the random assignment to either the control group or the treatment group, the CVs either included a matching score generated by the CV recommender system or not. According to the task description, the participants of both experiment groups were instructed to first read the job postings and the corresponding CVs thoroughly. Based on a careful assessment of the candidates and the requirements of the first job posting, the recruiters were asked to create a ranking in the survey tool based on the suitability of the candidates under the assumption that the top-10 ranked candidates would be invited for a further interview. Subsequently, the participants were encouraged to proceed with the creation of the ranking list for the second job posting. Since the ranking represents the final outcome of the experiment and is considered in the further data analysis, our study is designed as posttest-only control group. This approach allows us to avoid testing effects that could have had an impact on the participants' behaviour if they were exposed to any kind of information in advance (Gay et al., 2012).

5.4 Results

Regarding the participation rate, 89 professional recruiters voluntarily signed up for our experiment, out of which 74 completed the tasks (83% response rate). At the time of the experiment (January 2019), these 74 participants were employed in 22 large multinational companies. Among all participants, 74% were female, 83% were between 25 and 44 years old, and 78% had at least three years of experience in recruiting. To ensure objectivity within the quantitative data analysis, we manually extracted variables from all CVs in a two-stage procedure. First, variables were extracted independently by two of the authors. Subsequently, results were synchronized to reach consent and to apply consistent standards. In accordance with the P-J fit which determines the suitability between the KSA's of candidates and the job requirements (Edwards, 1991; Kristof-Brown, 2000), we extracted the following variables from all CVs: study duration (in years) and relevant working experience (in years). By conducting statistical tests, we were able to relate these variables to the observed behaviour of the participating recruiters. The data was pre-processed using the Python programming language and subsequently analysed using SPSS. Given the nature of our study, we tested for significance at a 10% level to avoid discarding interesting relationships (Rosnow and Rosenthal, 1989; Schumm et al., 2013). In regard to the following section, we present the results as mean ± standard deviation, unless we state otherwise. While screening the experiment data, we detected three cases in which participants only completed the marketing job posting, and one case in which only the development task was finished. We decided to keep these partial completions in our dataset to account for the rather small sample size.

To examine whether the top-10 rankings of recruiters who were supported with the matching score generated by the CV recommender system are more consistent and similar than those who rely on their own judgement, we first calculated pairwise correlations between the rankings of participants separately for the CV recommender system supported group and the non-CV recommender system supported group (in the following referred to as *inner group ranking correlation*). Here, the ranked candidates received their respective position, while candidates outside the top-10 were being ranked as 11th, thus creating a lot of ties in our rankings. Consequently, we chose *Kendall's tau* as correlation metric for this analysis, as this metric is more robust in the presence of ties in rankings (Kendall and Stuart, 1945). We then conducted two separate independent-samples t-tests (i.e., one for each job posting) to examine the effects of CV recommender system support on the inner group ranking correlation. The results of our quantitative analysis are summarized in Table 14.

Factor	**Task**	**Levels**	**Inner group rank. corr.**		**df**	**t**	**Sig.**	**Cohen's d**
			Mean	**Std. Dev.**				
CV recommender system support	Development	Supported	.440	.233	1235	-21.989	.000	1.281
		Unsupported	.144	.231				
	Marketing	Supported	.489	.274	1300	-18.958	.000	1.057
		Unsupported	.192	.288				
Note: Inner group ranking correlations are calculated as pairwise correlations between rankings from participants of the respective group, as measured by Kendall's tau. Results are based on independent-samples t-tests.								

Table 14. Effect of CV recommender system support on inner group ranking correlation

Based on our quantitative analysis we found statistically significant differences between the CV recommender system supported and non-CV recommender system supported groups with regard to the inner group ranking correlation score. The results showed that the inner group ranking correlation was higher in the CV recommender system supported (development task: .440 ± .233; marketing task: .489 ± .274) than in the non-CV recommender system supported groups (development task: .144 ± .231; marketing task: .192 ± .288). In other words that means that the rankings from recruiters who received the matching score generated by the CV recommender system were more strongly correlated with each other than rankings from recruiters without the CV recommender system support. For both groups, the effects were statistically significant (development task: $t = -21.989$, $p < .001$; marketing task: $t = -18.958$, $p < .001$) and effect sizes were larger than one standard deviation, as measured by *Cohen's d* (development task: 1.281; marketing task: 1.057).

According to our results, we can strongly support our anticipation that the top-10 rankings of recruiters within the CV recommender system supported group are more consistent and similar than those who did not received any matching score from the CV recommender system. We can further suspect that recruiters relied on the matching score generated by the CV recommender system. To further examine this finding, we also calculated the average correlation between the recruiters' rankings and the ranking proposed by the CV recommender system. We found a strong correlation for both tasks (development task: .583 ± .253; marketing task: .599 ± .268), which further supports our assumption. For comparison, in the unsupported groups the observed correlations were much lower (development task: .062 ± .231; marketing task: .080 ± .310).

To examine our second anticipation that the CVs of the top-10 ranked candidates which were selected using a CV recommender system possess stronger KSA's than those which were ranked without any CV recommender system support, we compared the ranked candidates of the control and the treatment group based on the extracted variables of study duration and relevant working experience. We calculated averages for ranked candidates on a per-recruiter basis and then compared between values from both groups using independent-samples t-tests. Once again, we considered rankings from development and marketing job postings separately. The quantitative results are summarized in Table 15.

Task	**Variable**	**Group**	**Mean**	**Std. Dev.**	**df**	**t**	**Sig.**	**Cohen's d**
Development	Study duration	Supported	4.909	.324	69	-1.532	.130	.365
		Unsupported	4.792	.311				
	Working experience	Supported	3.500	.505	69	-2.277	.026	.540
		Unsupported	3.194	.622				
Marketing	Study duration	Supported	5.063	.264	71	-2.537	.013	.604
		Unsupported	4.924	.190				
	Working experience	Supported	2.054	.308	71	-.670	.505	.154
		Unsupported	1.993	.470				
Note: Study duration and working experience are measured in years and were extracted from the submitted resumes. Results are based on independent-samples t-tests.								

Table 15. Effects of CV recommender system support on KSA levels of ranked candidates

By conducting our quantitative analysis we found that top-10 ranked candidates in CV recommender system supported settings displayed statistically significant stronger levels of KSA's than top-10 ranked candidates in non-CV recommender system supported settings in two out of four observed cases (development – working experience: t = -2.277, p = .026; marketing – study duration: t = -2.537, p = .013). For both cases we observed medium effect sizes (larger than .5), as measured by *Cohen's d* (development – working experience: .540, marketing – study duration: .604). In addition, we found a small effect size (larger than .2) for study duration in the development task, that was not statistically significant (t = -1.532, p =

.130, d = .365). Considering these findings, we can partially support our anticipation that candidates of the top-10 rankings possess stronger KSA’s in the cases when recruiters have been supported by the CV recommender system compared to the cases were recruiters have not received a matching score generated by the CV recommender system.

5.5 Discussion

To cope with the increasing amount of digital applicant data (Strohmeier and Piazza, 2015; van Esch et al., 2019) and to ensure fairness in the candidate selection phase (Gilliland, 1993; Thielsch et al., 2012; Ochmann and Laumer, 2019), research has increasingly focused on the development of CV recommender systems. These systems serve to identify the most suitable candidates for a given job by calculating the similarities between candidate profiles and job requirements. Thus, CV recommender systems are typically applied in the selection phase of the recruiting process (Schneider, 1981) with the purpose of estimating the P-J fit (Rynes and Gerhart, 1990; Adkins et al., 1994; Wilk and Sackett, 1996; Judge and Cable, 1997). While prior research on CV recommender systems has mainly focused on improving the performance of CV recommender systems on a technical level (e.g., Malinowski et al., 2006; Lu et al., 2013; Bansal et al., 2017), our study addresses the socio-technical context by concentrating on the interaction between the human recruiter and the algorithm (Green and Chen, 2019a; Grgic-Hlaca et al., 2019). In detail, we examine what impact the use of a CV recommender system has on procedural justice in the selection process. Therefore, we conduct an experiment with 74 professional recruiters from 22 multinational companies, where the task is to create top-10 rankings of candidates for two fictional job postings. According to our quantitative data analysis, we found statistically significant differences between the control and the treatment group with regard to the inner group ranking correlation score. We derive two main findings from our quantitative analysis. First, the analysis of our experiment indicates that the rankings correlated more strongly with each other when recruiters received the matching score generated by the CV recommender system than in the non-CV recommender system supported group. Since this stronger correlation is an indicator that the top-10 ranking list is more consistent and similar among the recruiters of the CV recommender system supported group, we can assume that the level of procedural justice increases through the assistance of the CV recommender system. Second, our quantitative results indicate that the CVs of the top-10 ranked candidates of the CV recommender system supported group contain stronger KSA’s in regard to working experience for the development job posting as well as in regard to study duration for the marketing job posting compared to the non-CV recommender system supported group. Due to the presence of these stronger KSA's in the top-10 rankings, our results indicate that KSA's are given more attention when creating the top-10 rankings with the support of a CV recommender system than if recruiters would make the decision on their own. In other words, CV recommender systems can help recruiters to base their decision-making on the pure set of KSA's, rather than being influenced by their own judgment or personal biases. Thus, if candidates possess KSA's required for a particular job posting and a CV recommender system is incorporated in the selection phase, the likelihood of these candidates being selected in the top-10 rankings tends to increase. To summarize, we show that incorporating CV recommender systems increases procedural justice in the selection phase as recruiters are more likely to adhere to the rule of consistency (Leventhal, 1980; Arvey and Renz, 1992; Gilliland, 1993) by ranking candidates in a more consistent and uniform manner. Moreover, we find that the candidates selected by CV recommender system supported recruiters typically possess stronger KSA's than the candidates selected by non-CV recommender system supported recruiters which can be considered as an indicator of ensuring the procedural rule of bias suppression (Leventhal, 1980; Arvey and Renz, 1992).

Our study offers significant theoretical contributions regarding research in the area of human-algorithm interaction. To the best of our knowledge, we are among the first to study the effects of CV recommender system application on procedural justice in the selection phase of the recruiting process. Our study showed that the decision-making process of professional recruiters can be influenced by a CV recommender system by creating more consistent and uniform rankings in which the selected candidates possess stronger KSA's. Thus, we provide quantitative evidence for findings of Thielsch et al. (2012) and Ochmann and Laumer (2019), i.e., that higher levels of objectivity and consistency can be achieved in the candidate selection phase when using an algorithmic aid instead of solely relying on human judgment. Consequently, we show that procedural justice in the selection phase of recruiting can be strengthened by deploying a CV recommender system. We propose that content-based CV recommender systems help recruiters to ensure the procedural rule of consistency (Leventhal, 1980; Arvey and Renz, 1992; Gilliland, 1993) by providing more consistent and uniform rankings. Moreover, relying on these types of systems might mitigate human biases in the recruiting process, such as subjective selection criteria by enabling accurate measurement of candidate's KSA's as proposed by the P-J fit (Caldwell and O Reilly, 1990; Edwards, 1991; Wilk and Sackett, 1996; Kristof-Brown, 2000).

Our findings also have significant implications for practitioners. We show that organizations should consider deploying CV recommender systems in the selection phase of the recruiting process. Here, the application of such systems might serve several purposes. First, using content-based CV recommender systems increases the likelihood that applicants with higher levels of KSA's will be included in candidate rankings. This way, organizations can ensure that they more strongly consider candidates with a high P-J fit. As a result, more suitable candidates might be identified more efficiently, preventing costly hiring mistakes in the process. Moreover, content-based recommender systems could be used to partly automate the selection process, which would allow to direct further resources towards cognitively more challenging tasks, e.g., estimating the P-O fit via in-person interviews. Second, the deployment of CV recommender systems might reduce existing biases in the recruiting process by making sure that candidate rankings are more consistent across different recruiters.

While our study adds value for both research and practice, it is affected by some limitations that offer opportunities for further research. Despite the fact that we designed our experiment according to realistic recruiting standards and practices by involving professional recruiters, providing real CVs, and using a content-based CV recommender system, we are aware that the experimental set-up has some shortcomings regarding the recruiting process in practice. With regard to the selection phase, our study differs from procedures used in practice to evaluate applicants where CVs are usually reviewed as they are received rather than consecutively in batches. In addition, recruiters would usually receive more information on required skills and context from the hiring manager instead of just referring to the available requirements of the job posting. Furthermore, the choice of a junior job posting could have an impact on the matching score generated by the CV recommender system as the submitted CVs might contain fewer keywords and details than for a professional job posting. Lastly, as we used only one commercially available content-based CV recommender system, we are well aware that the results might differ for alternative solutions.

To increase realism, future research could improve the experimental set-up by providing a centralized CV upload that allows recruiters to review CVs at the time of upload. Therefore, the timeframe of the experiment should also be extended from one to three months in order to make the decision-making process of candidate selection more realistic. In addition, the between-subject design could also be varied by adding another treatment group of recruiters who receive additional information on the key features that influence the generated matching score. Thereby, the effect of increased transparency for recruiters compared to recruiting settings with less information could be studied further. By expanding the research scope with a focus on transparency, additional insights could be gained as to whether recruiters would integrate the suggestions of CV recommender systems even more strongly into their decision-making process as the key features become more transparent. This future research would contribute significantly to the study of human-algorithm interactions in the field of recruiting.

5.6 Conclusion

In recent years, recruiting qualified and skilled talents has gained considerable importance as organizations consider their workforce as strategic assets. While digitization has contributed to the emergence of job portals, recruiters face the challenge of dealing with large amounts of digital applications (Black and van Esch, 2020). In order to cope with this amount of data, CV recommender systems have been developed to support recruiters in the selection phase. By computing the similarity of the candidates KSA’s and the job requirements, CV recommender systems are able to identify the most suitable candidates as requested by the demands-ability approach of the P-J fit (Edwards, 1991; Kristof-Brown, 2000). However, relatively little is known about the socio-technical context in which such systems are deployed (Green and Chen, 2019a; Grgic-Hlaca et al., 2019). Our study aimed to examine the impact of a CV recommender system on procedural justice in the selection phase of the recruiting process. Therefore, we conducted an experiment with 74 recruiters from 22 large multinational companies. Using a between-subject design, we compare top-10 rankings of potential candidates for two fictional job postings between recruiters who are supported by a content-based CV recommender system and unsupported recruiters. Two main observations can be drawn from our quantitative analysis. First, candidate rankings from the CV recommender system supported group exhibit higher levels of similarity than rankings from the non-CV recommender system supported group. Second, candidates selected by recruiters who received the matching score generated by the CV recommender system contain stronger KSA’s than candidates selected by recruiters who relied solely on their own judgment. Thus, we find quantitative evidence that the deployment of CV recommender systems can increase consistency and reduce personal bias in the selection phase of the recruiting process, which might improve procedural justice in this process.

6 Research Paper 2.B: Business Analytics for Sales Pipeline Management in the Software Industry

Title

Business Analytics for Sales Pipeline Management in the Software Industry: A Machine Learning Perspective

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Abstract

This study proposes a model designed to help sales representatives in the software industry to manage the complex sales pipeline. By integrating business analytics in the form of machine learning into lead and opportunity management, data-driven qualification support reduces the high degree of arbitrariness caused by professional expertise and experiences. Through the case study of a software provider, we developed an artifact consisting of three models to map the end-to-end sales pipeline process using real business data from the company's CRM system. The results show a superiority of the CatBoost and Random Forest algorithm over other supervised classifiers such as Support Vector Machine, XGBoost, and Decision Tree as the baseline. The study also reveals that the probability of either winning or losing a sales deal in the early lead stage is more difficult to predict than analyzing the lead and opportunity phases separately. Furthermore, an explanation functionality for individual predictions is provided.

Keywords

Sales Pipeline Process, Lead and Opportunity Management, Machine Learning

6.1 Introduction

The high rate of business changes and the ongoing digital transformation in the global environment compel modern enterprises to remain agile and competitive by evolving their business processes accordingly. Based on the concept of dynamic capabilities, organizations can maintain and even strengthen their competitive advantage particularly in times of market uncertainty and fierce competition by creating, renewing and orchestrating their resources and assets (Teece et al., 1997; Arndt et al., 2018). With the purpose of increasing business performance, companies have adopted business analytics on a large scale as data-driven decision-making procedures enhance business processes and enable the identification of market opportunities and threats (Akter et al., 2016; Popovič et al., 2018). From the perspective of dynamic capabilities (Teece et al., 1997; Arndt et al., 2018), applying business analytics technologies in Customer Relationship Management (CRM) systems drives business value steadily as Information Technology (IT) resources and corporate assets such as organizational data are integrated and reorganized. Nam et al. (Nam et al., 2019) demonstrate in their research that the increase in CRM performance depends positively on the usage of business analytics, whereby data quality must be continuously improved. In general, CRM applications facilitate the process of managing and coordinating customer interactions with the primary goal of ensuring long-term customer value by improving customer acquisition and increasing customer retention (Jackson, 2005; Buttle, 2008). Therefore, converging CRM systems and business analytics technologies enables firms to analyze and incorporate valuable insights in their customer interactions and decision-making procedures to maximize customer value.

The study of Ngai et al. (Ngai et al., 2009) presents that, besides statistical and mathematical approaches, the emergence of machine learning (ML) in the CRM context offers great potential for discovering and deriving insightful information from enterprise data. The increasing significance in customer centricity and the availability of customer data enable organizations to apply ML techniques, especially in the fields of customer identification, attraction, retention, and development. However, the majority of CRM literature focuses more on customer retention than on customer acquisition (Söhnchen and Albers, 2010) as the establishment of long lasting customer relations and the associated cross and upsell potentials have a positive impact on corporate profitability (Reinartz et al., 2003; Jahromi et al., 2014). Nevertheless, since customer acquisition strategies are considered as a counterpart to customer retention, companies must also ensure a clear focus on gaining new customers on a consistent basis. Customer acquisition strategies are crucial for a company’s success from the perspective of increasing market size in strategic industries, and exploiting new customer markets and product (Ang and Buttle, 2006;

Buttle, 2008). Acquiring new customers involves significant effort and expenses as the sales pipeline process embraces several stages from the initial contact to the final sales deal. In general, the first phase of identifying and addressing prospects who express first interest in purchasing a product is defined as lead management. The following phase of opportunity management includes all sales related activities that are tailored to the specific requirements of the sales prospect, and thus contribute to the successful closing of a sales deal (Smith et al., 2006; Lippold, 2016).

Since a data-driven decision-making process reduces the degree of human intuition through data analysis (Provost and Fawcett, 2013), this research paper proposes the integration of business analytics in the form of ML techniques in the lead and opportunity management phases. Despite the focus on applying ML methods in the CRM context such as in churn prediction (e.g., Coussement and DenPoel, 2008; Vafeiadis et al., 2015) and the tremendous efficiency potential in sales procedures, the amount of academic contributions in the field of sales pipeline management have been insufficient up until now. To date, only a few scholars have dedicated their research to the development of ML models that facilitate the sales pipeline qualification process by predicting the likelihood of winning a sales deal (D'Haen and Van Den Poel, 2013; Yan et al., 2015; Megahed et al., 2016). In contrast to their rather narrow view on either the lead or the opportunity phase, we developed an artifact that takes the entire end-to-end sales pipeline process into consideration; from the initial lead phase, to the opportunity phase, and finally to the sales deal closing. Furthermore, we place more emphasis on the high number of categorical features arising from the sales pipeline management than existing state-of-the-art models by applying the CatBoost classifier that achieves superior results through its specialization on categorical data. By integrating an explanation model, we additionally increase the transparency of current black-box algorithms and enable salespeople to understand the impact on individual feature values. To reflect highly complex sales structures and long sales cycles, our study is based on a case study of a company, specializing in enterprise application software. The suitability and usability of the artifact can thus be tested on other business-to-business (B2B) case studies with similar convoluted sales structures. Therefore, this research aims to analyze the prediction of all three sales pipeline scenarios: 1) lead-to-opportunity, 2) opportunity-to-sales deal and 3) lead-to-sales deal to embrace the involvement of both marketing and sales. Thus, we investigate the following research questions:

RQ1: Can ML techniques be applied to the end-to-end sales pipeline process to predict the purchase probability in the lead and opportunity stage?

RQ2: Which ML techniques achieve the best predictive performance in the lead and opportunity qualification process?

Due to the strong profitability pressure in the license-driven software industry, the primary objective is the development of ML models that support salespeople in the qualification process of leads and opportunities. To reduce the level of arbitrariness in managing the sales pipeline, we propose a data-driven approach based on ML techniques. The remainder of this paper is structured as follows: First, the theoretical background of the sales process and the ML methods are outlined. After elaborating the research setting, the results of this study are presented. In the subsequent sections, we discuss our conclusions, highlight the limitations, and propose opportunities for future research.

6.2 Theoretical Background

6.2.1 Sales Pipeline Process

Despite the high technical maturity of CRM systems, to date no universally acknowledged definition exists amongst scholars and practitioners (Paulissen et al., 2007). Most publications, however, share the common understanding that a CRM application embraces all touch points of a customer life cycle to ensure long-term customer value (I. J. Chen and Popovich, 2003; Kumar and Reinartz, 2012). Since CRM functions leverage business performance on a strategic, operational and analytical basis, the database is considered as a crucial corporate asset (Buttle, 2008). Combining the operational level of the lead and opportunity management with analytical CRM functions provides a central support for future sales potentials (Tanner et al., 2005; Torggler, 2008).

Due to the large amount of hidden information in sales data, adopting a data-driven approach through predictive analytics helps salespeople to prioritize promising prospects (Ngai et al., 2009). In general, a sales pipeline process follows the structure of a sales funnel that consists of lead generation, opportunity management and the final sales deal (Smith et al., 2006; Lippold, 2016). The lead stage comprises all marketing-related activities of identifying prospects that first express their interest in buying a product. After qualification and evaluation procedures conducted by marketing, the lead will be handed over to sales and converted into an opportunity. In this stage, salespeople take appropriate actions such as product demos and client meetings to maximize the likelihood of closing the sales deal. The primary goal is to ensure an increase in revenue and a growing customer base (Kawas et al., 2013). However, the qualification assessment is mainly influenced by personal judgement of the respective marketing or sales workforce. Relying on the professional competences and prior experiences leads to counterproductive effects as the personal bias might cause misjudgments within the sales pipeline (Monat, 2011). For instance, salespeople tend to deliberately manipulate the sales pipeline to achieve their own sales quotas. Prospects can be either underrated to avoid additional management attention or overrated to simulate the achievement of sales targets. In addition, sales negotiations may be intentionally postponed to upcoming quarters (Yan et al., 2015; X. Xu et al., 2017). In general, this qualification process requires a great effort as a recent appraisal states that “on average, sales reps spend 80 percent of their time qualifying leads and only 20 percent in closing” (Kyle, 2017).

Taken these challenges into account, fostering automation in the lead and opportunity management is perceived as a significant benefit for organizations. According to Syam and Sharma (2018), integrating ML techniques in the qualification assessment of leads and opportunities enables enterprises to simultaneously reduce subjective bias and to improve quality assurance. Due to these benefits, the development of ML models applicable for the sales pipeline is gaining importance in the research environment. For example, Yan et al. (2015) present a win-propensity model based on ML algorithms that is built upon static features including company profile characteristics such as deal size, geography and industry as well as interaction sequences captured by the pipeline system. A relatively high accumulation of interaction activities including login, browsing, and updating of leads within a short period of time indicates a higher chance of winning the deal. The model developed by Megahed et al. (2016) embraces the multi-stage sales pipeline by taking the diverse maturity levels of opportunities into account. As the focus rather lies on predicting the sales forecast generated by the opportunities, the sales pipeline growth towards the end of the target time period plays a crucial part. Another data-driven approach to prioritize prospects based on the likelihood of a purchase is presented by D’Haen and Van den Poel (2013). They propose a model that in the first phase applies unsupervised ML techniques to find similarities between existing customers and prospects and consequently rank them based on the sales probability. The second phase determines the actual probability of winning or losing the sales deal with the use of ML classifiers such as the logistic regression, decision trees, and neural networks. The third phase combines both approaches and therefore provides a ranked list of prospects. However, the prevalent black-box approach of ML models impedes the interpretation of findings as their complexity obfuscates the inner workings. This opacity makes it difficult for the recipient to understand how the output was achieved by the given input data (Diakopoulos, 2014; Burrell, 2016). In order to create transparency, Bohanec et al. (2017) present, in addition to the sales prediction, an explanation model that allows a deeper comprehensibility and transparent evaluation of the opportunity prediction. This model allows domain experts to evaluate the ML based results by incorporating the impact level of the given attributes.

6.2.2 Machine Learning Methods - Classification Techniques

The term machine learning describes a concept that enables computers to learn rather than being explicitly programmed (Samuel, 1959). In 1997, Tom Mitchell stated that "[a] computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E" (Mitchell, 1997, p. 2). Therefore, the goal of supervised learning is to learn a mapping function from input x to output y that correctly predicts the value of y when exposed to new data (Russell and Norvig, 2010; Murphy, 2012). Lead and opportunity management seems to be an appropriate field for the use of machine learning as organizations generally possess sufficient historical customer data. In the following, we would like to establish a common understanding of the supervised ML algorithms used in our artifact. To determine the best ML technique, we have set a traditional decision tree as the baseline.

<u>Random Forest</u>

As an advancement of decision trees, Random Forest is ideally suited to solve classification problems. The lack of robustness and the high instability of decision trees (Hastie et al., 2001) led to the development of Random Forest introduced by Breiman (2001). As an ensemble approach, the algorithm generates a large number of decision trees on which the majority of votes determines the most popular class. In general, each tree is grown by using only a subset of randomly selected predictors that ultimately predict the final class. In addition to the robustness against outliers and noise, a major advantage of this classifier lies in the deeper interpretability of the black-box structure (Breiman, 2001).

<u>Support Vector Machine</u>

Support Vector Machines (SVMs) were initially introduced by Cortes and Vapnik (1995) with the purpose of solving binary classification tasks. In a binary context, a SVM defines an optimal hyperplane that maximizes the margin between two classes with the nearest data points defined as a support vector. To solve non-linearly separable problems, kernel functions such as sigmoid, polynomial and radial basis function (RBF) are used as remedies. The idea is to implicitly map the original feature space into a higher dimensional feature space to separate data linearly by a hyperplane (Cortes and Vapnik, 1995). A SVM differs from other linear classifiers as the optimal linear separator can even be found in feature spaces with multiple dimensions (Russell and Norvig, 2021).

XGBoost

The eXtreme Gradient Boosting algorithm, shortened to XGBoost, developed by Chen and Guestrin (2016) has recently gained popularity in ML competitions. The fundamentals are based on the gradient boosting framework introduced by Friedman (2001) that is built on the tree ensemble model, allowing to group several weak learners into a strong learner. By following an adaptive strategy, each successive tree is created to predict the residual of the prior tree that will be added to the final prediction. XGBoost outperforms other algorithms in scalability and model performance as parallel and distributed computing is enabled and missing data is handled automatically (T. Chen and Guestrin, 2016).

CatBoost

The CatBoost algorithm, recently launched by the company Yandex, is an implementation of gradient boosting that handles categorical data. As the ensemble of trees can generally only handle numeric features, converting categorical features to numbers requires major preprocessing efforts such as the one-hot-encoding technique that transforms each category into binary variables. Instead of these time-consuming preprocessing steps, CatBoost handles categorical data efficiently as after performing randomly permutation, an average label value is computed for each example when the same value was set before the permutation. In addition, overfitting is prevented by using multiple permutations for training different models (Dorogush et al., 2018).

6.3 Research Setting

While several approaches exist to predict sales deals through ML techniques (D'Haen and Van Den Poel, 2013; Yan et al., 2015; Megahed et al., 2016; Bohanec et al., 2017), these state-of-the-art models bear deficiencies in at least two aspects. First, these studies limit their scope of research to either the lead or the opportunity phase, and thus do not reflect the different maturity levels of the end-to-end sales pipeline process. Second, the existing prediction models lack transparency due to their black-box approaches. In order to address these gaps, we apply the Design Science Research (DSR) (Hevner et al., 2004) to design an artifact for sales prediction along the end-to-end sales pipeline process. Since our objective is to develop a new prediction model for a known problem, the DSR contribution type is considered as an improvement (March and Smith, 1995). To revise the artifact, we follow the iterative design cycle of Takeda et al. (1990), comprising the DSR activities of awareness, suggestion, development, evaluation, and conclusion. In the first phase, we conducted a detailed literature research as presented in the previous chapter to identify the problem and specify the expectations. The second and third phases comprise model development activities including the definition of various sales pipeline scenarios and pre-processing steps such as class label verifications, feature selection techniques, and data cleansing, followed by the division of the dataset into training and test sets, the application of undersampling techniques and hyperparameter methods. Besides these activities as described in the following section, we have also defined metrics to compare the prediction performances of the selected algorithms. For the evaluation phase the case study was chosen as the evaluation type presented by Peffers et al. (2012) to test the artifact for its suitability and usability in a real-life situation. Details on the case study are presented in the section of dataset description, followed by the predictive performance results of the artifact.

6.3.1 Model Development

Since our objective is to cover the entire end-to-end sales pipeline process, we developed three classification models to predict the following cases: 1) lead-to-opportunity, 2) opportunity-to-sales deal, 3) lead-to-sales deal as illustrated in Figure 5. The first model reflects the case when a lead is either converted in an opportunity or discontinued. To take the existing sales pipeline procedure of the respective company into account, the second model embraces both opportunities arising from this conversion and the opportunities created directly by a salesperson. Unlike the first two models, the results of the third model focus on leads that have been either won as a sales deal or lost, meaning that directly created opportunities are not considered in the results of the end-to-end process. In terms of feature selection, we have excluded variables from the original dataset based on the following criteria: redundant features, amount of missing values that accounts for more than 50% of the dataset as well as name- and team-based variables (to avoid performance benchmarking). In order to evaluate the various classification methods described above, we split the dataset into a training and test set by randomly assigning 70% of the data to train the model and the remaining 30% to test the model on an unseen data sample. Due to the different phases along the sales process, the class labels refer either to the case where a lead will be converted or discontinued, or to the likelihood of winning or losing a sales deal. The average conversion rate of leads to sales deals of 10% in the B2B sector (Coe, 2004), however, leads to the presence of data imbalance. To reduce the risk of a class being favored by the presence of data imbalance, we use the technique of random undersampling on the training set, which eliminates random samples from the majority class.

In addition, we apply the hyperparameter optimization method GridSearch along with a 10-fold cross-validation to determine the best combination of parameter values. Regarding SVM, we set the RBF kernel as the default kernel function and conducted a parameter search of the penalty parameter C and the kernel parameter gamma (Hsu et al., 2003).

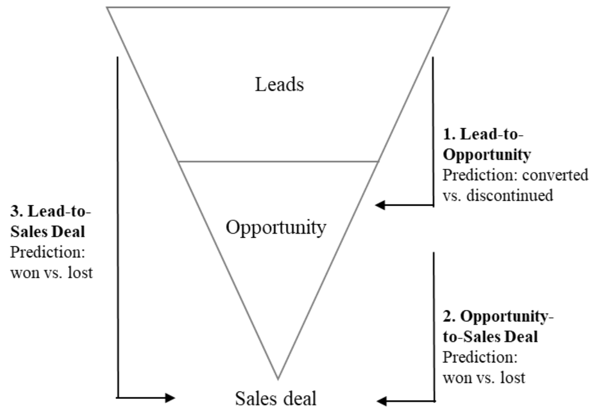

Figure 5. Sales pipeline

Tuning Random Forest refers to the optimal parameter selection of numbers of trees, max depth of trees, as well as minimum number of samples to split an internal node and to be at a leaf node, whereby the decision tree excludes the first mentioned parameter. The performance of XGBoost can be improved by finding the most favorable combination of the learning rate, the minimum sum of weights of all observations required in a child and the maximum depth of a tree. Finally, we tuned CatBoost by adjusting the learning rate and the tree depth.

6.3.2 Evaluation Metrics

To detect the best performing supervised classifier for the presented prediction task, appropriate evaluation metrics must be applied. The basis for these measures represents the confusion matrix which respectively denotes the true-positive and false-positive cases as TP and FP and describes true-negative and false-negative cases as TN and FN. For all three classification models, the Percentage Correctly Classified (PCC), also known as accuracy (Acc.), is calculated to indicate the ratio of correctly classified cases to the total number of classified records using the equation of (TP+TN)/ (TP+FP+TN+FN). To overcome the disadvantage of PCC's lack of robustness to data imbalance, the evaluation metrics are extended by the measures of sensitivity (Sens.), specificity (Spec.), precision (Prec.) and F1. Sensitivity refers to the true-positive rate as it reflects the proportion of positive cases that are correctly classified through the equation of TP/(TP+FN), whereby specificity measures the proportion of negatives that are correctly identified as negatives through the equation of TN/(TN+FP). In contrast, the precision calculates the probability of a sample classified as positive to be positive with the following equation TP/(TP+FP). However, since reaching good results with one of these measures does not necessarily imply good performance on the other, we use the evaluation metric F1 by calculating the equation of 2* (precision * sensitivity) / (precision + sensitivity) (Han et al., 2012; Murphy, 2012). Furthermore, in contrast to the presented point-wise evaluation metrics, we additionally measure the area under the receiving operating curve (AUC) which plots sensitivity and 1-specificity at various threshold settings. Taking all thresholds into account, the AUC measure is ideally suited to compare the overall performance of the presented classifiers (Davis and Goadrich, 2006).

6.3.3 Dataset Description

For this study, we have gathered B2B sales data from a software company listed in the Fortune 500 to develop a ML classification model that supports sales representatives in their lead and opportunity qualification process by providing the probability of a purchase. To reflect the complex sales processes in the license-driven industry and to make the decision-making procedures in the sales pipeline less arbitrary, this provider of enterprise application software serves as a case study. By obtaining real business data from the company's internal CRM system, the artifact is developed on industry-specific sales conditions and peculiarities. Capturing lead and opportunity data in the period from January 2015 to July 2017 clearly represents the long and complex sales cycle of enterprise application software. Furthermore, the dataset embraces all business regions of the software provider consisting of Middle and Eastern Europe (MEE), Middle East and Africa North (EMEAN), Europe, Middle East and Africa South (EMEAS), North America (NA), Latin America (LA), Asia Pacific Japan (APJ) and Greater China (GC). After applying feature selection techniques based on the mentioned specifications, the feature set contains 17 categorical and 19 numeric variables for the lead stage as well as 22 categorical and 20 numeric variables for the opportunity stage. Due to the compliance guidelines of the respective company, we can only outline the features in a broadly manner. Customer features refer, for example, to company size, industry, purchasing lifecycle, and location, whereby campaign features include campaign types, detailed descriptions as well as objectives. In addition to the sales channels and sales units being covered by the sales features, the product portfolio and deployment options are listed in the product features. Detailed information such as competitor, time and pipeline specifications are mentioned in lead-/opportunity-related features, which apply for both leads and opportunities. Furthermore, our assumption of unequal class label distribution is reflected in our dataset, which leads to data imbalance. As shown in Table 16., the relatively high imbalanced class distribution differs across the software provider's business regions, leading to the assumption that regional specific procedures exist in handling the sales pipeline.

Region	**1.Lead-Opportunity**	**2.Opportunity- Sales Deal**	**3.Lead-Sales Deal**
MEE	60% / 40%	34% / 66%	20% / 80%
NA	73% / 27%	22% / 78%	8% / 92%
LA	55% / 45%	18% / 82%	10% / 90%
APJ	93% / 7%	13% / 87%	4% / 96%
GC	78% / 22%	14% / 86%	8% / 92%
EMEAS	78% / 22%	24% / 76%	13% / 87%
EMEAN	75% / 25%	19% / 81%	8% / 92%

Table 16. Data imbalance

By applying random undersampling on the training set, we ensure a balanced label class distribution for training the models. In summary, it must be noted that after verifying the sales pipeline procedure with the company we can ensure that the three models reflect the existing sales pipeline process.

6.4 Results of Predictive Performance

To evaluate and compare the prediction performances of the induced classifiers, we train and test the supervised algorithms on all three sales pipeline scenarios 1) lead-to-opportunity, 2) opportunity-to-sales deal, 3) lead-to-sales deal separately, using real-life business data from the company. As the dataset reflects major regional differences in sales pipeline management, we must distribute the data records among the respective sales regions in order to reduce data bias. On the one hand, data bias might occur due to the conservative or likely lead and opportunity conversion procedures as well as the different CRM maintenance in each region. On the other hand, data bias might be caused by the behavior of the salesperson himself as his personal preferences and professional experiences could have influenced the decision in the lead or opportunity phase. By analyzing the model on a regional level, we were able to eliminate data bias caused by regional differences. However, the reduction of human intuition requires further research in non-standard ML approaches to solve the problems of subjectivity and noisy labels which is outlined in detail in the last chapter. Despite relatively similar results across the globe, we present the predictive performance of a particular sales region which remains anonymous due to compliance guidelines. This choice is based on the strong sales success and the high market share of this sales territory as well as the limited space of this research paper. After randomly dividing the data into the training and test set as well as eliminating data imbalance on the training set by using the random undersampling technique, we receive a total of 36929 unique leads for this sales region, splitted into 24170 records for training and 12759 for testing the first model. The second model is developed through the availability of 26216 unique opportunities, resulting in 16046 training samples and 10170 testing samples. Since the data imbalance of the end-to-end sales process in terms of won sales deals leads to an insufficient sample size, the third model is initially trained and tested on the basis of opportunity records. To ensure consistency with the lead data, these opportunities were selected based on an identical feature set and the involvement of a marketing campaign, as being a key feature of the lead phase. Subsequently, the classification model is then tested with historical lead data whose records resulted in either a closed or a lost sales deal. Therefore, for the second test series alone, we have a total of 10730 unique leads at our disposal that exhibit sales negotiation histories within this region. To avoid data redundancies in the third model, we ensure that the opportunity information arising from leads is eliminated in the initial dataset for training and testing the third model, and that it is only used in the second testing phase. In general, all supervised algorithms including the baseline, Random Forest, SVM, XGBoost and CatBoost are applied on the test set for the selected sales region. Table 17. gives an overview of the predictive performances of all three classification models in terms of accuracy, sensitivity, specificity and F1. When comparing classification techniques, all four algorithms offer similar performances and exceed the baseline. Taking accuracy into account, CatBoost is with 78% and 79% the best classifiers in the first two models, whereby the same moderate results are also reached by SVM in the first and by XGBoost in the second. In the third model, Random Forest exceeds the results of the other algorithms with an accuracy of 71%. In terms of sensitivity and specificity, it is striking that the first two models show only minimal differences of just 0.05% between these evaluation metrics, indicating that no class is preferred. In contrast, the specificity of the third model far exceeds the sensitivity for all classifiers. These large discrepancies point out that the cases of losing the sales deals in the lead stage are more often correctly classified than the positive cases. Regarding F1, it can be observed that the relatively high results in the first and the second model indicate high performance and equality of sensitivity and precision. However, the relatively low F1 results of the third model are caused by the large discrepancies mentioned above. Since the best classifier cannot be clearly identified, with the given evaluation metrics, we also compare the AUC performance shown in Table 18. In terms of the lead- opportunity model, CatBoost outperforms the other classifiers with an AUC of 0.86, confirming the results of accuracy.

Methods	**1. Lead-Opportunity**				
	Acc.	Sens.	Spec.	Prec.	F1
Baseline	0.74	0.74	0.75	0.81	0.77
Random Forest	0.77	0.75	0.80	0.84	0.80
SVM	**0.78**	0.78	0.78	0.83	0.81
XGBoost	0.77	0.76	0.78	0.83	0.80
CatBoost	**0.78**	0.76	0.80	0.84	0.80
	2. Opportunity-Sales Deal				
Baseline	0.75	0.75	0.75	0.61	0.67
Random Forest	0.77	0.78	0.77	0.64	0.70
SVM	0.77	0.78	0.77	0.64	0.70
XGBoost	**0.79**	0.79	0.79	0.66	0.72
CatBoost	**0.79**	0.80	0.78	0.66	0.72
	3. Lead-Sales Deal				
Baseline	0.57	0.48	0.59	0.23	0.31
Random Forest	**0.71**	0.35	0.80	0.31	0.33
SVM	0.64	0.26	0.75	0.21	0.23
XGBoost	0.67	0.32	0.76	0.25	0.28
CatBoost	0.58	0.56	0.59	0.26	0.36

*Acc.=Accuracy, Sens.=Sensitivity, Spec.=Specificity, Prec.=Precision

Table 17. Predictive performance results

With regard to the AUC of 0.88, the probability of winning or losing a sales deal is also best predicted with CatBoost, as the results of accuracy and F1 prove. As the best AUC of the third model yields 0.63, the Random Forest far exceeds the other results of 0.54 (SVM), 0.59 (XGBoost), 0.60 (CatBoost) and 0.59 (Baseline). In contrast to the other sales pipeline models, the Random Forest is therefore seen as the best performing supervised algorithm for predicting the probability of a sales deal in the initial lead phase. Examining the best results across the three sales pipeline models, it is obvious that the third model with a difference of 23-25% in AUC performs much worse than the pure lead and opportunity models. In addition to the evaluation metrics, the proposed artifact also provides an explanation model for a lead or an opportunity. Instead of showing salespeople only the accuracy, the implementation of a novel explanation technique, presented by Ribeiro et al. (2016) allows to explain individual predictions by learning an interpretable model locally around them. Figure 6. depicts the explanation model of a randomly selected opportunity in relation to its feature importance using the Random Forest classifier. The prediction probabilities are displayed on the left, whereby the two graphs on the right assist salespeople to understand which feature values were most relevant for predicting the outcome. Considering this example, the values of product feature 3, customer features 4 and 1 positively influence the likelihood, while product feature 1, opportunity features 2 and 3 have the opposite effect.

Methods	1.Lead-Opportunity	2.Opportunity- Sales Deal	3.Lead-Sales Deal
Baseline	0.84	0.83	0.59
Random Forest	0.85	0.86	**0.63**
SVM	0.85	0.85	0.54
XGBoost	0.85	0.87	0.59
CatBoost	**0.86**	**0.88**	0.60

Table 18. AUC metric

This visualization allows salespeople to incorporate data-driven approaches in their qualification process.

6.5 Discussion

In this study, we propose three ML models as an artifact that support salespeople in their qualification process for the following sales pipeline scenarios 1) lead-to-opportunity, 2) opportunity-to-sales deal, 3) lead-to-sales deal. The results in accuracy and AUC of the first two classification models show that CatBoost clearly outperforms the other supervised algorithms. Due to this strong predictive performance, we would like to emphasize the attractiveness of this algorithm which refers to the sophisticated support of categorical features. Instead of converting each categorical value into binary values through the widely-used one-hot-encoding technique, CatBoost applies an efficient encoding method that leads to quality improvement by reducing overfitting. Since lead and opportunity data usually contain many categorical features such as in our case in marketing campaign, customer, sales and product data, this supervised algorithm is ideally suited to identify promising prospects. Predicting the sales probability in the early lead stage is best performed by Random Forest whose results significantly outperform SVM, XGBoost, CatBoost, and the baseline in terms of accuracy and AUC. Given the nature of Random Forest, our expectations regarding the strong predictive performance and the robustness to outliers and noise of this classifier were clearly met. To our knowledge, our study is among the first to demonstrate the high predictive performance of CatBoost in the lead and opportunity management through the excellent processing of categorical data. Despite the large presence of categorical data and the focus on supervised ML techniques, the study of D'Haen and Van den Poel (2013) and Bohanec et al. (2017) only apply standard ML algorithms such as decision tree, logistic regression, and neural networks. However, as our study shows, CatBoost is ideally suited for the lead and opportunity management which is characterized by its large amount of categorical data.

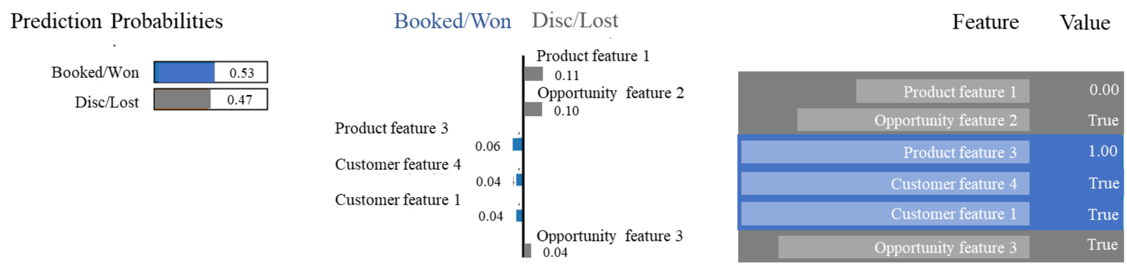

Figure 6. Explanation model

Unlike existing approaches, our artifact examines the end-to-end sales pipeline process by developing and comparing the predictive performances of the three sales pipeline models, covering the entire process of leads, opportunities and sales deals. In contrast to purely limiting the scope of research to either the lead (D'Haen and Van Den Poel, 2013) or the opportunity (Megahed et al., 2016; Bohanec et al., 2017) phase, our artifact takes the specific maturity levels of leads and opportunity into consideration. The marketing-oriented activities in the lead stage as well as the sales specific activities in the opportunity phase are clearly covered by the three models. In contrast, the model of Yan et al. (2015), for example, does not consider crucial marketing-related information in the lead phase. Therefore, our study explicitly reflects the different phases along the sales funnels by carefully taking the maturity levels of leads and opportunities into account. Nevertheless, the large differences in performance between the three prediction scenarios also reflect the usability of the artifact. The very low AUC of the third model depicts that the likelihood of sales deals in the early lead stage can hardly be predicted. The large gap between sensitivity and specificity as well as the resulting poor F1 performance also point to the same assumption. Despite identical feature sets, a possible reason could be that the feature values of the opportunities, on which the model is initially trained, are more advanced along the sales cycle than the lead information available for testing the model. To give an example from our specific dataset, the product information of opportunities is much more mature compared to leads as product requirements of enterprise application software, budget information and, general conditions are usually shared and communicated within the sales negotiations. Taking the results of this study into account, we can emphasize that mapping an end-to-end sales pipeline process into a single classification model does not yield the expected performance. Therefore, two separate lead and opportunity models, as presented in this study, are more suitable to predict whether a lead will be converted or discontinued, or a sales deal will be won or lost. This approach ensures that the different maturity levels of the lead and opportunities phases are reflected in the feature values. Furthermore, our artifact extends the existing state-of-the-art black-box prediction models (D'Haen and Van Den Poel, 2013; Yan et al., 2015; Megahed et al., 2016) by applying the novel explanation technique by Ribeiro et al. (2016). Instead of just displaying the prediction performances, salespeople are able to analyze the impact of the individual feature values in order to follow the decision-making process based on ML techniques. Consequently, the first two models are highly recommended to assist sales representatives in qualifying their sales pipeline through data-driven decision support. In addition, it should be noted that our artifact is trained and tested using original real-life data extracted from the company's CRM, rather than pseudo tests and manually added attributes (D'Haen and Van Den Poel, 2013; Bohanec et al., 2017). Overall, by comparing the results of Random Forest, SVM, XGBoost, CatBoost, and the baseline across the lead and opportunity phases, we would like to emphasize that our research serves as a benchmark that has not yet been examined to this extent.

This research paper makes several contributions to research and practice. We designed a first version of an artifact for sales prediction along the end-to-end sales pipeline process whose applicability and suitability can be further tested and developed on other case studies with similar complex sales pipeline processes. By explicitly taking the lead and the opportunity phase into account, we were able to reflect the different maturity levels across these sales processes. After evaluating the artifact through the case study of an enterprise application software provider, we observed that mapping an end-to-end sales pipeline process into two separate lead and opportunity models yields superior results than a single prediction model. When dealing with categorical features, we were also able to prove that the CatBoost algorithm is ideally suited, whereby the other results can also be used as a sophisticated benchmark for other sales pipeline applications. Furthermore, instead of only displaying the predictive performance, our artifact helps even salespeople to understand the ML based decision-making process with its explanation model by demonstrating the most relevant feature values. Above all, the applicability of the models requires no human expertise about the algorithm running in the background. By providing the individual prediction probabilities and the explanation overview, the model can be used intuitively by sales representatives without extensive training.

6.6 Limitations and Future Research

While we firmly believe that this research paper adds value to the current literature, our study is affected by some limitations and therefore offers opportunities for further research. First, the presented artifact should be tested on other case studies with similar complex sales pipelines to prove its suitability and usability in industry-wide situations. Second, in view of the mentioned interpretation capabilities, it would make sense to extend the explanation model from individual to overarching predictions. Instead of looking at the success rate of a particular lead or opportunity, finding clusters of feature values such as certain industries coupled with specific marketing campaigns can be crucial for determining positive sales indicators. Third, through the availability of a larger dataset and the associated higher degree of complexity, we are striving to apply deep learning approaches to improve performance of sales pipeline models. However, it should be noted that deep learning models offer only limited interpretability of predictions due to their black-box character. Fourth, since in a license-driven industry greater accuracy has a significant impact on a company's profitability, further research must clearly focus on enhancing the predictive performance through other methods. Incorporating non-standard ML approaches could be necessary, for example, to address the problem of subjectivity and noisy labels caused by different regional sales pipeline procedures, diverging professional backgrounds and work experiences. The ability to learn with noisy labels is required if the dataset could be biased due to a salesperson's behavior who systematically discontinues leads as soon as a certain feature value occurs. To give an example, a sales representative may intentionally discontinue a prospect that belongs to a certain industry. In addition, counterfactual inference is also seen as a non-standard ML approach that should be further investigated. The underlying idea is to establish an understanding about the behavior of complex systems interacting with their environment to better predict the consequences of system changes. As part of sales pipeline management, the selection of marketing campaigns is ideal for a counterfactual analysis as the personal network of a salesperson could act as a confounder that chooses the marketing campaign to address the prospect. Based on the available historical data further research could conduct an experiment to assess a customer's potential response to winning or losing a sales deal if a marketing campaign N had been replaced by N´. These proposed methods could significantly improve the prediction of the purchase probability of leads and opportunities.

7 Overarching Contributions and Concluding Remarks

To further advance the transformation of AI throughout the business environment, AI's adoption rate in industries and business functions needs to be steadily increased. Despite AI's potential, organizations have difficulty fully implementing AI applications into their core business practices (Balakrishnan et al., 2020; Chui et al., 2021). Organizations need to approach AI differently, particularly because AI applications are designed as intelligent agents that can simulate human intelligence in perception, reasoning, learning, and interaction (Russell and Norvig, 2021). These capabilities shape not only the factors that influence AI adoption; they also alter organizations' decision-making processes. To promote AI adoption in organizations, this thesis focuses on the dynamics surrounding AI adoption at the organizational level.

The corresponding contributions to theory and practice, as well as the concluding remarks, are outlined in the following sections, in addition to the limitations of the respective research papers.

7.1 Theoretical Contributions

Motivated by the assumption that AI adoption is far from trivial, RQ1 of this thesis seeks to identify factors that influence AI adoption in organizations. In line with previous innovation studies (e.g., Zhu, Kraemer, et al., 2006; Gutierrez et al., 2015; W. Xu et al., 2017), research papers 1.A and 1.B indicate that generic factors derived from the TOE framework and the organizational readiness concept have an impact on AI adoption. For instance, compatibility plays an essential role in the technological context as AI applications need to be fully compatible with existing IT architecture and its respective systems. In addition, research paper 1.B reveals that process compatibility is particularly important for end users as they are more likely to use AI applications if they do not experience any interruptions in their workflows. In the organizational context, for instance, top management has a major impact on the success of AI implementations when they articulate their long-term visions for AI, define appropriate strategies, and allocate necessary resources. Research paper 1.A indicates that in the environmental context, organizations should, for instance, ensure compliance with data protection regulations when implementing AI applications. In addition to these generic factors, research papers 1.A and 1.B also identified factors that are of particular importance in the context of AI. A prerequisite for training AI models with historical datasets is data quality with high accuracy, consistency, and reliability. To avoid unbiased outcomes in autonomous decision-making, establishing ethical guidelines can increase trust among end users in the use of AI applications. Furthermore, a close collaborative work model between different organizational teams can improve their evaluation of AI use cases and their technical assessments of AI applications.

Besides these technological, organizational, and environmental factors, national culture could also be a decisive factor in AI adoption. Drawing on Hofstede's (2001) national cultural framework, research paper 1.A shows that discrepancy in the national cultural dimensions of power distance, masculinity, uncertainty avoidance, and long-term orientation can cause national cultural differences in AI adoption. According to these findings, uncertainty avoidance, for instance, can explain different approaches in data management. Since cultures with high uncertainty avoidance scores tend to avoid unpredictable situations by establishing well-defined procedures and rules, Germany is inclined to ensure data quality as a preparatory measure. In contrast, as a culture with a low uncertainty avoidance score, the United States is more willing to take risks and therefore does not pay as much attention to ensuring data quality as a preparatory action.

Furthermore, by considering AI adoption as a multi-stage rather than a single-stage process, research paper 1.B provides valuable insights into the differentiating and opposing effects of the factors that influence the initiation, adoption, and routinization stages. The actions of top management are an excellent example of how these factors can impact change throughout the AI adoption process. Top management has no significant impact on the initiation stage, but a positive significant impact on the adoption stage and a negative significant impact on the routinization stage. Due to these differentiating and opposing effects, organizations should take the entire adoption process into account when implementing AI applications.

In RQ2, this thesis seeks to examine the impact of AI on the decision-making process in recruiting as well as marketing and sales. To ensure procedural justice in the candidate selection phase in recruiting, CV recommender systems have been developed to identify the most suitable candidate for a given job. An experiment in research paper 2.A shows that a ranking of the top-10 candidates for a job correlated more strongly with one another when recruiters received a matching score generated by the CV recommender system than in the control group, where recruiters relied on their own judgment. Furthermore, the results indicate that focus on the candidates' knowledge, skills, and abilities is greater when recruiters are supported by the CV recommender system. In other words, incorporating a CV recommender system into recruiters' decision-making processes can increase procedural justice in candidate selection by ensuring the rule of consistency. With respect to decision-making in lead-and-opportunity management, AI can facilitate the identification of promising prospects in the sales pipeline. Research paper 2.B develops three classification models for predicting the likelihood of turning a lead or an opportunity into a sales deal by applying machine learning techniques. While CatBoost is the best-performing supervised machine learning algorithm in the models of lead-to-opportunity and opportunity-to-sales deal, random forest outperforms the other machine learning algorithms in the lead-to-sales deal model. Rather than presenting predictive performance, decision-making can be facilitated by incorporating an explanation model.

In light of these findings, this thesis emphasizes that AI adoption is far from trivial and involves significant organizational changes. To ensure successful AI adoption, organizations need to consider the AI-specific factors of data quality, ethics, and collaborative work that can facilitate the implementation of AI applications in addition to the generic factors that arise from established innovation adoption frameworks. Despite the complex nature of change, the impact of AI on the decision-making process is beneficial for organizations.

7.2 Practical Contributions

In addition to its theoretical contributions to research, this thesis also provides valuable guidance on AI adoption to managers and decision-makers. Since organizations tend to face challenges in implementing AI applications, the factors presented in this thesis might help them as facilitators. While these factors highlight challenges that might occur during AI implementation, they also serve as preparatory measures for the early stages of AI adoption. By considering AI adoption as a multi-stage rather than a single-stage process, organizations have the opportunity to appropriately address the factors at each stage. For instance, since the identification of AI use cases and the technical assessment of AI applications occur in the initiation phase, organizations should emphasize collaborative work between teams. It is of utmost importance that functional and data science teams jointly discuss and agree on the functional and technical requirements related to AI from the beginning. To ensure the actual implementation of AI applications, organizations should pay attention that top management is devoted to allocating the necessary resources in the adoption phase. As end users are more likely to incorporate AI applications into their work routines if they experience no interruptions, organizations should focus on ensuring process compatibility in the routinization stage. By dividing the adoption process into its different stages and considering the differentiating and opposing effects of the factors on each stage, managers could contribute to successful AI implementations in their organizations.

In addition to the technological, organizational, and environmental factors as well as the distinct adoption stages, this thesis suggests that managers should also be aware of which national culture their organization belongs to. Drawing on Hofstede's (2001) national cultural framework, factors might have a different impact on AI adoption depending on the national culture. Managers of organizations in Germany or the United States may need to take diverse preparatory measures for AI adoption, such as in dealing with data management. Therefore, this thesis recommends that managers should recognize the national culture to which their organization belongs as the respective national cultural dimensions may affect the success of AI adoption.

Apart from AI adoption at the organizational level, managers should also address the implications of AI adoption on the operational level. By augmenting the decision-making process with AI capabilities, manually managed workflows can be improved significantly. Managers need to select use cases where the decision-making process requires substantial manual effort and compare machine learnings' predictive performances. This thesis highlights two use cases in which AI could contribute to workflow optimization, and there are a variety of other decision-making processes that possess the potential for improvement.

7.3 Concluding Remarks

As a result of its significant potential, AI is increasingly widespread across industries and is shaping the entire business environment. By leveraging business process automation, cognitive insights, and cognitive engagement, organizations strive to implement AI applications into their business practices (Davenport and Ronanki, 2018). Since AI applications are designed as intelligent agents that possess learning and autonomy capabilities (Russell and Norvig, 2021), AI adoption involves far-reaching complex changes for organizations. To support organizations in overcoming the difficulties in implementing AI applications, this thesis articulates the dynamics of AI adoption at an organizational level. Drawing on four research papers using qualitative, quantitative, experimental, and model development research designs, this thesis seeks to guide organizations on AI adoption. The findings reveal that, in addition to the generic factors derived from existing innovation adoption frameworks, AI-specific factors, such as data quality, ethical guidelines, and collaborative work, also have an impact on the initiation, adoption, and routinization stages of AI. Furthermore, the findings suggest that organizations should consider national culture as the influence of technological, organizational, and environmental factors on AI adoption may vary depending on the national culture to which the organization belongs. In addition to AI adoption, AI's impact on organizational decision-making processes is addressed. Using the examples of candidate selection in recruiting and lead-and-opportunity management in marketing and sales, the findings show that manual decision-making processes can be optimized by incorporating AI applications. AI increases procedural justice in the candidate selection process by ensuring consistency and facilitates the identification of promising prospects in the sales pipeline.

Apart from these valuable findings, this thesis provides further opportunities for future research related to AI adoption. In addition to the future research suggestions presented in the respective research papers, the following ideas might be of great interest to the AI adoption research community. The cross-cultural dynamics and the impact of national culture on AI adoption could be analyzed in more depth. Combining innovation adoption frameworks, the multi-stage adoption process, and Hofstede’s (2001) national cultural framework could furnish new insights into how national culture affects the entire AI adoption process. Considering the initiation, adoption, and routinization stages separately allows researchers to examine whether national cultural differences occur during the distinct adoption stages. Using a quantitative rather than a qualitative research design in this approach would contribute to the research as the impact of Hofstede’s (2001) national cultural dimensions on the distinct adoption stages has not been validated in the context of AI. Instead of only focusing on two Western countries, future research could expand the scope by involving developing and newly industrialized countries. Further examining these cross-cultural dynamics could evolve the research on AI adoption.

Appendix

Dependent Variables	
INI	Your organization intends to use AI applications if possible.; Your organization collects information about AI applications with the possible intention of using it.; Your organization evaluates AI use cases.; Your organization conducts pilot test(s) to evaluate AI applications. (Chong and Chan, 2012; Martins et al., 2016)
ADO	Your organization invests resources to adopt productive AI applications. (Martins et al., 2016)
ROUT	The use of AI applications has been incorporated into the end user's regular work practice.; The end user's use of AI applications is pretty much integrated as part of his/her normal work routine.; The end user's use of AI applications is now a normal part of his/her work.; The end user uses AI applications in a standardized way during his/her daily work tasks. (Maas et al., 2018)
Independent and Moderator Variables	
EUR	EUR1: The use of AI applications is difficult for end users to learn. EUR2: AI applications are difficult for end users to operate compared to traditional systems. EUR3: AI applications are difficult for end users to maintain compared to traditional systems. (W. Xu et al., 2017)
TMS	TMS1: Top management articulates a vision for the use of AI applications. TMS2: Top management articulates a strategy for the use of AI applications. TMS3: Top management establishes goals for the use of AI applications. TMS4: Top management defines deployment standards for AI applications. (Rai et al., 2009)
PC	PC1: AI applications complement the main traditional systems (e.g., legacy system). PC2: AI applications fit well with the main needs of your organization. PC3: AI applications fit well with the main work processes of your organization. (Venkatesh and Bala, 2012; W. Xu et al., 2017)
FR	FR1: Your organization has the financial resources to purchase hardware and software required for AI. FR2: Your organization has the financial resources to implement AI. (Chong and Chan, 2012)
EUT	EUT1: Your organization extensively trains end users in using AI applications. EUT2: Your organization provides complete instructions and practices for using AI applications. EUT3: End users receive sufficient training to use the AI applications effectively. (Schillewaert et al., 2005)
EG	Your organization must adhere to ethical guidelines in the process of… EG1: ... designing AI use cases. EG2: … pre-processing the training set. EG3: … developing AI models. (Tractinsky and Jarvenpaa, 1995)
CW	During AI projects, the data science and functional teams involved … CW1: … have frequent contacts on a regular basis. CW2: … have open and two-way communication. CW3: … have informal communication. CW4: … have many different channels to communicate. CW5: … influence each other's decisions through discussion rather than requests. (Cao et al., 2010)

DQ	The training data used in AI applications … DQ1: … are accurate. DQ2: … are reliable. DQ3: … are current. DQ4: … are consistent. (Tractinsky and Jarvenpaa, 1995)
DS	How sensitive do you perceive the information requested by AI? DS1: Demographics (e.g., gender) DS2: Secure identifiers (e.g., medical history) DS3: Contact information DS4: Community interaction (e.g., social network profile) DS5: Personal preference DS6: Financial information of people (Kehr et al., 2015)

Table 19. Items of the dependent, independent, and moderator variables.

References

Adamopoulou, E. and Moussiades, L. (2020). “An Overview of Chatbot Technology.” In: *Proceedings of the International Conference on Artificial Intelligence Applications and Innovations*.

Adams, J. S. (1965). “Inequity in Social Exchange.” In: L. Berkowitz (Ed.), *Advances in Experimental Social Psychology* (pp. 267–299). New York: Academic Press.

Adkins, C. L., Russel, C. J. and Werbel, J. D. (1994). “Judgments of Fit in the Selection Process: The Role of Work Value Congruence.” *Personnel Psychology*, *47*(3), 605–623.

Adomavicius, G. and Tuzhilin, A. (2005). “Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions.” *IEEE Transactions on Knowledge and Data Engineering*, *17*(6), 734–749.

Aggarwal, C. C. (2016). *Recommender Systems*. Cham: Springer International Publishing.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R. and Childe, S. J. (2016). “How to Improve Firm Performance Using Big Data Analytics Capability and Business Strategy Alignment?” *International Journal of Production Economics*, *182*, 113–131.

Almalis, N. D., Tsihrintzis, G. A., Karagiannis, N. and Strati, A. D. (2016). “FoDRA - A New Content-Based Job Recommendation Algorithm for Job Seeking and Recruiting.” In: *Proceedings of the 6th International Conference on Information, Intelligence, Systems and Applications*.

Alshare, K. A., Mesak, H. I., Grandon, E. E. and Badri, M. A. (2011). “Examining the Moderating Role of National Culture on an Extended Technology Acceptance Model.” *Journal of Global Information Technology Management*, *14*(3), 27–53.

Alsheibani, S., Cheung, Y. and Messom, C. (2018). “Artificial Intelligence Adoption: AI-Readiness at Firm-level.” In: *Proceedings of the 22nd Pacific Asia Conference on Information Systems*.

Alsheibani, S., Messom, C. and Cheung, Y. (2019). “Towards an Artificial Intelligence Maturity Model: From Science Fiction to Business Facts.” In: *Proceedings of the 23rd Pacific Asia Conference on Information Systems*.

Ang, L. and Buttle, F. (2006). “Managing For Successful Customer Acquisition: An Exploration.” *Journal of Marketing Management*, *22*(3–4), 295–317.

Anton, E., Behne, A. and Teuteberg, F. (2020). “The Humans Behind Artificial Intelligence – An Operationalisation of AI Competencies.” In: *Proceedings of the 28th European Conference on Information Systems*.

Arndt, F., Pierce, L. and Teece, D. J. (2018). “The Behavioral and Evolutionary Roots of Dynamic Capabilities.” *Industrial and Corporate Change, 27*(2), 413–424.

Arnold, V. and Sutton, S. G. (1998). “The Theory of Technology Dominance: Understanding the Impact of Intelligent Decision Aids on Decision Maker’s Judgments.” *Advances in Accounting Behavioral Research, 1*(3), 175–194.

Arvey, R. D. and Renz, G. L. (1992). “Fairness in the Selection of Employees.” *Journal of Business Ethics, 11*(5–6), 331–340.

Åslund, O. and Skans, O. N. (2012). “Do Anonymous Job Application Procedures Level the Playing Field?” *Industrial and Labor Relations Review, 65*(1), 82–107.

Awad, E., Dsouza, S., Kim, R., Schulz, J., Henrich, J., Shariff, A., … Rahwan, I. (2018). “The Moral Machine Experiment.” *Nature, 563*, 59–64.

Awoyemi, J. O., Adetunmbi, A. O. and Oluwadare, S. A. (2017). “Credit Card Fraud Detection Using Machine Learning Techniques: A Comparative Analysis.” In: *International Conference on Computing, Networking and Informatics*.

Baker, J. (2012). “The Technology-Organization-Environment Framework.” In: Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information Systems Theory - Explaining and Predicting Our Digital Society* (pp. 231–245). New York: Springer Science and Business Media.

Balakrishnan, T., Chui, M., Hall, B. and Henke, N. (2020). *Global Survey: The State of AI in 2020. McKinsey Global Publishing*.

Bansal, S., Srivastava, A. and Arora, A. (2017). “Topic Modeling Driven Content Based Jobs Recommendation Engine for Recruitment Industry.” *Procedia Computer Science, 122*, 865–872.

Benbya, H., Pachidi, S. and Jarvenpaa, S. L. (2021). “Artificial Intelligence in Organizations: Implications for Information Systems Research.” *Journal of the Association for Information Systems, 22*(2), 281–303.

Berente, N., Gu, B., Recker, J. and Santhanam, R. (2021). “Managing Artifical Intelligence.” *MIS Quarterly, 45*(3), 1433–1450.

Black, J. S. and van Esch, P. (2020). “AI-Enabled Recruiting: What Is It and How Should a Manager Use It?” *Business Horizons, 63*(2), 215–226.

Bobadilla, J., Ortega, F., Hernando, A. and Gutiérrez, A. (2013). “Recommender Systems Survey.” *Knowledge-Based Systems, 46*, 109–132.

Bohanec, M., Borštnar, M. K. and Robnik-Šikonja, M. (2017). “Explaining Machine Learning Models in Sales Predictions.” *Expert Systems with Applications, 71*, 416–428.

Borgman, H. P., Bahli, B., Heier, H. and Schewski, F. (2013). “Cloudrise: Exploring Cloud Computing Adoption and Governance with the TOE Framework.” In: *Proceedings of the 46th Hawaii International Conference on System Sciences*.

Breiman, L. (2001). “Random Forests.” *Machine Learning, 45*, 5–32.

Bresnahan, T. F. and Trajtenberg, M. (1995). “General Purpose Technologies “Engines of Growth”?” *Journal of Econometrics, 65*(1), 83–108.

Bretz, R. D., Ash, R. A. and Dreher, G. F. (1989). “Do People Make the Place? An Examination of the Attraction-Selection-Attrition Hypothesis.” *Personnel Psychology, 42*(3), 561–581.

Brynjolfsson, E., Hitt, L. and Kim, H. (2011). “Strength in Numbers: How Does Data-Driven Decision-Making Affect Firm Performance?” In: *Proceedings of the 32nd International Conference on Information Systems*.

Brynjolfsson, E. and Mcafee, A. (2017). “The Business of Artificial Intelligence — What It Can and Cannot Do for Your Organization.” *Harvard Business Review*.

Brynjolfsson, E. and Mitchell, T. M. (2017). “What Can Machine Learning Do? Workforce Implications.” *Science, 358*(6370), 1530–1534.

Brynjolfsson, E., Rock, D. and Syverson, C. (2017). *Artificial Intelligence and The Modern Productivity Paradox: A Clash of Expectations and Statistics* (Nber Working Paper Series, National Bureau of Economic Research).

Buck, C., Hennrich, J., Kauffmann, A. L., Hennrich, J. and Kauffmann, A. L. (2021). “Artificial Intelligence in Radiology – A Qualitative Study on Imaging Specialists’ Perspectives.” In: *Proceedings of the 42nd International Conference on Information Systems*.

Burke, R. (2002). “Hybrid Recommender Systems: Survey and Experiments.” *User Modeling and User-Adapted Interaction, 12*, 331–370.

Burrell, J. (2016). "How the Machine "Thinks": Understanding Opacity in Machine Learning Algorithms." *Big Data and Society, 3*(1).

Burton-Jones, A. and Straub, D. W. (2006). "Reconceptualizing System Usage: An Approach and Empirical Test." *Information Systems Research*, *17*(3), 228–246.

Buttle, F. (2008). *Customer Relationship Management: Concepts and Technologies*. *Customer Relationship Management: Second Edition* (2nd ed.). Abingdon: Routledge.

Caldwell, D. F. and O Reilly, C. A. (1990). "Measuring Person–Job Fit Using a Profile Comparison Process." *Journal of Applied Psychology*, *75*(6), 648–657.

Campbell, D. T. and Stanley, J. C. (1963). *Experimental and Quasi-Experimental Designs for Research*. Boston: Houghton Mifflin Company.

Cao, M., Vonderembse, M. A., Zhang, Q. and Ragu-Nathan, T. S. (2010). "Supply Chain Collaboration: Conceptualisation and Instrument Development." *International Journal of Production Research*, *48*(22), 6613–6635.

Chandra, S. and Kumar, K. N. (2018). "Exploring Factors Influencing Organizational Adoption of Augmented Reality in E-Commerce: Empirical Analysis Using Technology-Organization-Environment Model." *Journal of Electronic Commerce Research*, *19*(3), 237–265.

Chatman, J. A. (1991). "Matching People and Organizations: Selection and Socialization in Public Accounting Firms." *Administrative Science Quarterly*, *36*(3), 459–484.

Chen, I. J. and Popovich, K. (2003). "Understanding Customer Relationship Management (CRM): People, Process and Technology." *Business Process Management Journal*, *9*(5), 672–688.

Chen, T. and Guestrin, C. (2016). "XGBoost: A Scalable Tree Boosting System." In: *Proceedings of the 22nd International Conference on Knowledge Discovery and Data Mining.*

Cheng, Y., Tang, X., Zhang, X. and Xiong, H. (2021). "Effectiveness of AI in Strategic Decision Making: An Empirical Study on Identifying High-Potential Talents." In: *Proceeding of the 42nd International Conference on Information Systems*.

Chin, W. W. (1998). "Issues and Opinion on Structural Equation Modeling." *MIS Quarterly*, *22*(1), 7–16.

Chong, A. Y. L. and Chan, F. T. S. (2012). "Structural Equation Modeling for Multi-stage

Analysis on Radio Frequency Identification (RFID) Diffusion in the Health Care Industry." *Expert Systems with Applications*, *39*(10), 8645–8654.

Chowdhury, G. G. (2005). "Natural Language Processing." *Annual Review of Information Science and Technology*, *37*(1), 51–89.

Christin, A. (2017). "Algorithms in Practice: Comparing Web Journalism and Criminal Justice." *Big Data and Society*, *4*(2).

Chugh, R., Macht, S. and Hossain, R. (2022). "Robotic Process Automation: A Review of Organizational Grey Literature." *International Journal of Information Systems and Project Management*, *10*(1).

Chui, M., Hall, B., Alex Singla and Sukharevsky, A. (2021). *Global Survey: The State of AI in 2021. McKinsey Global Publishing.*

Coe, J. M. (2004). "The Integration of Direct Marketing and Field Sales to Form a New B2B Sales Coverage Model." *Journal of Interactive Marketing*, *18*(2), 62–74.

Cohen, J. (1992). "Quantitative Methods in Psychology: A Power Primer." *Psychological Bulletin*, *112*(1), 155–159.

Cohen, R. L. (1987). "Distributive Justice: Theory and Research." *Social Justice Research*, *1*, 19–40.

Collins, C., Dennehy, D., Conboy, K. and Mikalef, P. (2021). "Artificial Intelligence in Information Systems Research: A Systematic Literature Review and Research Agenda." *International Journal of Information Management*, *60*(4).

Cooper, R. B. and Zmud, R. W. (1990). "Information Technology Implementation Research: A Technological Diffusion Approach." *Management Science*, *36*(2), 123–139.

Cortes, C. and Vapnik, V. (1995). "Support-Vector Networks." *Machine Learning*, *20*, 273–297.

Coussement, K. and DenPoel, D. Van. (2008). "Improving Customer Attrition Prediction by Integrating Emotions from Client/Company Interaction Emails and Evaluating Multiple Classifiers." *Expert Systems with Applications*, *36*(3), 6127–6134.

Cruz-Jesus, F., Pinheiro, A. and Oliveira, T. (2019). "Understanding CRM Adoption Stages: Empirical Analysis Building on the TOE Framework." *Computers in Industry, 109*.

D'Haen, J. and Van Den Poel, D. (2013). "Model-Supported Business-to-Business Prospect

Prediction based on an Iterative Customer Acquisition Framework." *Industrial Marketing Management, 42*(4), 544–551.

Damanpour, F. and Schneider, M. (2006). "Phases of the Adoption of Innovation in Organizations: Effects of Environment, Organization and Top Managers." *British Journal of Management*, *17*(3), 215–236.

Dastin, J. (2018). "Amazon Scraps Secret AI Recruiting Tool that Showed Bias against Women." Retrieved from https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G

Davenport, T. H. (2018a). "From Analytics to Artificial Intelligence." *Journal of Business Analytics, 1*(2), 73–80.

Davenport, T. H. (2018b). *The AI Advantage: How to Put the Artificial Intelligence Revolution to Work*. Cambridge: MIT Press.

Davenport, T. H. and Ronanki, R. (2018). "Artificial Intelligence for the Real World." *Harvard Business Review*.

Davis, J. and Goadrich, M. (2006). "The Relationship between Precision-Recall and ROC curves." In: *Proceedings of the 23rd International Conference on Machine Learning* (Vol. 148, pp. 233–240).

Dean, A., Voss, D. and Draguljić, D. (2017). *Design and Analysis of Experiments* (2nd ed.). Cham: Springer International Publishing AG.

Deutsch, M. (1975). "Equity, Equality, and Need: What Determines Which Value Will Be Used as the Basis of Distributive Justice?" *Journal of Social Issues, 31*(3), 137–149.

Diakopoulos, N. (2014). *Algorithmic Accountability Reporting: On the Investigation of Black Boxes*. *Columbia Journalism School*.

Dinev, T., Goo, J., Hu, Q. and Nam, K. (2009). "User Behaviour towards Protective Information Technologies: The Role of National Cultural Differences." *Information Systems Journal*, *19*(4), 391–412.

Dorogush, A. V., Ershov, V. and Gulin, A. (2018). "CatBoost: Gradient Boosting with Categorical Features Support." *Computing Research Repository*.

Dremel, C., Engel, C. and Mikalef, P. (2020). "Looking Beneath the Surface - Concepts and Research Avenues for Big Data Analytics Adoption in IS Research." In: *Proceedings of the 41st International Conference on Information Systems*.

Eckhardt, A., Laumer, S., Maier, C. and Weitzel, T. (2014). “The Transformation of People, Processes, and IT in E-Recruiting: Insights from an Eight-Year Case Study of a German Media Corporation.” *Employee Relations, 36*(4), 415–431.

Edwards, J. (1991). “Person-Job Fit: A Conceptual Integration, Literature Review and Methodological Critique.” In: T. Cooper, C. L. and Robertson (Ed.), *International Review of Industrial and Organizational Psychology* (pp. 283–357). New York: John Wiley & Sons.

Eisenhardt, K. M. (1989). “Building Theories from Case Study Research.” *Academy of Management Review*, *14*(4), 532–550.

Eisenstein, J. (2018). *Introduction to Natural Language Processing*. Cambridge: MIT Press.

Eitle, V. and Buxmann, P. (2020). “Cultural Differences in Machine Learning Adoption: An International Comparison between Germany and the United States.” In: *Proceedings of the 28th European Conference on Information Systems*.

Faerber, F., Weitzel, T., Keim, T. and Färber, F. (2003). “An Automated Recommendation Approach to Selection in Personnel Recruitment.” In: *Proceedings of the 9th Americas Conference on Information Systems*.

Feigenbaum, E. A. and Buchanan, B. G. (1993). “DENDRAL and Meta-DENDRAL: Roots of Knowledge Systems and Expert System Applications.” *Artificial Intelligence, 59*(1–2), 233–240.

Fichman, R. G. (2000). “The Diffusion and Assimilation of Information Technology Innovations.” In: R. W. Zmud (Ed.), *Framing the Domains of IT Management: Projecting the Future Through the Past*. Cincinnati: Pinnaflex Educational Resources.

Fornell, C. and Larcker, D. F. (1981). “Evaluating Structural Equation Models with Unobservable Variables and Measurement Error.” *Journal of Marketing Research, 18*(1), 39–50.

Friedman, J. H. (2001). “Greedy Function Approximation: A Gradient Boosting Machine.” *The Annals of Statistics, 29*(5), 1189–1232.

Fu, R., Yan Huang and Param Vir Singh. (2021). “Crowds, Lending, Machine, and Bias.” *Information Systems Research*, *32*(1).

Fukas, P., Rebstadt, J., Remark, F. and Thomas, O. (2021). “Developing an Artificial Intelligence Maturity Model for Auditing.” In: *Proceedings of the 29th European*

Conference on Information Systems.

Gallivan, M. J. (2001). “Organizational Adoption and Assimilation of Complex Technological Innovations: Development and Application of a New Framework.” *Database for Advances in Information Systems*, *32*(3), 51–85.

Gangwar, H., Date, H. and Ramaswamy, R. (2015). “Understanding Determinants of Cloud Computing Adoption Using an Integrated TAM-TOE Model.” *Journal of Enterprise Information Management*, *28*(1), 107–130.

Gaskin, J. and Lowry, P. B. (2014). “Partial Least Squares (PLS) Structural Equation Modeling (SEM) For Building And Testing Behavioral Causal Theory: When To Choose It And How To Use It.” *IEEE Transactions on Professional Communication*, *57*(2), 123–146.

Gay, L. R., Mills, G. E. and Airasian, P. (2012). *Educational Research Competencies for Analysis and Applications* (10th ed.). Upper Saddle River: Pearson Education, Inc.

Gefen, D., Straub, D. and Boudreau, M. C. (2000). “Structural Equation Modeling and Regression: Guidelines for Research Practice.” *Communications of the Association for Information Systems*, *4*(7).

German Federal Ministry for Economic Affairs and Climate Action. (2018). “Federal Government Adopts Artificial Intelligence Strategy.”

Gilliland, S. W. (1993). “The Perceived Fairness of Selection Systems: An Organizational Justice Perspective.” *Academy of Management Review*, *18*(4), 694–734.

Goodfellow, I., Bengio, Y. and Courville, A. (2016). *Deep Learning*. Cambridge: MIT Press.

Gorry, G. A. and Morton, M. S. S. (1971). *A Framework for Management Information Systems*. Massachusetts.

Green, B. and Chen, Y. (2019a). “Disparate Interactions: An Algorithm-in-the-Loop Analysis of Fairness in Risk Assessments.” In: *Proceedings of the 2019 Conference on Fairness, Accountability, and Transparency* (pp. 90–99).

Green, B. and Chen, Y. (2019b). “The Principles and Limits of Algorithm-in-the-Loop Decision Making.” In: *Proceedings of the ACM on Human-Computer Interaction*.

Greenberg, J. and Colquitt, J. A. (2005). *Handbook of Organizational Justice*. Mahweh: Lawrence Erlbaum Associates.

Grgic-Hlaca, N., Engel, C. and Gummadi, K. P. (2019). "Human Decision Making with Machine Advice: An Experiment on Bailing and Jailing." In: *Proceedings of the ACM on Human-Computer Interaction*.

Griffith, D. A., Hu, M. Y. and Ryans, J. K. (2000). "Process Standardization across Intra- and Inter-Cultural Relationships." *Journal of International Business Studies, 31*(2), 303–324.

Groth, O. J., Nitzberg, M., Zehr, D., Straube, T. and Kaatz-Dubberke, T. (2019). *Comparison of National Strategies to Promote Artificial Intelligence*. Berlin.

Grover, V. and Goslar, M. D. (1993). "The Initiation, Adoption, and Implementation of Telecommunications Technologies in U.S. Organizations." *Journal of Management Information Systems*, *10*(1), 141–163.

Gutierrez, A., Boukrami, E. and Lumsden, R. (2015). "Technological, Organisational and Environmental Factors Influencing Managers' Decision to Adopt Cloud Computing in the UK." *Journal of Enterprise Information Management*, *28*(6), 788–807.

Hair, J., Black, W. C., Babin, B. J., Anderson, R. E. and Tatham, R. L. (2006). *Multivariate Data Analysis* (6th ed.). Upper Saddle River: Pearson Prentice Hall.

Hair, J. F., Hult, G. T. M., Ringle, C. M. and Sarstedt, M. (2016). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Los Angeles: Sage Publications.

Hamm, P. and Klesel, M. (2021). "Success Factors for the Adoption of Artificial Intelligence in Organizations: A Literature Review." In: *Proceedings of the 27th Americas Conference on Information Systems*.

Han, J., Kamber, M. and Pei, J. (2012). *Data Mining: Concepts and Techniques* (3rd ed.). Waltham: The Morgan Kaufmann Series.

Hastie, T., Tibshirani, R. and Friedman, J. (2001). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York: Springer-Verlag.

Hevner, A. R., Ram, S., March, S. T. and Park, J. (2004). "Design Science in Information Systems Research." *MIS Quarterly*, *28*(1), 75–105.

Hofmann, P., Oesterle, S., Rust, P. and Urbach, N. (2019). "Machine Learning Approaches along the Radiology Value Chain - Rethinking Value Propositions." In: *Proceedings of the 27th European Conference on Information Systems*.

Hofstede, G. (2001). *Culture's Consequences: Comparing Values, Behaviors, Institutions,* *and Organizations Across Nations* (2nd ed.). Thousand Oaks: Sage Publications.

Holmström, J. (2021). "From AI to Digital Transformation: The AI Readiness Framework." *Business Horizons*, *65*(3), 329–339.

Hsu, C., Chang, C. and Lin, C. (2003). *A Practical Guide to Support Vector Classification*. Taipei.

Hu, L. T. and Bentler, P. M. (1999). "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives." *Structural Equation Modeling*, *6*(1).

ISO. (2021). *ISO 8373:2021 Robotics — Vocabulary*. Geneva.

Jackson, T. W. (2005). "CRM : From "Art to Science."" *Journal of Database Marketing & Customer Strategy Management*, *13*(1), 76–92.

Jahromi, A. T., Stakhovych, S. and Ewing, M. (2014). "Managing B2B Customer Churn, Retention and Profitability." *Industrial Marketing Management*, *43*(7), 1258–1268.

Jöhnk, J., Weißert, M. and Wyrtki, K. (2021). "Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors." *Business and Information Systems Engineering*, *63*(1), 5–20.

Judge, T. A. and Cable, D. M. (1997). "Applicant Personality, Organizational Culture, and Organization Attraction." *Personnel Psychology*, *50*(2), 359–394.

Jussupow, E., Spohrer, K., Heinzl, A. and Gawlitza, J. (2021). "Augmenting Medical Diagnosis Decisions? An Investigation into Physicians' Decision-Making Process with Artificial Intelligence." *Information Systems Research*, *32*(3), 713–735.

Kappelman, L., Johnson, V. L., Maurer, C., Guerra, K., McLean, E., Torres, R., … Kim, K. (2020). "The 2019 SIM IT Issues and Trends Study." *MIS Quarterly Executive*, *19*(1), 69–104.

Karunagaran, S., Mathew, S. K. and Lehner, F. (2016). "Differential Adoption of Cloud Technology: A Multiple Case Study of Large Firms and SMEs." In: *Proceedings of the 37th International Conference on Information Systems*.

Kawas, B., Squillante, M. S., Subramanian, D. and Varshney, K. R. (2013). "Prescriptive Analytics for Allocating Sales Teams to Opportunities." In: *Proceedings of the 13th International Conference on Data Mining Workshops*.

Keen, P. G. W. (1980). *Decision Support Systems: A Research Perspective*. Massachusetts.

Kehr, F., Kowatsch, T., Wentzel, D. and Fleisch, E. (2015). “Blissfully Ignorant: The Effects of General Privacy Concerns, General Institutional Trust, and Affect in the Privacy Calculus.” *Information Systems Journal*, *25*(6), 607–635.

Keil, M., Tan, B. C., Wei, K.-K., Saarinen, T., Tuunainen, V. and Wassenaar, A. (2000). “A Cross-Cultural Study on Escalation of Commitment Behavior in Software Projects.” *MIS Quarterly*, *24*(2), 299–325.

Kendall, M. G. and Stuart, A. (1945). *The Advanced Theory of Statistics* (2nd ed.). London: Charles Griffin Company Limited.

Kirk, R. E. (2013). *Experimental Design* (4th ed.). Thousand Oaks: SAGE Publications.

Kristof-Brown, A. L. (2000). “Perceived Applicant Fit: Distinguishing between Recruiters’ Perceptions of Person-Job and Person-Organization Fit.” *Personnel Psychology*, *53*(3), 643–671.

Kristof-Brown, A. L., Zimmerman, R. D. and Johnson, E. C. (2005). “Consequences of Individuals’ Fit at Work: A Meta-Analysis of Person-Job, Person-Organization, Person-Group, and Person-Supervisor FIT.” *Personnel Psychology*, *58*(2), 281–342.

Kristof, A. L. (1996). “Person-Organization Fit: An Integrative Review of Its Conceptualizations, Measurement, and Implications.” *Personnel Psychology*, *49*(1), 1–49.

Kroeber, A. L. and Kluckhohn, C. (1952). “Culture: A Critical Review of Concepts and Definitions.” *Peabody Museum of American Archaeology and Ethnology*, *47*(1).

Kruse, L., Wunderlich, N. and Beck, R. (2019). “Artificial Intelligence for the Financial Services Industry: What Challenges Organizations to Succeed.” In: *Proceedings of the 52nd Hawaii International Conference on System Sciences*.

Kumar, V. and Reinartz, W. (2012). *Customer Relationship Management: Concept, Strategy, and Tools*. *Digital Marketing Fundamentals: From Strategy to ROI* (2nd ed.). Berlin: Springer-Verlag GmbH.

Kyle, P. (2017). “Why AI Won’t Replace (Great) Salespeople.” Retrieved from https://www.entrepreneur.com/article/292162

Laut, P., Dumbach, P. and Bjoern M. Eskofier. (2021). “Integration of Artificial Intelligence in the Organizational Adoption – A Configurational Perspective.” In: *Proceedings of the*

42nd International Conference on Information Systems.

Lee, S. G., Trimi, S. and Kim, C. (2013). "The Impact of Cultural Differences on Technology Adoption." *Journal of World Business, 48*(1), 20–29.

Leidner, D. E. and Kayworth, T. (2006). "Review: A Review of Culture in Information Systems Research: Toward a Theory of Information Technology Culture Conflict." *MIS Quarterly, 30*(2), 357–399.

Leventhal, G. S. (1980). "What Should Be Done With Equity Theory?" In: K. J. Gergen, M. S. Greenberg, & R. H. Willis (Eds.), *Social Exchange* (p. 27–55). Boston: Springer.

Liang, H., Saraf, N., Hu, Q. and Xue, Y. (2007). "Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management." *MIS Quarterly, 31*(1), 59–87.

Lin, H.-F. and Lin, S.-M. (2008). "Determinants of E-Business Diffusion: A Test of the Technology Diffusion Perspective." *Technovation*, *28*(3), 135–145.

Lippold, D. (2016). *Akquisitionsgrundlagen im B2B-Bereich*. Wiesbaden: Springer Gabler.

Liu, J., Wang, G. and Huang, L. (2021). "Relational Time Series Forecasting for Retail Drugstores : A Graph Neural Network Approach." In: *Proceedings of the 42nd International Conference on Information Systems*.

Lokuge, S., Sedera, D., Grover, V. and Xu, D. (2018). "Organizational Readiness for Digital Innovation: Development and Empirical Calibration of a Construct." *Information and Management*, *56*(3), 445–461.

Lops, P., Gemmis, M. De and Semeraro, G. (2011). "Content-Based Recommender Systems: State of the Art and Trends." In: F. Ricci, L. Rokach, & B. Shapira (Eds.), *Recommender Systems Handbook* (pp. 73–105). New York: Springer.

Loucks, J., Huofer, S., Jarvis, D. and Muphy, T. (2019). *Future in the Balance? How Countries Are Pursuing an AI Advantage*. Deloitte Center for Technology, Media & Telecommunications.

Low, C., Chen, Y. and Wu, M. (2011). "Understanding the Determinants of Cloud Computing Adoption." *Industrial Management and Data Systems*, *111*(7), 1006–1023.

Lu, Y., El Helou, S. and Gillet, D. (2013). "A Recommender System for Job Seeking and Recruiting Website." In: *Proceedings of the 22nd International Conference on World Wide Web* (pp. 963–966).

Maas, J. B., Van Fenema, P. C. and Soeters, J. (2018). "Post-Implementation ERP Usage: A Longitudinal Study of the Impact of Control and Empowerment." *Information Systems Management*, *35*(4), 330–347.

MacKenzie, S. B., Podsakoff, P. M. and Podsakoff, N. P. (2011). "Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques." *MIS Quarterly*, *35*(2), 293–334.

Madhavan, P. and Wiegmann, D. A. (2007). "Similarities and Differences between Human-Human and Human-Automation Trust: An Integrative Review." *Theoretical Issues in Ergonomics Science*, *8*(4), 277–301.

Malinowski, J., Keim, T., Wendt, O. and Weitzel, T. (2006). "Matching People and Jobs : A Bilateral Recommendation Approach." In: *Proceedings of the 39th Hawaii International Conference on System Sciences*.

March, S. T. and Smith, G. F. (1995). "Design and Natural Science Research on Information Technology." *Decision Support Systems*, *15*(4), 251–266.

Martins, R., Oliveira, T. and Thomas, M. A. (2016). "An Empirical Analysis to Assess the Determinants of SaaS Diffusion in Firms." *Computers in Human Behavior*, *62*, 19–33.

Martinsons, M. G. and Davison, R. M. (2007). "Strategic Decision Making and Support Systems: Comparing American, Japanese and Chinese Management." *Decision Support Systems*, *43*(1), 284–300.

May, A., Dremel, C., Sagodi, A. and van Giffen, B. (2020). "Realizing Digital Innovation from Artificial Intelligence." In: *Proceedings of the 41st International Conference on Information Systems*.

McCoy, S., Galletta, D. F. and King, W. R. (2005). "Integrating National Culture into IS Research: The Need for Current Individual Level Measures." *Communications of the Association for Information Systems*, *15*, 211–224.

Megahed, A., Yin, P. and Nezhad, H. R. M. (2016). "An Optimization Approach to Services Sales Forecasting in a Multi-Staged Sales Pipeline." In: *Proceedings of the International Conference on Services Computing*.

Meyer, A. D. and Goes, J. B. (1988). "Organizational Assimilation of Innovations: A Multilevel Contextual Analysis." *Academy of Management Journal*, *31*(4), 897–923.

Mikolov, T., Chen, K., Corrado, G. and Dean, J. (2013). "Efficient Estimation of Word

Representations in Vector Space." In: *Proceedings of Workshop at International Conference on Learning Representations*.

Miles, M. B. and Huberman, A. M. (1994). *Qualitative Data Analysis: An Expanded Sourcebook* (2nd ed.). Thousand Oaks: Sage Publications.

Mitchell, T. M. (1997). *Machine Learning*. New York: McGraw-Hill Education Ltd.

Monat, J. P. (2011). "Industrial Sales Lead Conversion Modeling." *Marketing Intelligence & Planning*, *3*(29), 178–194.

Moore, G. C. and Benbasat, I. (1991). "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation." *Information Systems Research*, *2*(3), 192–222.

Mora, M., Forgionne, G., Cervantes, F., Gelman, O., Garrido, L. and Gupta, J. N. D. (2005). "Toward a Comprehensive Framework for the Design and Evaluation of Intelligent Decision-making Support Systems (i-DMSS)." *Journal of Decision Systems*, *14*(3), 321–344.

Muchinsky, P. M. and Monahan, C. J. (1987). "What Is Person-Environment Congruence? Supplementary versus Complementary Models of Fit." *Journal of Vocational Behavior*, *31*(3), 268–277.

Murphy, K. P. (2012). *A Probabilistic Perspective*. Cambridge: MIT Press.

Nam, D., Lee, J. and Lee, H. (2019). "Business Analytics Use in CRM: A Nomological Net from IT Competence to CRM Performance." *International Journal of Information Management*, *45*, 233–245.

Ngai, E. W. T., Xiu, L. and Chau, D. C. K. (2009). "Application of Data Mining Techniques in Customer Relationship Management: A Literature Review and Classification." *Expert Systems with Applications*, *36*(2), 2592–2602.

Nguyen, D. K., Broekhuizen, T., Dong, J. Q. and Verhoef, P. C. (2019). "Digital Readiness: Construct Development and Empirical Validation." In: *Proceedings of the 40th International Conference on Information Systems*.

Nunnally, J. C. (1967). *Psychometric Theory*. New York: McGraw-Hill.

Ochmann, J. and Laumer, S. (2019). "Fairness as a Determinant of AI Adoption in Recruiting: An Interview-Based Study." In: *Proceedings of the 24th Diffusion Interest Group In Information Technology*.

Oliveira, T. and Martins, M. R. O. (2011). “Literature Review of Information Technology Adoption Models at Firm Level.” *Electronic Journal Information Systems Evaluation, 14*(1), 110–121.

Ostroff, C. (1993). “The Effects of Climate and Personal Influence on Individual Behavior and Attirudes in Organizations.” *Organizational Behavior and Human Decision Processes*, *56*(1), 56–90.

Ötting, S. K. and Maier, G. W. (2018). “The Importance of Procedural Justice in Human–Machine Interactions: Intelligent Systems as New Decision Agents in Organizations.” *Computers in Human Behavior*, *89*, 27–39.

Paulissen, K., Milis, K., Brengman, M., Fjermestad, J. and Romano, N. C. (2007). “Voids in the Current CRM Literature: Academic Literature Review and Classification (2000-2005).” In: *Proceedings of the 40th Hawaii International Conference on System Sciences*.

Pazzani, M. J. and Billsus, D. (2007). “Content-based Recommendation Systems.” In: P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), *The Adaptive Web* (pp. 325–341). Berlin: Springer-Verlag.

Peffers, K., Rothenberger, M., Tuunanen, T. and Vaezi, R. (2012). “Design Science Research Evaluation.” In: *Proceedings of the 7th Design Science Research in Information Systems*.

Phillips-Wren, G. (2013). “Intelligent Decision Support Systems.” In: M. Doumpos & E. Grigoroudis (Eds.), *Multicriteria Decision Aid and Artificial Intelligence: Links, Theory and Applications* (pp. 25–44). Chichester: John Wiley & Sons.

Pierce, J. L. and Delbecq, A. L. (1977). “Organization Structure, Individual Attitudes and Innovation.” *The Academy of Management Review, 2*(1), 27–37.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y. and Podsakoff, N. P. (2003). “Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies.” *Journal of Applied Psychology, 88*(5), 879–903.

Popovič, A., Hackney, R., Tassabehji, R. and Castelli, M. (2018). “The Impact of Big Data Analytics on Firms’ High Value Business Performance.” *Information Systems Frontiers, 20*(2).

Porter, M. and Millar, V. E. (1985). “How Information Gives You Competitive Advantage.” *Harvard Business Review*.

Prim, A. L., Filho, L. S., Zamur, G. A. C. and Di Serio, L. C. (2017). "The Relationship Between National Culture Dimensions And Degree Of Innovation." *International Journal of Innovation Management*, *21*(1).

Provost, F. and Fawcett, T. (2013). "Data Science and its Relationship to Big Data and Data-Driven Decision Making." *Big Data*, *1*(1), 51–59.

Pumplun, L., Fecho, M., Islam, N. and Buxmann, P. (2021). "Machine Learning Systems in Clinics - How Mature Is the Adoption Process in Medical Diagnostics?" In: *Proceedings of the 54th Hawaii International Conference on System Sciences*.

Pumplun, L., Tauchert, C. and Heidt, M. (2019). "A New Organizational Chassis for Artificial Intelligence - Exploring Organizational Readiness Factors." In: *Proceedings of the 27th European Conference on Information Systems*.

Radhakrishnan, J. and Gupta, S. (2021). "Exploring the Artificial Intelligence Adoption Journey-A Multiple Case Studies Approach." In: *Proceedings of the 25th Pacific Asia Conference on Information Systems*.

Rai, A., Brown, P. and Tang, X. (2009). "Organizational Assimilation of Electronic Procurement Innovations." *Journal of Management Information Systems*, *26*(1), 257–296.

Ramezani, M., Bergman, L., Thompson, R., Burke, R. and Mobasher, B. (2008). "Selecting and Applying Recommendation Technology." *Workshop on Recommendation and Collaboration*.

Rana, R., Staron, M., Hansson, J., Nilsson, M. and Meding, W. (2014). "A Framework for Adoption of Machine Learning in Industry for Software Defect Prediction." In: *Proceedings of the 9th International Conference on Software Engineering and Applications* (pp. 383–392).

Ransbotham, B. S., Khodabandeh, S., Fehling, R., Lafountain, B. and Kiron, D. (2019). "Winning with AI." *MIT Sloan Management Review*.

Reinartz, W., Krafft, M. and Hoyer, W. D. (2003). "The CRM Process : Its Measurement and Impact on Performance." *Journal of Marketing*, *1*, 77–99.

Ribeiro, M. T., Singh, S. and Guestrin, C. (2016). ""Why Should I Trust You?" Explaining the Predictions of Any Classifier." In: *Proceedings of the 22nd International Conference on Knowledge Discovery and Data Mining* (pp. 1135–1144).

Ricci, F., Rokach, L. and Shapira, B. (2011). *Recommender Systems Handbook*. New York: Springer.

Rogers, E. (1983). *Diffusion of Innovations* (3rd ed.). New York: Free Press.

Rogers, E. (1995). *Diffusion of Innovations* (4th ed.). New York: Free Press.

Rosnow, R. L. and Rosenthal, R. (1989). “Statistical Procedures and the Justification of Knowledge in Psychological Science.” *American Psychologist*, *44*(10), 1276–1284.

Russell, S. J. and Norvig, P. (2010). *Artificial Intelligence: A Modern Approach* (3rd ed.). Hoboken: Pearson Education.

Russell, S. J. and Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Hoboken: Pearson Education.

Rynes, S. and Gerhart, B. (1990). “Interviewer Assessments of Applicant “Fit”: An Exploratory Investigation.” *Personnel Psychology*, *43*(1), 13–35.

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

Samuel, A. L. (1959). “Some Studies in Machine Learning Using the Game of Checkers.” *IBM Journal of Research and Development*, *3*(3), 210–229.

Sarker, S., Xiao, X., Beaulieu, T. and Lee, A. S. (2018). “Learning from First-Generation Qualitative Approaches in the IS Discipline: An Evolutionary View and Some Implications for Authors and Evaluators.” *Journal of the Association for Information Systems*, *19*(8), 752–774.

Schafer, J. B. ;, Frankowski, D., Herlocker, J. and Sen, S. (2007). “Collaborative Filtering Recommender Systems.” In: P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), *The Adaptive Web* (pp. 291 – 324). Berlin: Springer-Verlag.

Schillewaert, N., Ahearne, M. J., Frambach, R. T. and Moenaert, R. K. (2005). “The Adoption of Information Technology in the Sales Force.” *Industrial Marketing Management*, *34*(4), 323–336.

Schneider, B. (1981). “An Interactionist Perspective on Organizational Effectiveness.” *Industrial / Organizational Psychology*.

Schneider, B. (1987). “The People Make the Place.” *Personnel Psychology*, *40*(3), 437–453.

Schneider, B. (2001). “Fits about Fit.” *Applied Psychology*, *50*(1), 141–152.

Schumm, W. R., Pratt, K. K., Hartenstein, J. L., Jenkins, B. A. and Johnson, G. A. (2013). “Determining Statistical Significance (Alpha) and Reporting Statistical Trends: Controversies, Issues, and Facts.” *Comprehensive Psychology*, *2*(1).

Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V. and Biancone, P. (2021). “The Role of Artificial Intelligence in Healthcare : A Structured Literature Review.” *BMC Medical Informatics and Decision Making*, *21*(125).

Seddon, P. B., Constantinidis, D., Tamm, T. and Dod, H. (2017). “How Does Business Analytics Contribute to Business Value?” *Information Systems Journal*, *27*(3), 237–269.

Sekiguchi, T. (2004). “Person-Organization Fit and Person-Job Fit in Employee Selection: A Review of the Literature.” *Osaka Keidai Ronshu*, *54*(6), 179–196.

Sezer, O. B., Gudelek, M. U. and Ozbayoglu, A. M. (2020). “Financial Time Series Forecasting with Deep Learning: A Systematic Literature Review: 2005–2019.” *Applied Soft Computing Journal*, *90*.

Simon, H. A. (1955). “A Behavioral Model of Rational Choice.” *The Quarterly Journal of Economics*, *69*(1), 99–118.

Simon, H. A. (1957). *Models of Man: Social and Rational*. New York: John Wiley & Sons, Inc.

Simon, H. A. (1960). *The New Science of Management Decision*. New York: Harper Brothers.

Simon, H. A. (1977). *The New Science of Management Decision* (Revised Ed). Englewood Cliffs: Prentice-Hall.

Smith, T. M., Gopalakrishna, S. and Chatterjee, R. (2006). “A Three-Stage Model of Integrated Marketing Communications at the Marketing-Sales Interface.” *Journal of Marketing Research*, *43*(4), 564–579.

Söhnchen, F. and Albers, S. (2010). “Pipeline Management for the Acquisition of Industrial Projects.” *Industrial Marketing Management*, *39*(8), 1356–1364.

Sprenger, M. and Mettler, T. (2015). “Service Robots.” *Business & Information Systems Engineering*, *57*(4), 271–274.

Srite, M. and Karahanna, E. (2006). “The Role of Espoused National Cultural Values in Technology Acceptance.” *MIS Quarterly*, *30*(3), 679–704.

Stecher, P., Pohl, M. and Turowski, K. (2020). "Enterprise Architecture's Effects on Organizations' Ability to Adopt Artificial Intelligence - A Resource-based Perspective." In: *Proceedings of the 28th European Conference on Information Systems*.

Strohmeier, S. and Piazza, F. (2015). "Artificial Intelligence Techniques in Human Resource Management—A Conceptual Exploration." In: C. Kahraman & S. Ç. Onar (Eds.), *Intelligent Techniques in Engineering Management* (pp. 149–172). Cham: Springer International Publishing.

Sturm, T., Koppe, T., Scholz, Y. and Buxmann, P. (2021). "The Case of Human-Machine Trading as Bilateral Organizational Learning." In: *Proceedings of the 42th International Conference on Information Systems*.

Syam, N. and Sharma, A. (2018). "Waiting for a Sales Renaissance in the Fourth Industrial Revolution: Machine Learning and Artificial Intelligence in Sales Research and Practice." *Industrial Marketing Management, 69,* 135–146.

Szeliski, R. (2010). *Computer Vision: Algorithms and Applications*. London: Springer.

Takeda, H. and Veerkamp, P. (1990). "Modeling Design Processes." *AI Magazine*, *11*(4), 37–48.

Tanner, J. F., Ahearne, M., Leigh, T. W., Mason, C. H. and Moncrief, W. C. (2005). "CRM in Sales-Intensive Organizations: A Review and Future Directions?" *Journal of Personal Selling and Sales Management, 25*(2), 169–180.

Teece, D. J., Pisano, G. and Shuen, A. (1997). "Dynamic Capabilities and Strategic Management." *Strategic Management Journal, 18*(7), 509–533.

Thielsch, M., Träumer, L. and Pytlik, L. (2012). "E-Recruiting and Fairness : The Applicant's Point of View." *Information Technology and Management, 13*(2), 59–67.

Thompson, V. A. (1969). *Bureaucracy and Innovation*. Huntsville: University of Alabama Press.

Thong, J. Y. L. (1999). "An Integrated Model of Information Systems Adoption in Small Businesses." *Journal of Management Information Systems*, *15*(4), 187–214.

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P. and Fischl, M. (2021). "Artificial Intelligence in Supply Chain Management: A Systematic Literature Review." *Journal of Business Research, 122,* 502–517.

Torggler, M. (2008). "The Functionality and Usage of CRM Systems." *International Journal* *of Computer and Systems Engineering*, *2*(5), 772–779.

Tornatzky, L. G. and Fleischer, M. (1990). *The Process of Technological Innovation*. Massachusetts: Lexington Books.

Tractinsky, N. and Jarvenpaa, S. L. (1995). “Information Systems Design Decisions in a Global versus Domestic Context.” *MIS Quarterly*, *19*(4), 507–534.

Trompenaars, F. and Hampden-Turner, C. (1997). *Riding The Waves of Culture: Understanding Diversity in Global Business*. London: Nicholas Brealey Publishing.

Tung, L. L. and Rieck, O. (2005). “Adoption of Electronic Government Services among Business Organizations in Singapore.” *Journal of Strategic Information Systems*, *14*(4), 417–440.

Vafeiadis, T., Diamantaras, K. I., Sarigiannidis, G. and Chatzisavvas, K. C. (2015). “A Comparison of Machine Learning Techniques for Customer Churn Prediction.” *Simulation Modelling Practice and Theory*, *55*.

van Esch, P., Black, J. S. and Ferolie, J. (2019). “Marketing AI Recruitment: The Next Phase in Job Application and Selection.” *Computers in Human Behavior*, *90*, 215–222.

Venkatesh, V. and Bala, H. (2012). “Adoption and Impacts of Interorganizational Business Process Standards: Role of Partnering Synergy.” *Information Systems Research*, *23*(4), 1131–1157.

Webster, J. and Watson, R. T. (2002). “Analyzing the Past to Prepare for the Future: Writing a Literature Review.” *MIS Quarterly*, *26*(2), 8–18.

Weill, P. and Vitale, M. (1999). “Assessing the Health of an Information Systems Applications Portfolio: An Example from Process Manufacturing.” *MIS Quarterly*, *23*(4), 601–624.

Weiner, B. J. (2009). “A Theory of Organizational Readiness for Change.” *Implementation Science*, *4*(69).

Weiner, B. J., Amick, H. and Lee, S. Y. D. (2008). “Conceptualization and Measurement of Organizational Readiness for Change. A Review of the Literature in Health Services Research and Other Fields.” *Medical Care Research and Review*, *65*(4), 379–436.

Wilk, S. and Sackett, P. R. (1996). “Longitudinal Analysis of Ability-Job Complexity Fit and Job Change.” *Personnel Psychology*, *49*(4), 937–967.

Wu, I. L. and Chuang, C. H. (2010). “Examining the Diffusion of Electronic Supply Chain Management with External Antecedents and Firm Performance: A Multi-stage Analysis.” *Decision Support Systems, 50*(1), 103–115.

Xu, W., Ou, P. and Fan, W. (2017). “Antecedents of ERP Assimilation and its Impact on ERP Value: A TOE-based Model and Empirical Test.” *Information Systems Frontiers*, *19*(1), 13–30.

Xu, X., Tang, L. and Rangan, V. (2017). “Hitting Your Number or Not? A Robust & Intelligent Sales Forecast System.” In: *Proceedings of the International Conference on Big Data, Big Data*.

Yan, J., Zhang, C., Zha, H., Gong, M., Sun, C., Huang, J., … Yang, X. (2015). “On Machine Learning towards Predictive Sales Pipeline Analytics.” In: *Proceedings of the 29th National Conference on Artificial Intelligence* (Vol. 29).

Yin, R. . (2014). *Case Study Research: Design and Methods* (5th ed.). Thousand Oaks: Sage Publications.

Yoo, S. K. and Kim, B. Y. (2018). “A Decision-Making Model for Adopting a Cloud Computing System.” *Sustainability, 10*(8).

Zhang, Z., Nandhakumar, J., Hummel, J. T. and Waardenburg, L. (2020). “Addressing the Key Challenges of Developing Machine Learning AI Systems for Knowledge-Intensive Work.” *MIS Quarterly Executive*, *19*(4), 221–238.

Zhu, K., Dong, S., Xu, S. X. and Kraemer, K. L. (2006). “Innovation Diffusion in Global Contexts: Determinants of Post-Adoption Digital Transformation of European Companies.” *European Journal of Information Systems*, *15*(6), 601–616.

Zhu, K. and Kraemer, K. L. (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, K. L. 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., Kraemer, K. L. 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.

Zhu, K., Kraemer, K. L., Xu, S. 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.