Digital Technologies for Digital Innovation: Unlocking Data and Knowledge to Drive Organizational Value Creation

at the Department of Law and Economics
of the Technical University of Darmstadt

Dissertation

by

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submitted in fulfillment of the requirements for the
degree of Doctor rerum politicarum
(Dr. rer. pol.)

First assessor: Prof. Dr. Peter Buxmann
Second assessor: Prof. Dr. Alexander Benlian
Darmstadt 2022

Koppe, Timo: Digital Technologies for Digital Innovation: Unlocking Data and Knowledge to Drive Organizational Value Creation

Darmstadt, Technical University of Darmstadt

Dissertation published on TUprints in 2022

Day of the viva voce: 17 November 2022

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Timo Koppe

Darmstadt, 20 May 2022

Abstract

The rise of digitization has radically transformed innovation processes of today's companies and is increasingly challenging existing theories and practices. Digital innovation can describe both the use of digital technologies during the innovation process and the outcome of innovation. This thesis aims to improve the understanding of digital innovation in today's digitized world by contributing to the theoretical and practical knowledge along the four organizational activities of the digital innovation process: initiation, development, implementation, and exploitation. In doing so, the thesis pays special attention to the use of digital technologies and tools (e.g., machine learning, online crowdsourcing platforms, etc.) that unlock knowledge and data to facilitate new products, services, and other value streams.

When initiating digital innovations, organizations seek to identify, assimilate, and apply valuable knowledge from within and outside the organization. This activity is crucial for organizations as it determines how they address the increasing pressure to innovate in their industries and markets while innovation processes themselves are changing and becoming more distributed and open. Papers A and B of this thesis address this phase by examining how digital technologies are changing knowledge gathering, e.g., through new ways of crowdsourcing ideas and facilitating cooperation and collaboration among users and innovation collectives.

Paper A focuses on organizational culture as a critical backdrop of digital innovations and explores whether it influences the implementation of idea platforms and, in this way, facilitates the discovery of innovations. The paper reveals that the implementation of idea platforms is facilitated by a culture that emphasizes policies, procedures, and information management. Additionally, the paper highlights the importance of taking organizational culture into account when introducing a new technology or process that may be incompatible with the existing culture.

Paper B examines newly formed innovation collectives and initiatives for developing ventilators to address shortages during the rise of the COVID-19 pandemic. The paper focuses on digital technologies enabling a transformation in the way innovation collectives form, communicate, and collaborate - all during a period of shutdown and social distancing. The paper underlines the role of digital technologies and collaboration platforms through networking, communication, and decentralized development. The results show that through the effective use of digital technologies, even complex innovations are no longer developed only in large enterprises but also by innovation collectives that can involve dynamic sets of actors with diverse goals and capabilities. In addition, established organizations are increasingly confronted with community innovations that offer complex solutions based on a modular architecture characteristic of digital innovations.

Such modular layered architectures are a critical concept in the development of digital innovations. This phase of the digital innovation process encompasses the design, development, and adoption of technological artifacts, which are explored in Sections C and D of this paper.

Paper C focuses on the latter, the adoption of digital services artifacts in the plant and mechanical engineering industry. The paper presents an integrative model based on the Technology-Organization-Environment (TOE) framework that examines different contextual factors as important components of the introduction, adoption, and routinization of digital service innovations. The results provide a basis for studying the assimilation of digital service innovations and can serve as a reference model for informing managerial decisions.

Paper D, in turn, focuses on the design and development of a technology artifact. The paper focuses on applying cloud-based machine learning services to implement a visual inspection system in the manufacturing industry. The results show, for one, the value of standardization and vendor-supplied IS architecture concepts in digital innovation and, for another, how such innovations can facilitate further innovations in manufacturing.

The implementation of digital innovations marks the third phase of the digital innovation process, which is addressed in Paper E. It encompasses organizational changes that occur during digital innovation initiatives. This phase emphasizes change through digital innovation initiatives within the organization (e.g., strategy, structure, people, and technology) and across the organizational environment.

Paper E investigates how digital service innovations impact industrial firms, relationships between firms and their customers, and product/service offerings. The paper uses work systems theory as a theoretical foundation to structure the results and analyze them through the lens of service systems. While this analysis helps to identify the organizational changes that result from the implementation of digital innovations, the paper also provides a basis for further research and supports practitioners with systematic analyses of organizational change.

The last phase of the digital innovation process is about exploiting existing systems/data for new purposes and innovations. In this regard, it is important to better understand the improvements and effects in the domains beyond the sheer outcome of digital innovation, such as organizational learning or organizational change capabilities. Paper F of this thesis investigates the exploitation of digital innovations in the context of organizational learning. One aspect of this addresses how individuals within the organization leverage innovation to explore and exploit knowledge.

Paper F utilizes the organizational learning perspective and examines the dynamics of human learning and machine learning to understand how organizations can benefit from their respective idiosyncrasies in enabling bilateral learning. The paper demonstrates how bilateral human-machine learning can improve the overall performance using a case study from the trading sector. Drawing on these findings, the paper offers new insights into the coordination of human learning and machine learning, and moreover, the collaboration between human and artificial intelligence in organizational routines.

Zusammenfassung (Deutsche Übersetzung des Abstracts)

Die voranschreitende Digitalisierung hat die Innovationsprozesse der heutigen Unternehmen radikal verändert und stellt bestehende Theorien und Praktiken zunehmend in Frage. Digitale Innovation kann sowohl die Nutzung digitaler Technologien während des Innovationsprozesses als auch das Ergebnis der Innovation beschreiben. Diese Dissertation soll das Verständnis der Digitalen Innovation in der heutigen digitalisierten Welt verbessern, indem sie einen Beitrag zum theoretischen und praktischen Wissen entlang der vier organisatorischen Aktivitäten des digitalen Innovationsprozesses leistet: Anbahnung, Entwicklung, Umsetzung und Verwertung. Besonderes Augenmerk wird dabei auf den Einsatz digitaler Technologien und Tools gelegt (z. B. maschinelles Lernen, Online-Crowdsourcing-Plattformen usw.), die Wissen und Daten freisetzen, um neue Produkte, Services und andere Wertströme zu ermöglichen.

Bei der Initiierung Digitaler Innovationen sind Unternehmen bestrebt, wertvolles Wissen innerhalb und außerhalb des Unternehmens zu identifizieren, zu assimilieren und anzuwenden. Diese Tätigkeit ist für Unternehmen von entscheidender Bedeutung, da sie bestimmt, wie sie dem zunehmenden Innovationsdruck in ihren Branchen und Märkten begegnen, während sich die Innovationsprozesse selbst verändern und immer verteilter und offener werden. Die Paper A und B dieser Dissertation befassen sich mit dieser Phase, indem sie untersuchen, wie digitale Technologien das Sammeln von Wissen verändern, z. B. durch neue Möglichkeiten des Crowdsourcing von Ideen und die Erleichterung der Kooperation und Zusammenarbeit zwischen Nutzern und Innovationskollektiven.

Paper A konzentriert sich auf die Organisationskultur als entscheidenden Bestandteil für digitale Innovationen und untersucht, ob sie die Implementierung von Ideenplattformen beeinflusst und auf diese Weise die Entdeckung von Innovationen fördert. Das Paper zeigt, dass die Implementierung von Ideenplattformen durch eine Kultur begünstigt wird, die den Schwerpunkt auf Richtlinien, Verfahren und Informationsmanagement legt. Darüber hinaus wird hervorgehoben, wie wichtig es ist, die Organisationskultur zu berücksichtigen, wenn eine neue Technologie oder ein neuer Prozess eingeführt wird, der möglicherweise nicht mit der bestehenden Kultur vereinbar ist.

Paper B befasst sich mit neu gegründeten Innovationskollektiven und Initiativen zur Entwicklung von Beatmungsgeräten, um den Mangel im Zuge der COVID-19-Pandemie zu beheben. Das Paper konzentriert sich auf digitale Technologien, die einen Wandel in der Art und Weise ermöglichen, wie sich Innovationskollektive bilden, kommunizieren und zusammenarbeiten - und das alles in einer Zeit des Stillstands und der sozialen Distanzierung. Das Paper unterstreicht die Rolle digitaler Technologien und Kollaborationsplattformen durch Vernetzung, Kommunikation und dezentralisierte Entwicklung. Die Ergebnisse zeigen, dass durch den effektiven Einsatz digitaler Technologien selbst komplexe Innovationen nicht mehr nur in großen Unternehmen entwickelt werden, sondern auch von Innovationskollektiven, die dynamische Gruppen von Akteuren mit unterschiedlichen Zielen und Fähigkeiten umfassen können. Darüber hinaus werden etablierte Organisationen zunehmend mit Innovationen aus Communities konfrontiert, die komplexe Lösungen auf der Basis einer für digitale Innovationen charakteristischen modularen Architektur anbieten.

Solche modularen, geschichteten Architekturen sind ein kritisches Konzept bei der Entwicklung digitaler Innovationen. Diese Phase des digitalen Innovationsprozesses umfasst den Entwurf, die Entwicklung und die Übernahme von technologischen Artefakten, die in den Paper C und D dieser Dissertation untersucht werden.

Paper C befasst sich mit der Übernahme digitaler Dienstleistungsartefakte in der Industrie des Anlagen- und Maschinenbauindustrie. Das Paper stellt ein integratives Modell vor, das auf dem Technology-Organization-Environment (TOE) Framework basiert und verschiedene Kontextfaktoren als wichtige Komponenten der Einführung, Adoption und Anwendung von digitalen Serviceinnovationen untersucht. Die Ergebnisse bieten eine Grundlage für die Untersuchung der Assimilation von digitalen Serviceinnovationen und können als Referenzmodell für Managemententscheidungen dienen.

Paper D wiederum befasst sich mit der Gestaltung und Entwicklung eines technologischen Artefakts. Der Beitrag befasst sich mit der Anwendung von Cloud-basierten maschinellen Lerndiensten zur Implementierung eines visuellen Inspektionssystems in der Fertigungsindustrie. Die Ergebnisse zeigen zum einen den Nutzen von Standardisierungs- und herstellerseitigen IS-Architekturkonzepten für digitale Innovationen und zum anderen, wie solche Innovationen weitere Innovationen in der Fertigung ermöglichen können.

Die Implementierung digitaler Innovationen bildet die dritte Stufe des digitalen Innovationsprozesses, die in Paper E behandelt wird. Sie umfasst organisatorische Veränderungen, die während digitaler Innovationsinitiativen auftreten. In dieser Phase liegt der

Schwerpunkt auf Veränderungen durch digitale Innovationsinitiativen innerhalb der Organisation (z. B. Strategie, Struktur, Mitarbeiter/innen und Technologie) und im organisatorischen Umfeld.

Paper E untersucht, wie sich digitale Serviceinnovationen auf Industrieunternehmen, die Beziehungen zwischen Unternehmen und Kunden sowie auf Produkt- und Dienstleistungsangebote auswirken. Das Paper verwendet die Arbeitssystemtheorie als theoretische Grundlage, um die Ergebnisse zu strukturieren und sie durch die Perspektive der Service Systeme zu analysieren. Während diese Analyse hilft, die organisatorischen Veränderungen zu identifizieren, die aus der Implementierung digitaler Innovationen resultieren, bietet das Papier auch eine Grundlage für weitere Forschung und unterstützt Praktiker mit systematischen Analysen des organisatorischen Wandels.

In der letzten Phase des digitalen Innovationsprozesses geht es darum, bestehende Systeme/Daten für neue Zwecke und Innovationen zu nutzen. In diesem Zusammenhang ist es wichtig, die Verbesserungen und Auswirkungen in den Bereichen jenseits des reinen Ergebnisses der digitalen Innovation besser zu verstehen, z. B. organisatorisches Lernen oder organisatorische Veränderungsfähigkeit. Papier F dieser Arbeit untersucht die Nutzung digitaler Innovationen im Kontext des organisatorischen Lernens. Ein Aspekt dabei ist die Frage, wie Einzelpersonen innerhalb der Organisation die Digitale Innovation nutzen, um neues Wissen zu erforschen und zu nutzen.

Paper F nutzt die Perspektive des organisatorischen Lernens und untersucht die Dynamik des menschlichen Lernens und des maschinellen Lernens, um zu verstehen, wie Organisationen von ihren jeweiligen Eigenheiten profitieren können, um bilaterales Lernen zu ermöglichen. Anhand einer Fallstudie aus dem Handelssektor wird gezeigt, wie bilaterales Lernen zwischen Menschen und Maschinen die Gesamtleistung der Organisation verbessern kann. Auf der Grundlage dieser Ergebnisse bietet das Paper neue Einblicke in die Koordination von menschlichem und maschinellem Lernen und darüber hinaus in die Zusammenarbeit zwischen menschlicher und künstlicher Intelligenz in organisatorischen Abläufen.

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List of Abbreviations

AGI	Allianz Global Investors
AI	artificial intelligence
AISeL	AIS electronic Library
AOI	automated optical inspection
AVE	average variance extracted
BDA	big data analytics
CA	cronbach's alpha
CC	cloud computing
CR	composite reliability
CS	company size
CVF	competing values framework
DC	development culture
DOI	diffusion of innovation
DSRM	Design Science Research Methodology
EC	ethical culture
GC	group culture
GUI	graphical user interface
H	hypothesis
HC	hierarchical culture
HTMT	heterotrait-monotrait-ratio
IIP	implementation
IoT	internet of things
IS	information systems
IT	information technology
ML	machine learning
MLaaS	machine learning as a service
MOI	manual optical inspection
OC	organizational culture
PBC	performance-based contracting

PCA	principal component analysis
PHM	prognostics and health management
PSS	product-service systems
RC	rational culture
ROI	return on investment
RQ	research question
SD	standard deviation
SEM	structural equation modeling
SVC	support vector classifier
TOE	Technology-Organization-Environment
VHB	Verband der Hochschullehrer für Betriebswirtschaft e.V.
VIF	variance inflation factors
WSLC	work system lifecycle
WST	work system theory

1 Introduction

1.1 Motivation

In today's world, digital technologies offer new opportunities for creating new products, services, and business models through their unique properties and, in this way, change the way innovation is organized (Yoo et al. 2012). For instance, the remarkable connectivity and embeddedness of digital technologies enable innovation involving dynamic groups of actors with different roles and capabilities (Nambisan et al. 2017; Wang 2021). At the same time, digital technologies are radically changing the nature of products and services, and the way businesses operate (Yoo et al. 2010). Nowadays wearable devices, sensors, mobile networks, 3D printing, and onward digital technologies are already shaping the physical world to such an extent that human decisions and actions are, in some cases, already being replaced by artificial intelligence and robotics (Baskerville et al. 2020).

Within research, digital innovation is concerned with innovation processes and outcomes. A broader conceptualization of digital innovation itself, widely used in the literature (Oberländer et al. 2021), understands digital innovation as "a product, process or business model that is perceived as new, requires significant changes on the part of adopters, and is embodied in or enabled by IT" (Fichman et al. 2014, p. 333). Accordingly, the result of innovation does not necessarily have to be digital as long as digital technologies and digitized processes enable it (Nambisan et al. 2017; Oberländer et al. 2021).

Given today's relatively cheap, easy-to-use, and globally available digital infrastructures that are transforming economies and societies, digital innovation has become significant for all industries (Fichman et al. 2014). From the perspective of established companies, digital innovation is perceived as both an opportunity and a threat (Hanelt et al. 2021; Oberländer et al. 2021). For example, digital platforms like Uber or Netflix are disrupting established businesses without having to invest deeply in resources (Oberländer et al. 2021). Moreover, digital technologies can empower small and mid-size enterprises to compete with larger rivals or benefit developing countries by allowing them to leapfrog development stages (Ramdani et al. 2022). On the flip side, digital technologies are helping incumbents in streamlining processes, efficiently customizing products for their customers, enabling new services and business models, and acting as a key driver of economic value and competitive advantage (Baskerville et al. 2020; Fichman et al. 2014).

As a result, it has never been more important for researchers and practitioners to better understand the mechanisms behind digital innovation, leading to a great need for new theories on the logic of innovation processes and outcomes (Baskerville et al. 2020; Fichman et al. 2014; Nambisan et al. 2017). As such, this thesis aims to contribute to the knowledge of digital innovation by further investigating digital innovation activities in organizations: the initiation, development, implementation, and exploitation of digital innovations (Kohli and Melville 2019). In this context, particular emphasis is placed on the use of digital technologies and tools (e.g., machine learning, online crowdsourcing platforms, etc.) that enable digital innovations such as new products, services, and other forms of value creation.

Starting with the initiation of digital innovation, the goal is to identify, assimilate, and apply useful knowledge from within and outside the organization that relates to problems and opportunities suitable for digital innovation (Drechsler et al. 2020; Kohli and Melville 2019). Although this phase is particularly important, as innovation pressures for today's firms are increasing while innovation processes are changing, becoming more distributed and open (Bogers and West 2012), prior literature leaves many research questions unanswered (Kohli and Melville 2019). In initiating digital innovation, Kohli and Melville (2019) emphasize the ability of organizations to generate and apply knowledge, leading to digital innovation. This process can be supported by IT tools, such as online crowd-sourced innovation platforms. Here, digital infrastructure and tools can provide access to the "wisdom of the crowds" (Surowiecki 2004) while facilitating cooperation and collaboration, sharing insights and experiences, or building social networks among users (Yoo et al. 2012). To address this research stream, two papers in this thesis examine the role of digital technologies in gathering knowledge through user crowds and innovation collectives, both inside and outside companies. Here, Paper A focuses on organizational culture as a critical backdrop for the front-end of innovation (e.g., Brown and Woodland 1999; Curry and Stancich 2000) and examines whether it influences the implementation of idea platforms and in this way facilitates innovation discovery. Paper B, in turn, looks at digital technologies that enable change in the innovation process and the ways in which innovation collectives form, communicate and collaborate. It also examines innovation outcomes and their design and production, against the backdrop of shutdown and social distancing during the COVID-19 crisis.

Initiation is followed by the development of digital innovation, which involves the design, development, and adoption of technological artifacts. It is about how technological artifacts are developed and why they are adopted (Kohli and Melville 2019). In this context, current research emphasizes the importance of understanding not only what promotes adoption and assimilation but also what impedes them (Kohli and Melville 2019; Ramdani et al. 2022). Paper C contributes to the adoption and diffusion research stream of digital innovation by providing insights into the introduction, adoption, and routinization of digital service artifacts in the machinery and manufacturing industry. Paper D, in turn, focuses on a single technological artifact and attempts to determine how the technological artifact should be designed and developed. The artifact itself is about applying cloud-based machine learning services to implement a visual inspection system in the manufacturing industry. The paper contributes to the value of standardization and vendor-supplied IS architecture concepts for digital innovations and demonstrates how such innovations can facilitate further innovations in manufacturing (Kohli and Melville 2019). Implementation is the subsequent phase in the digital innovation process and addresses the organizational changes that occur with digital innovation initiatives (Kohli and Melville 2019; Ramdani et al. 2022). These changes go beyond new organizational logics for digital innovation, such as a more distributed and networked organization, as they potentially drive a transformation of structure, strategy, capabilities, and technology platforms (Drechsler et al. 2020). In this area, the interplay of legacy and emerging elements of organization and technology leads to paradoxes and tensions that shape digital innovation and offer promising avenues for future research (Drechsler et al. 2020). Paper E of this thesis contributes to this topic by examining how digital service innovations affect industrial firms, the relationships between firms and their customers, and product/service offerings.

Finally, very little literature addresses issues related to the use of digital innovations (Kohli and Melville 2019). Here, organizations focus on using existing systems/data for new purposes and innovations. Along these lines, it is also critical to better understand improvements and implications in areas beyond the pure outcome of digital innovation, such as organizational learning or organizational change capabilities (Kohli and Melville 2019). To address this knowledge gap, Paper F of this thesis examines the use of digital innovations in the context of organizational learning, focusing on how individuals within the organization leverage ML systems to explore and leverage knowledge. From an organizational learning perspective, the dynamics of human learning and machine learning are explored to understand how organizations can benefit from each’s idiosyncrasies to enable bilateral learning.

1.2 Structure of the Thesis

The thesis is organized into nine chapters. After this introductory chapter, Chapter 2 presents common theoretical and methodological foundations. The core part of the cumulative dissertation includes six papers published in peer-reviewed conference proceedings that aim to improve the understanding of digital innovation activities. These papers are listed in Table 1.

Initiation of digital innovations	Paper A	Koppe, T. 2021. "**Many Hands Make Light Work: The Influence of Organizational Culture on Idea Platform Implementation**," in: Proceedings of the 16th International Conference on Wirtschaftsinformatik, Online Conference, VHB-Ranking: C.
	Paper B	Koppe, T., and Eckert, B. A. 2021. "**Innovation Collectives in Response to the Covid-19 Crisis: How Digital Technologies Facilitate the Innovation Process of Ventilator Development**," in: Proceedings of the 25th Pacific Asia Conference on Information Systems, Online Conference, VHB-Ranking: C.
Development of digital innovations	Paper C	Koppe, T., and Islam, N. 2021. "**Digital Service Innovation in Plant and Mechanical Engineering: Exploring Contextual Factors in the Innovation Process**," in: Proceedings of the 54th Hawaii International Conference on System Sciences. Online Conference: pp. 4600-4609, VHB-Ranking: C.
	Paper D	Koppe, T., and Schatz, J. 2021. "**Cloud-Based ML Technologies for Visual Inspection: A Case Study in Manufacturing**," in: Proceedings of the 54th Hawaii International Conference on System Sciences. Online Conference: pp. 1020-1029, VHB-Ranking: C.
Implementation of digital innovations	Paper E	Koppe, T., and Honetschläger, K. 2021. "**Exploring Service Innovation in Manufacturing Firms through the Lens of Service Systems: A Structured Literature Review**," in: Proceedings of the 25th Pacific Asia Conference on Information Systems, Online Conference, VHB-Ranking: C.
Exploitation of digital innovations	Paper F	Sturm, T.*, Koppe, T.*, Scholz, Y., and Buxmann, P. 2021. "**The Case of Human-Machine Trading as Bilateral Organizational Learning**." in: Proceedings of the 42^{nd} International Conference on Information Systems (ICIS), Austin, TX, USA, VHB-Ranking: A. *) shared first authorship

Table 1. List of publications included in this dissertation.

The structure of the thesis and thus the sequence of papers is based on the four activities of the digital innovation process in organizations: initiation, development, implementation, and exploitation. In response to the first activity of the digital innovation process, Paper A and B deal with the initiation of digital innovation. Paper A (Chapter 3) addresses the front-end of innovation without explicitly focusing on digital innovation as an outcome of the innovation process. Instead, it examines the implementation of idea platforms as information systems (IS) in organizations and looks at the internal organizational environment, including culture. Paper B (Chapter 4), in turn, focuses on several characteristics of digital innovation initiation that were prominent at the beginning of the COVID-19 crisis and constitute several current research areas. The paper illustrates how innovation processes have changed in an increasingly digital world, aims to better understand the various mechanisms of digital innovation, and provides empirical evidence for new theories of digital innovation management.

Papers C and D deal with the development of digital innovation. Referring to the initiation of digital innovations, Paper C (Chapter 5) looks at the initiation, adoption, and routinization of digital service innovations in the plant and mechanical engineering industry. Paper D (Chapter 6) deals with a particular digital innovation in plant and mechanical engineering. The paper examines the design and development of a visual inspection solution implemented with Machine Learning as a Service as a technological artifact.

In the third phase of the digital innovation process, the implementation of digital innovations, the focus rests on the organizational changes that occur in digital innovation initiatives. In doing so, Paper E (Chapter 7) examines how digital service innovations affect industrial companies, e.g., product and service offerings, and the relationships between companies and customers.

Finally, Chapter 8 (i.e., Paper F) deals with the exploitation of digital innovations. Digital innovation initiatives and efforts implemented in companies create new potential/data that leads to further innovations and improvements. Here, Article F of this thesis examines how collaboration between human and artificial intelligence can be coordinated in organizational routines. In doing so, it examines how individuals within the organization use innovation to explore and leverage knowledge. Based on these findings, the article offers new insights into human and machine learning coordination.

Overall, six different research methods are employed in the six papers of this thesis (see Table 2, column 2) and multiple theoretical frameworks and theories (see Table 2, column 3).

Chapter and Research Paper	Research Type and Methodology	Applied theoretical Frameworks / Theory
Chapter 3 Research Paper A: Implementation of Idea Platforms	Quantitative survey study	Competing Values Framework
Chapter 4 Research Paper B: Innovation Collectives in Response to the COVID-19 Crisis	Mixed-method case study with expert interviews and crawled newspaper data analysis	/
Chapter 5 Research Paper C: Digital Service Innovation in Plant and Mechanical Engineering	Qualitative study based on expert interviews	Technology-Organization-Environment (TOE) framework, Innovation Diffusion Theory
Chapter 6 Research Paper D: Cloud-based ML Technologies for Visual Inspection	Design science research study	/
Chapter 7 Research Paper E: Service Innovation Through the Lens of Service Systems	Structured literature review	Work System Theory
Chapter 8 Research Paper F: Human-Machine Trading as Bilateral Organizational Learning	Abductive analysis of digital trace data	Organizational Learning Theory

Table 2. Outline of research papers.

Among the papers of this thesis are three exploratory case studies that contribute to evolving theory in their field: First, Paper B is a positivist case study that uses a mixed-method approach to analyze both qualitative and quantitative data. Overall, data from 118 cases are collected by searching news articles in an academic newspaper search engine and enriching this information with official websites. These cases are analyzed with descriptive and statistical methods. In addition, Paper B includes eight semi-structured in-depth interviews as qualitative analysis to explore specific initiatives in more detail and shed light on the underlying mechanisms of the innovation process. Second, research paper D presents a single-case study that applies the

Design Science Research method to develop and test a situated implementation of an IS artifact. The instantiation of the visual inspection software artifact is designed, developed, demonstrated, and evaluated in the context of a real-world production process. Lastly, Paper F takes an abductive, pragmatic approach to human-machine pattern recognition to analyze digital trace data describing the trading behavior of humans and ML systems. The paper uses the organizational learning perspective to explore the emerging bilateral human-AI dynamic and its impact on organizational performance.

In addition to the case studies in this thesis, Paper A applies a quantitative research design based on an online survey (N=81) among IT and innovation managers from different organizations. It uses the competing values framework to measure organizational culture and test theory. In addition, Paper A also examined the planned and actual implementation of idea platforms to inspire theory building and identify other criteria that influence the value proposition of idea platforms in organizations. Paper C, in turn, aims to explore key factors that influence digital service innovation in a broader context. Therefore, the paper uses expert interviews (N=10) to gain qualitative insights, which are then structured using the TOE framework as a conceptual framework. Lastly, research paper E employs a structured literature review and embeds the findings within the work system framework and work system life cycle model.

2 Theoretical Foundations

This chapter presents an overview of the common fundamentals of this thesis. First, the concept of digital innovation stands out, which structures and integrates the research papers of this thesis. Second, the subsequent sections provide an outline of digital services and business models that are explored in the adoption and implementation of digital innovations in organizations. The last two sections present digital technologies, those that are important for the industrial sector, and artificial intelligence.

2.1 Digital Innovation

In their literature review, Kohli and Melville (2019) presented a theoretical framework for digital innovation (see Figure 1), which provides the structure for this thesis. In their findings on the existing literature, digital innovation is conceptualized as sequential innovation process over time – yet its steps do not have to be in a sequential order or present in all digital innovation efforts (Kohli and Melville 2019). As already presented and described in the introduction of this thesis, the steps of the process represent the actions and activities of an organization in its digital innovation efforts: initiate, develop, implement, and exploit. In addition, Kohli and Melville's (2019) theoretical framework includes three other components, namely the external competitive environment, the internal organizational environment, and the digital innovation outcomes that interplay with the digital innovation process.

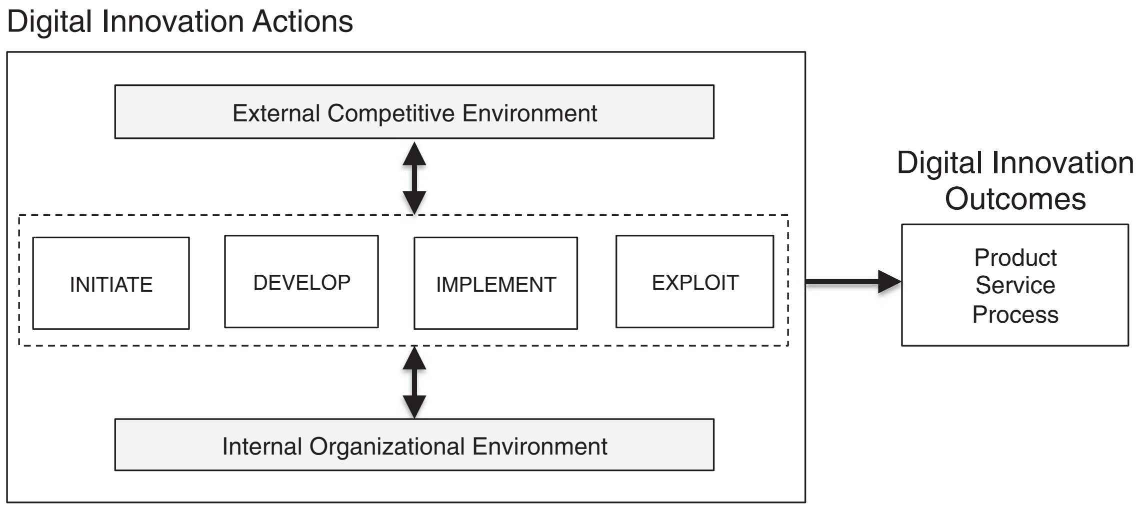

Figure 1. Theoretical framework of digital innovation by Kohli and Melville (2019)

With the increasing number of scholars studying digital innovation, paradoxes and dilemmas in developing, adopting, and managing digital innovation in organizations are coming into the focus of research (e.g., Ciriello et al. 2019; Lyytinen et al. 2016; Nambisan et al. 2017; Tiwana et al. 2010; Yoo et al. 2010). These scholars, in turn, increasingly challenge the explanatory power and usefulness of existing innovation theory and related organizational research (Nambisan et al. 2017). According to Nambisan et al. (2017), at least three fundamental assumptions in innovation management are challenged by digital innovation. These three are briefly stated in the following. First, digital artifacts (products or services) are editable, open, transferable, etc., due to the unique characteristics of digital technologies. As a result, digital artifacts lose their clear boundaries in terms of their scope and features and evolve over time, blurring innovation outcomes and the stages of the innovation process. Second, digital technologies enable the participation of more distributed and diverse innovation agencies and collectives in the innovation process allowing space- and time-independent collaboration on innovations. Third and finally, the interactions between innovation processes and outcomes are becoming more complex and dynamic, influencing each other.

Altogether, this transition from innovation to digital innovation opens up new research opportunities to which this thesis aims to contribute.

2.2 Digital Service and Business Models as Digital Innovation Outcomes

The digital innovation process results in new products, services, and processes (Kohli and Melville 2019). These outcomes, in turn, do not necessarily have to be digital or contain any digital components at all (Nambisan et al. 2017; Oberländer et al. 2021). Despite this, this thesis focuses on digital innovations in the process, in which digital technologies play a central role. This means that the outcome itself takes on their characteristics: Digital technologies include a high degree of interconnectivity and multi-layer modular architecture which pass to the outcome. Further, the re-programmability, homogenization of data, and self-referentiality of digital technologies stand out as characteristics (Yoo et al. 2010).

Although the high relevance of technology-based service and business model innovations is not a new phenomenon in research and practice, they have further gained considerable importance, not least due to the significance of digital technologies in industrial-age products (Lusch and Nambisan 2015). In the same way, novel services and business model innovations in the industry have attracted much attention and are being pursued by companies, e.g., object self-service (Fleisch et al. 2015), condition monitoring and predictive maintenance (Bulger et al. 2014), or cloud computing and similar "-as-a-service" business models (Stuckenberg et al. 2011). Although many of these business models and services drive innovation efforts by today's organizations, they often struggle to implement them and generate sustainable business profits (Ardolino et al. 2018; Frank et al. 2019a). Consequently, it is important for research and practice to better understand the innovation process they emerge from (Kohli and Melville 2019; Ramdani et al. 2022).

2.3 Industrial Internet Technologies and the Manufacturing Sector

As in most industries, digitization has meanwhile reached traditional sectors and businesses, e.g., plant and mechanical engineering. Here, companies are questioning how digital technologies can lead to further innovation. This may not be obvious, especially since their current business is characterized mainly by physical goods and communication (e.g., Buse et al. 2001). For this reason, these industries focus particularly on innovations and business models linked to a product and are referred to as Product-Service Systems (PSS) or hybrid value bundles (Jaspert and Dohms 2020; Veit et al. 2014). PSS describe services linked to products. Depending on the design of the PSS, the emphasis can be on the product or the service. The latter extreme is also known as performance-based contracting (PBC), in which the producer does not sell to the customer but provides and operates for the customer (e.g., Belz and Wuensche 2007; Buse et al. 2001; Kim et al. 2007).

With the help of digital technologies, organizations in traditional industries and businesses have the opportunity to deliver some existing services more efficiently while making some novel services possible in the first place (Shim et al. 2019). Examples include IoT technologies that enable the monitoring and collection of machine data (Wortmann and Flüchter 2015) and algorithms that analyze the health of machines to enable predictions about the basic maintenance and optimization of these machine components in production (Lee et al. 2013). Simultaneously, digitalization has also led to more generated data from machines and production and increased sensor technology and actuators directly on the equipment. In research, these topics are nested under the terms of the Industrial Internet or “Industry 4.0” (Gölzer et al. 2015; Lasi et al. 2014). Here, digital service innovation has been prominent as an important research topic (Baines et al. 2017; Bilgeri et al. 2017b), and the role of digital technologies in transforming services and business models of industrial companies is still poorly explored (Ardolino et al. 2018).

2.4 Artificial Intelligence and Machine Learning

In recent years, one digital technology in particular has stood out for its transformative potential to reshape our society and economy (Sturm et al. 2021): machine learning (ML), which enables modern artificial intelligence (AI). Indeed, several technological breakthroughs revealed that ML is capable of outperforming human performance in a variety of contexts, such as mastering the game Go (Silver et al. 2017) and StarCraft (Vinyals et al. 2019), or image classification (He et al. 2015). Driven by these technological advances, more and more companies are eager to deploy ML-based AI systems in their processes to improve their organizational performance (e.g., Bean 2019; Insights 2018). In doing so, organizations are targeting, how they can use AI to automate (sub-)tasks within routines (e.g., Brynjolfsson and Mitchell 2017), while expanding AI to more and more domains and contexts (Berente et al. 2021). These tasks may even include applications where AI systems manage information autonomously and solve complex decision problems on their own initiative, such as Google's Waymo, which makes (semi-)autonomous decisions (Berente et al. 2021).

However, it is essential to consider more than just the benefits of increased performance when implementing AI systems. Companies should also understand how their actions and processes are affected by intelligent automated systems (e.g., Leavitt et al. 2021; Murray et al. 2021; Rai et al. 2019b; Schuetz and Venkatesh 2020). For instance, such systems have the advantage that they do not make decisions emotionally but based on statistics and data (e.g., Lindebaum et al. 2020; Mitchell et al. 2018; Simon 1987). In this way, many cognitive limitations of human action can be avoided (e.g., Argote et al. 2020; March 1991). Despite these advantages, it is not yet understood what other consequences the use of AI instead of humans would have for organizational learning and performance. For example, it is well known that such systems have difficulty with "out-of-box" thinking, the "frame problem" (e.g., Salovaara et al. 2019), and suffer from the dilemma between "exploration" and "exploitation" (e.g., March 1991).

Broadly speaking, further research is needed on ML and related digital technologies that address the impact of such digital innovations, e.g., on business performance (Ramdani et al. 2022). To this end, this thesis includes two papers (i.e., Papers D and F) that aim to shed light on ML as a technology to foster digital innovation.

3 Paper A: Many Hands Make Light Work: The Influence of Organizational Culture on Idea Platform Implementation

Title

Many Hands Make Light Work: The Influence of Organizational Culture on Idea Platform Implementation

Authors

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Publication Outlet

Proceedings of the 16th International Conference on Wirtschaftsinformatik (WI 2021), Essen, Germany

Abstract

Recent years have seen an increasing emphasis on IT-enabled crowdsourcing for innovation in organizations. However, information systems literature has so far paid little attention to the role of information systems in idea crowdsourcing, including its relation to organizational culture. To address this research gap, we conducted a quantitative study with IT and innovation managers from various organizations (N=81) to explore whether culture influences the implementation of idea platforms. Our key findings show that idea platform implementation is facilitated by a culture that emphasizes policies, procedures, as well as information management (hierarchical culture). Although a culture of creativity should be stimulated in the front-end of innovation, the results indicate that idea platforms are predominantly used in conjunction with a strong internal focus and set of values.

Keywords

Crowdsourcing; Organizational Culture; Idea Platform; Innovation; Quantitative Study.

3.1 Introduction

The emergence and diffusion of digital technologies confront organizations with significant pressure to innovate and renew themselves. For this purpose, organizations are exploring new ways to identify promising opportunities and examine how their organizational knowledge can lead to the introduction of innovation (Drechsler et al. 2020; Kohli and Melville 2019), especially since innovation processes are becoming more distributed and open (Bogers and West 2012). In this regard, organizations can leverage a multitude of methods and measures of innovation management that have been established in recent years. They use open innovation, co-creation, and crowdsourcing to break out of their traditional innovation process (Ili et al. 2010).

Especially crowdsourcing has increased popularity as a method for gathering ideas and innovation (Simula and Vuori 2012; Zuchowski et al. 2016). Simultaneously, the rapid development of social information technologies and platforms provide new ways to enable crowdsourcing. These technologies facilitate cooperation and collaboration between users, exchange of insights and experiences, build social networks (Yoo et al. 2012), connect intelligence, and thus access to the "wisdom of the crowds" (Surowiecki 2004). In this paper, we refer to idea platforms as specific crowdsourcing IT tools for collecting, discussing, enhancing, and evaluating ideas (Zuchowski et al. 2016). Thereby, information systems (IS) play a huge role in enabling and shaping crowdsourcing for innovation and will become more relevant in the future since, e.g., ideas are valuable data (Simula and Vuori 2012). However, IS literature has so far paid little attention to the role of IS in idea crowdsourcing (Majchrzak and Malhotra 2013; Zuchowski et al. 2016). Instead, prior management research has largely dealt with the optimal design of idea competitions, i.e., the motivation of employees (Nov 2007; Wasko and Faraj 2005), characteristics of idea authors (Poetz and Schreier 2012; Schemmann et al. 2016), and the role of community functions (Bullinger and Möslein 2010; Zhu et al. 2019). Still, many IT-based idea competitions fail to achieve active participation (Leimeister et al. 2014). Simula and Vuori (2012) state that organizational culture (OC) can be seen as an issue when motivating participants to submit their ideas to IT platforms. At the same time, internal idea crowdsourcing can also support OC (Simula and Vuori 2012). Prior research indicates that IT tools, i.e., idea platforms, must be in line with complementary non-IT resources, like culture, to leverage value for the business (Kohli and Grover 2008). For example, idea competitions need to emphasize a climate of cooperation and competition at the same time (Hutter et al. 2011). Against this background, we examine the influence of OC on the current status of idea platform implementation. For this purpose, we use the competing values framework (CVF) to measure OC, which is common and frequently used in this context (Denison et al. 1991; Iivari and Huisman 2007; McDermott and Stock 1999; Quinn and Rohrbaugh 1983). Our research question is: How do the organizational culture dimensions influence idea platform implementation? To answer the research question, we conducted a quantitative study with IT and innovation managers from various organizations (N=81). In this context, we also examined the planned versus the actual implementation of idea platforms in an additional part to inspire theory building (Malhotra and Grover 1998). Our research goal is to indicate further criteria that influence the value contribution of idea platforms in organizations.

The remainder of this paper is structured as follows. After describing on the theoretical background and research design, we analyze the relationship between organizational culture and idea platform as well as differences in the planning and actual implementation of idea platforms. Finally, we discuss theoretical and practical implications as well as limitations and further research based on the findings of the empirical analysis.

3.2 Theoretical Background

3.2.1 IT-enabled Crowdsourcing for Innovation

The first phase of an organization's innovation process comprises the activities of generating and selecting ideas. This phase is referred to as the front-end of innovation or as the "fuzzy" front-end. It is described as informal, knowledge-intensive, and irregular (van den Ende et al. 2015). These characteristics make it particularly difficult to manage this phase. This is also due to the fact that innovation management faces the challenge of creating a balance between a context of supporting and stimulating as well as orientation and focus (Birkinshaw and Gibson 2004). Support and stimulation refer to creating a culture of creativity that enables employees and external users to increase the number and novelty of ideas. Simultaneously, the number of ideas is supposed to be reduced through orientation and focus to enhance quality and strategic direction (van den Ende et al. 2015). Relevant ideas do not only emerge within the organization but can also be developed with the concept open innovation. This approach enables knowledge across organization boundaries and identifies and captures external knowledge to support the internal innovation process (Chesbrough 2003). The inclusion of external sources of innovation has several advantages, e.g., it gives organizations access to distant knowledge that is far from an organization’s current knowledge base (Afuah and Tucci 2012). A popular mechanism of gaining access to little explored and a richly heterogeneous pool of knowledge through online infrastructure is called crowdsourcing (Allen et al. 2018). Crowdsourcing refers to the outsourcing of a variety of tasks (West and Bogers 2014). In crowdsourcing, an open call is used to address a “crowd” and, thus, a group of individuals. Afuah and Tucci (2012) distinguish two forms of crowdsourcing. First, in the competition-based approach, each individual chooses to work on their own solution to the problem. The best solution is selected as the winning solution. Second, in the collaboration-based approach, members of the crowd decide whether they want to collaborate on solving the problem. The result is a common solution of the crowd.

Idea crowdsourcing can be implemented in different formats and is often named differently: Idea competitions, challenges, contests, and tournaments. Members of the crowd can be, e.g., customers, partners, or employees (Ebner et al. 2009). Beyond that a distinction is made between design dimensions, such as task/topic specificity, target group, contest period, reward/motivation, or evaluation (Mortara et al. 2013). In this context, the task of an IT-enabled idea platform is to support the various formats and processes through its functionalities. Due to the diversity and the different naming conventions, we broadly refer to idea platforms as an online IT tool for collecting, discussing, enhancing, and evaluating ideas.

3.2.2 Organizational Culture

According to Hofstede and Hofstede (2005), organizational culture is "the collective programming of the mind which distinguishes the members of one group or category of people from another." OC affects all areas of a company and has far-reaching consequences (Schein 1990). In particular, it influences the attitude of employees, e.g., job satisfaction (Kirkman and Shapiro 2001), the operational performance of organizations, e.g., innovative strength (Naranjo ‐ Valencia et al. 2011), and the financial performance of organizations, e.g., profitability (Narver and Slater 1990). At the same time, the OC has an integration function for the employees of a company by conveying cohesion and a common identity. Recognized behavior patterns influence the behavior of employees and, thus, also their innovative behavior (Hauschildt et al. 2016).

Although the OC is difficult to influence, management can still actively influence it and create the conditions for an innovation-friendly culture. By consistently participating in innovation projects and supporting employees, organizations can ensure that all employees have a positive experience with innovation. According to the basic assumptions of the OC, these experiences are condensed into a common, fundamental innovation image among the employees (Hauschildt et al. 2016). To achieve the goal of an innovation-conscious company, Hauschildt et al. (2016) recommends to break down bureaucracy and to use innovation-promoting elements. This includes, among other things, promoting cooperation between different business functions and, in some cases, different business units (Grote et al. 2012).

An understanding of OC is also essential for IS research, as it can influence the successful implementation and use of IS. For example, culture plays a role in management processes that directly or indirectly impacts information technology (Leidner and Kayworth 2006). Furthermore, introducing IT often encounters cultural resistance (Coombs et al. 2016). For these reasons, extensive literature on the relationship between IT and culture was produced, which Leidner and Kayworth (2006) examined and synthesized. They identified two relevant topics in IT cultural research:

1. Culture and IS Development - The core of this topic is how culture influences the design of IS. It has been shown that in a culture where uncertainty is avoided, project risks are perceived differently and are more likely to be abandoned. It is also advantageous if the values of the OC match the values of the information system to be developed.
2. Culture, IT Adoption, and Diffusion - The core of this topic is whether culture influences the adoption and diffusion of IT. The dominant idea is that uncertainty avoidance plays a significant role in deciding how groups adopt and disseminate information and communication technologies. Most studies conclude that those who avoid uncertainty tend to adapt more slowly to new information technologies.

3.3 Research Model

To investigate the cultural factors affecting the implementation of an IT-enabled idea platform, we have oriented to the procedure of Ruppel and Harrington (2001), which contributes to the topic ‘Culture, IT Adoption, and Diffusion’. In their study, they examined the relationship between OC and intranet implementation in organizations. As a result, the acceptance of intranets is much more likely if there is a development culture. Ruppel and Harrington’s study is based on the Competing Values Framework (CVF) (Quinn and Rohrbaugh 1983) and was extended by them to include the ethical dimension. In research, the CVF is widely used to conceptualize OC (Denison et al. 1991; Quinn and Rohrbaugh 1983) and to investigate the relationships and effects of OC (Iivari and Huisman 2007; McDermott and Stock 1999). The CVF distinguishes four types of OC based on two dimensions. The first dimension represents the degree to which the company’s focus is internal or external. The internal focus emphasizes the integration and maintenance of the socio-technical system, while the external focus is on competition and interaction with the organizational environment. The second dimension refers to the differences between change and stability, with change focused on flexibility and spontaneity, while stability focuses on control, continuity and, order (Quinn and Rohrbaugh 1983). The resulting four types of OC are called group, development, rational, and hierarchical culture (Denison et al. 1991).

3.3.1 Hypothesis Development

Organizations with a developmental culture value flexibility and have an external focus. They are therefore not oriented towards their own company, but towards the market and the company's environment. The core of the development culture refers to growth, creativity, and continuous adaptation to external requirements, which are strongly market- and environment-related. Management believes in survival and growth through innovation (Cooper 1994; Cooper and Quinn 1993). Hence, it can be assumed that organizations with this culture know the advantages of idea platforms and are prepared to use them for themselves to remain competitive: *H1 - There is a positive correlation between development culture and the implementation of idea platforms.*

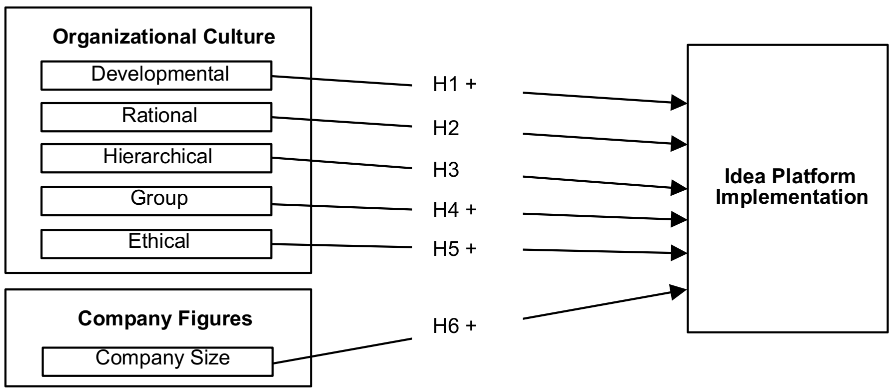

Figure 2. The theoretical model

A company with a rational culture has a strong external focus and a focus on control. The main management activities are focused on maximizing profit through planning, control, and goal setting. By emphasizing order and stability, control structures with varying degrees of formalization and centralization are created to deal with contextual factors such as company size and environmental uncertainty (Ruppel and Harrington 2001). Organizations with this culture focus primarily on competition and the optimization of their operations. We can assume that organizations with a rational culture will quickly become aware of the introduction of idea platforms through their external focus, but that the desire for order can stifle innovation. Since these effects are likely to balance each other out, we do not expect any significant influence of rational culture on the implementation of idea platforms: *H2 - There is no correlation between rational culture and the implementation of idea platforms.*

In a hierarchical culture, the corporate environment is not seen as an essential factor. Management's interest focuses on measurement, documentation, and information management. The focus of these organizations is on control. Idea platforms can support an internal use in defined user groups as well as the implementation of clear processes for the idea process (Elerud-Tryde and Hooge 2014). Idea platforms can also support the collection of ideas for continuous improvements and suggestions. However, the success of an idea platform in the innovation Front-end is supported by a creative and encouraging culture (Hauschildt et al. 2016; Hutter et al. 2011). In contrast, a hierarchical culture focuses on internal orientation and order. Therefore, we assume that the effects are likely to balance each other out: *H3 - There is no correlation between hierarchical culture and the implementation of idea platforms.*

In a group culture, maintaining the company and its human resources is critical, with a focus on cohesive relationships, individual engagement and participation. While this culture is internally focused, it also values flexibility. Managers encourage dialogue, participation, and training of employees to achieve this goal. As they value employee participation, we believe idea platforms are an appropriate tool for organizations with a strong group culture. Idea platforms collect ideas by single employees as well as by groups, respectively (Björk and Magnusson 2009). Besides, idea platforms can support various social and community functions, which make idea competitions even more successful (Björk et al. 2011; Blohm et al. 2011; Bullinger and Möslein 2010). *H4 - There is a positive correlation between group culture and the implementation of idea platforms.*

Ethical culture reflects trust and an ethical working environment. Ruppel and Harrington expend the Competing Values Framework by this dimension since the CVF does not include specific measures for trust and an ethical work environment. Following them, there is no exchange of knowledge without a climate of trust (Brown and Woodland 1999; Curry and Stancich 2000). Therefore, our assumption is *H5 - There is a positive correlation between ethical culture and the implementation of idea platforms.*

Finally, we believe that idea platforms are used independently of corporate industries because, the overall pressure to innovate in the economy has increased. However, we also believe the challenge to manage ideation initiatives increases with the company size. This would confirm other studies that report that web-based ideation systems are used especially within large organizations (Beretta et al. 2018; Elerud-Tryde and Hooge 2014; Zhu et al. 2019). *H6 - There is a positive correlation between company size and the implementation of idea platforms*

3.3.2 Data Collection, Research Design and Measurements

We chose an online survey as the instrument for collecting the data for our study. Prior studies on organizational culture indicate that questionnaires are a reliable and well-established method for this kind of study (Ruppel and Harrington 2001). In addition, the degree of anonymity in online questionnaires is perceived as very high, which tends to lead to greater openness and less often to social desirability bias (Scholl 2018). When selecting participants for the study via social business networks, we considered three criteria. First of all, we address participants from various organizations in different industries and sizes. Our ambition is to reach a broad cross-section of organizations to compare the impact of different cultural types on the implementation of idea platforms between these organizations. Secondly, we restricted the job profiles during our search for participants. Following Ruppel and Harrington (2001), IT managers are argued to be an appropriate source of evaluation of the overall culture and the extent of IT implementation. Since our focus is on the implementation of idea platforms, we filtered for IT managers as well as managers working in the area of innovation. We believe they are best placed to assess the company's innovation process and tools because they shape it or are at least directly involved in it. Before we sent the survey by e-mail, we tested the survey in a pre-test with five other researchers as well as two external managers in the field of innovation management. After our test and revision, we sent e-mails to our recipient list, introducing the project. The participants were informed which profile they should bring along so that they fit as a participant. We distributed the online survey to participants during August and November 2019. Our participant profiles in Table 3 shows that our participant selection was successful and matches our participant profile.

At the very beginning of the online survey, we informed the participants on the welcome page that there are no wrong answers, that they should answer honestly, and we ensured that all answers are processed anonymously. In addition, we have included information on processing time, target group specifications, and the topic without mentioning the term idea platforms. This was done to avoid the participants to be subject of a common method bias as well as a social desirability bias (Mummendey and Grau 2008; Podsakoff et al. 2003). We adapted the items (including reverse items) and overall questionnaire structure from Ruppel and Harrington (2001) to measure the OC. The construct name/culture type was not mentioned to avoid influencing the respondents. Since the questions have already proven to be reliable, we did not expect a ceiling or floor effect for the items. We furthermore included an attention check (Meade and Craig 2012). All OC items were measured using a five-point Likert scale. After the questionnaire part on OC, we provided our definition of idea platforms to create a common understanding of the following questions. When asked about the progress of the introduction of an idea platform, the participant could select between the following options: "An idea platform: (a) has not yet been relevant and is, therefore, not in use (b) was evaluated, but we consciously decided against a deployment at this point (c) is being planned and evaluated (d) is currently being introduced (e) is in use (f) was used and abolished again".

<table>
<tr><th colspan="4">Organization profiles</th><th colspan="4">Individual profiles</th></tr>
<tr><th>Business area (multiple selection possible)</th><th>%</th><th>Organization size (in persons)</th><th>%</th><th>Professional field of activity</th><th>%</th><th>Management Responsibility</th><th>%</th></tr>
<tr><td>Chemistry / Pharma</td><td>24,7</td><td>less than 10</td><td>2,5</td><td>Communication</td><td>1,2</td><td rowspan="3">Management level (no staff responsibility)</td><td rowspan="3">19,8</td></tr>
<tr><td>Communication</td><td>3,7</td><td>10 to 49</td><td>6,2</td><td>Finance & Controlling</td><td>1,2</td></tr>
<tr><td>Consumer goods (e.g., food)</td><td>4,9</td><td>50 to 249</td><td>8,6</td><td>Human resources</td><td>1,2</td></tr>
<tr><td>Electrics / Electronics</td><td>9,9</td><td>250 to 499</td><td>25,9</td><td>IT</td><td>43,2</td><td rowspan="3">Lower management level (e.g., team leader, group leader)</td><td rowspan="3">14,8</td></tr>
<tr><td>Finance / Insurance</td><td>13,6</td><td>500 to 999</td><td>34,6</td><td>Manufacturing & Production</td><td>0</td></tr>
<tr><td>Human health</td><td>11,1</td><td>1,000 to 4,999</td><td>8,6</td><td>Marketing</td><td>3,7</td></tr>
<tr><td>IT</td><td>19,8</td><td>5,000 to 19,999</td><td>7,4</td><td>Purchase & Sales</td><td>1,2</td><td rowspan="3">Middle management (e.g., department-, division heads)</td><td rowspan="3">42,0</td></tr>
<tr><td>Mechanical engineering</td><td>8,6</td><td>20,000 to 99,999</td><td>1,2</td><td>Research & Development</td><td>25,9</td></tr>
<tr><td>Service</td><td>7,4</td><td>100,000 or more</td><td>4,9</td><td>Other activity</td><td>22,2</td></tr>
<tr><td>Transport</td><td>1,2</td><td colspan="4" rowspan="3"></td><td rowspan="3">Upper management level (e.g., executive board)</td><td rowspan="3">23,5</td></tr>
<tr><td>Vehicle construction</td><td>2,5</td></tr>
<tr><td>Others</td><td>25,9</td></tr>
</table>

Table 3. Profiles of responding organizations and individuals (N=81)

Later, we grouped the options a), b) & f) as (1) "no use", options c) & d) as (2) "planning" and option e) as (3) "in use". This categorical measure is preferable to a dichotomous use/non-use variable. It allows the variables to be analyzed in terms of the progress of the idea platform implementation (Ruppel and Harrington 2001).

Since there are not many comparable studies on the implementation of idea platforms focusing on the software component, we surveyed additional variables on the actual or planned design of idea platforms. For group (1) "no use", we asked for reasons for the decision against the implementation of an idea platform as an open question, as well as whether the participant was involved in the decision. For group (2) "planning" and (3) "in use", we surveyed the type of use, the associated objectives, and the frequency of use. The questions of group (3) correspond in content to the questions of group (2) and differ only in the tense of the question. These additional measurement instruments were developed by us for this study. We validated these questions with two experts in the field of consulting and software solutions for idea and innovation management solutions.

3.3.3 Data Analysis

We used SmartPLS software (v.3.2.8) for structural equation modeling and analysis of the organizational culture constructs as well as idea platform implementation. This software was also used together with the bootstrap resampling method to determine the significance of the paths within the structural model. This method is especially appropriate to handle small sample sizes (Hair Jr et al. 2016).

Construct	Reliability and Validity			Heterotrait-Monotrait Ratio (HTMT) of Correlations					
	Cr. α	**CR**	**AVE**	**DC**	**EC**	**GC**	**HC**	**IIP**	**RC**
Develop. Culture (**DC**)	0.810	0.884	0.795						
Ethical Culture (**EC**)	0.701	0.818	0.603	0.446					
Group Culture (**GC**)	0.660	0.823	0.705	0.662	0.651				
Hierarch Culture (**HC**)	0.731	0.875	0.779	0.191	0.212	0.249			
Implementation (**IIP**)*	1.00*	1.00*	1.000	0.124	0.135	0.214	0.320		
Rational Culture (**RC**)	0.667	0.821	0.607	0.362	0.480	0.537	0.136	0.062	
Company Size (**CS**)*	1.00*	1.00*	1.000	0.018	0.082	0.113	0.168	0.267	0.089

Table 4. Cronbach's α, Composite Reliability, AVE, HTMT (*single item constructs)

Before running the analysis in SmartPLS, we inverted the reversed items and removed 7 participants who did not pass our attention check. Furthermore, we searched for straight-liner and racer in our data, which did not appear. The remaining sample size was 81. Then, we performed a Partial Least Squares Regression (PLS Regression). Factor analysis following the procedure of Hair Jr et al. (2016) led to the removal of two items: one from rational culture and one from ethical culture. Afterward, we successfully checked the loading of each item on the respective construct, which needs to be greater than the cross-loadings to all other constructs (Bagozzi and Yi 2012), which could be confirmed. The reliabilities of measures were tested using Cronbach's α, Composite Reliability (CR), AVE and, HTMT, as shown in Table 4. All Cr. α values are above 0.6 as a threshold for internal consistency reliability. Furthermore, AVE values are above 0.5 and CR values above 0,8 (Hair Jr et al. 2016). Since the Fornell-Larcker criterion is considered less reliable for discriminant validity in variance-based structural equation models (Henseler et al. 2015), such as the present one, the HTMT was used and showed good results with all values below the more conservative threshold of 0.85. Therefore, we can assume that the resulting measures had good internal reliability and validity. Lastly, we tested for multicollinearity between the constructs by calculating the related variance inflation factors (VIF). With a maximum VIF of 1.754, all values are well below the cutoff criterion of 5 (Hair Jr et al. 2016).

Next, we analyzed our additional variables for the actual or planned design of idea platforms. Thereby, we mainly carried out group comparisons between the two groups (2) “planning” and (3) “in use”. First, we isolated the data of the two groups from the first group. When capturing the type of implementation and objectives of the platform through our items, we allowed clicking the option "I can't judge". The removal of incomplete data records brought us to a sample size of 45 for our group comparison. This was to ensure that only participants who were able to assess the design criteria of the idea platform were evaluated.

To test if the proportions in group 2 and group 3 are not equal (H_0: $P_1 = P_2$), we used the chi-square test of homogeneity (Marascuilo and MacSweeney 1977). Therefore, we reviewed four assumptions that are necessary to perform this test. First, our independent variable group was measured at the dichotomous level. All other dependent variables, which were tested individually, were also dichotomous variables. Second, by having different participants in each group, we could confirm that our observations have independence, which means there is no relationship between the observations in each group or between the groups themselves. Third, in our study design, we did purposive sampling through the characteristic of implementation of an idea platform. Lastly, our minimum sample size was greater than five for each expected frequency (Hollander et al. 2013). We were able to confirm all the requirements for this test.

3.4 Results

Our analysis was performed by a bootstrapping algorithm with 5,000 subsamples within SmartPLS software. In total, 21,3% of the variance in idea platform implementation is explained by the organizational culture and company size (R square = 0.213).

Only hypothesis H2 of the OC dimensions was supported since there is no significant relationship between a rational culture and idea platform implementation. Surprisingly, we found a positive correlation between the hierarchical culture orientation and idea platform implementation: the more hierarchical a culture is perceived, the more likely an idea platform is implemented ($p=0.004$, $f^2=0,107$). The f^2 effect size can be interpreted as a small to medium effect size (Hair Jr et al. 2016).

The group culture ($p=0.089$, $f^2=0.055$) had a weak f^2 effect size and was not significant at a significance level of 5%. It was, however, marginally significant ($p < 0.1$), which is worth mentioning due to an explorative character of the study, where a significant level of 10% is often assumed in research (Hair Jr et al. 2016). The other cultures did not exhibit any significant association with idea platform.

Lastly, H6 could be confirmed ($p=0.013$, $f^2=0,069$), having a weak f^2 effect size. Thereby, it could be confirmed that the company size has a significant positive influence on the introduction of an idea platform.

In the second part of the study, we analyzed whether the two groups (2) 'in planning' and (3) 'in use' pursue different objectives when implementing idea platforms. For this purpose, we defined seven objectives in advance, referred to as O1-O7, which are described in this section, along with their results. The difference between the two implementation groups was not statistically significant ($p > .05$) for the following objectives: 'Finding ideas for new innovations in the core business (**O2**)', 'Finding ideas for new innovations in new business areas (**O3**)', 'Creating knowledge exchange, communication and awareness for strategic topics (**O4**)' and 'Building an innovation culture (**O7**)'. Therefore, we fail to reject the null hypothesis (H_0: $P_1 = P_2$) and can assume that there are non-statistically significant differences in proportions.

The two goals 'Continuous improvement of business processes (**O1**)' and 'Search for solutions to known and concrete problems (problem-oriented) (**O6**)' were statistically significantly different ($p < .05$). Fourteen participants (73,7%) plan to implement problem-oriented initiatives on the idea platform compared to 10 participants (38,5%) who actually implement problem-oriented initiatives, a statistically significant difference in proportions of .352, $p = .019$. Even greater is the difference with 'Continuous improvement of business processes'. Here, 7 participants (36,8%) plan to implement idea platforms for continuous improvement compared to 21 participants (80,8%), a statistically significant difference in proportions of .44, $p = .003$.

Less strong is the difference with 'Breaking down silos and bringing together employees from different expertise and functions (**O5**)'. Here, 12 participants (63,2%) planned to explicitly pursue this goal with the implementation of the idea platform compared to 9 participants

(34,6%) who actually pursue this goal with the deployment, a difference in proportions of .286, p = .058.

Furthermore, we also used the test of two proportions to analyze the differences between three different usage types: ‘submit ideas on any topic at any time’, ‘participate in targeted and time-limited campaigns of a specific user group’, and ‘take part in company-wide idea challenges’. None of the differences were significant. Besides, none of the other control variables were significant.

3.5 Discussion

Commencing with the theoretical implications, the results of our study confirm that the OC as a whole influence the current status of idea platform implementation. Our analysis shows that 15.9% of the implementation status can be attributed to the organizational culture (21.3%, including company size). Hence we can conclude that idea platforms are not only used to transform OC (Ebner et al. 2009) but that a corresponding OC makes the implementation of idea platforms more likely. Thereby, we contribute to the research stream ‘Culture, IT Adoption, and Diffusion’ (Leidner and Kayworth 2006). Against our assumption, we show that idea platform implementation is facilitated by a hierarchical culture that emphasizes policies, procedures, and information management. A possible explanation for this could be that internal idea competitions harmonize better with the internal focus of the hierarchical culture than, e.g., an open innovation platform would have done. Idea platforms, as software tools, can support to structure their ideation process (Elerud-Tryde and Hooge 2014) and, thus, the management in its efforts for internal order. This effect is reinforced by the fact that a large proportion of idea platforms are used to collect continuous improvements in operational improvement, which is characterized by a very formal and regulated process. The results also show that a stronger group culture has a (marginally significant) positive effect on the level of idea platform implementation, as hypothesized. Organizations fostering a group culture emphasize employee involvement, which may be realized through idea platforms (Björk and Magnusson 2009). Alongside employee participation the group culture also embraces personal dialogue (Ruppel and Harrington 2001). When managers promote ideation techniques through dialogue, this may weaken the additional benefit from idea competitions for them and, thus, limiting the significant influence in our model. Next, as hypothesized, a stronger rational culture was not related to idea platform implementation. Organizations with a rational culture may be familiar with idea platforms and their potential for open innovation through their external focus but have no preference for or against their use. The benefit of using idea platforms is not only derived from the ideas themselves. Other advantages can arise, such as the identification of key individuals, which is also interesting from the point of view of the promoter theory in innovation management (Witte 1977). However, these kinds of advantages are usually difficult to measure, which is not in line with a strong rational culture since it values objective-based measures. If crowdsourced and open innovation can provide more objective measures in the future, we imagine that a rational culture will have a positive impact on the implementation of idea platforms. Then, there was no positive correlation between development culture and the implementation of an idea platform. Organizations with a development culture are focused on growth and innovation. However, it does not appear that idea platforms are currently used in practice to promote innovation nor open innovation. Lastly, our hypothesis about a positive correlation between ethical culture and the implementation of idea platforms could not be confirmed either. Our survey measures on objectives indicate that using an idea platform to facilitate knowledge exchange is the least pursued objective between our participants. Against this background, ethical culture may have less influence on the design of the platform in terms of knowledge exchange.

Overall, we believe that the significant relationship between organizations with a strong group and hierarchical cultures and idea platforms can be explained by the way the idea platform is designed. In the past, idea platforms were initially intended for internal use. This internal focus was also shaped by the culture in which idea platforms were used since both significant cultures share this orientation in the CVF. In recent years, organizations have begun to open up their innovation processes and diffuse them more widely (Ili et al. 2010). However, especially in B2B (Simula and Vuori 2012), idea platforms that open up to involve larger crowds may not encounter a culture that promotes innovation and creativity and therefore may not achieve active participation or expected results (Leimeister et al. 2014). This fact reinforces the current discussion about the uncertain overall value of crowdsourced ideation initiatives (Mortara et al. 2013).

Moving beyond theoretical implications, our study also has practical implications for idea platform provider, innovation managers, and organizations implementing idea platforms. Our study highlights the importance of taking OC into account when introducing a new technology or process that may be incompatible with the existing culture. Our analysis of planned versus the actual implementation objectives further indicates that idea platform usage will shift towards crowdsourced idea generation with a higher degree of innovation (e.g., less continuous improvement and more problem-oriented usage). Furthermore, culture also influences the design of idea platforms as well as the adoption and influence of IT Tools (Leidner and Kayworth 2006), as with idea platforms. As a result, organizations must be aware of their existing organizational culture when implementing and designing idea platforms to meet their expectations. Adoption is more likely when the values of a group match the values of information technology (Leidner and Kayworth 2006) as well as the design of idea platform needs to be in line with complementary factors of strategy and structure (Kohli and Grover 2008).

3.6 Limitations and Future Research

Certainly, this study also has its limitations. First, we only used a 5-step Likert scale in order not to overwhelm the respondents. In combination with the low number of items per construct, the lower gradation leads to a worse differentiation of persons, organizations, and cultures. The significance of the results is, therefore, weakened. Furthermore, we sent the survey to unknown contacts and busy managers. This resulted in a low response rate (around 8%). Because of this, the generalizability of these findings is somewhat in question. Since we defined idea platforms very broadly in our study, we have not been able to measure the impact of culture on specific deployment forms. However, this was not intended and opens up the field for further research.

Further research could focus on specific applications of idea platforms as open innovation, specific idea competition formats, or similar. It is particularly interesting to see whether an OC that promotes the implementation of idea platforms also increases their chances of success and user satisfaction. Moreover, it would be particularly relevant in practice to know whether OC can also provide negative effects. This would enable organizations to decide more quickly whether i.e. idea competitions are a suitable method for them. Further research is necessary to see the influence of the idea platform on the culture. In particular, we could imagine that certain designs of idea platforms could even reinforce some cultures. Next, further research is needed to identify the advantages and role of an idea platform as a digital platform. The influence of the properties of digital goods, in particular network effects, on idea platforms can be investigated. Finally, more research is required to explore the advantages of idea platforms, taking into account the promoter theory, in connection with areas of social network analysis, the identification of key persons for the success of idea platforms, and innovation in general.

4 Paper B: Innovation Collectives in Response to the COVID-19 Crisis: How Digital Technologies Facilitate the Innovation Process of Ventilator Development

Title

Innovation Collectives in Response to the COVID-19 Crisis: How Digital Technologies Facilitate the Innovation Process of Ventilator Development

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Publication Outlet

Proceedings of the 25th Pacific Asia Conference on Information Systems (PACIS 2021), Dubai, UAE

Abstract

The rise of the COVID-19 pandemic around the globe led to a sudden increase in demand for medical ventilators to treat severely ill patients. In this work, we conduct case study research on the initiatives founded during the beginning of the COVID-19 pandemic that developed ventilators to address this shortage. Using a mixed-method design, we investigate the development of these ventilators, emphasizing digital technologies that enable a shift in the way innovation collectives form, communicate, and collaborate during a phase of shutdown and social distancing. First, we identify and gather data from 118 initiatives and use quantitative analysis to discover correlations among the data. Then, as qualitative analysis, we conduct interviews to shed light on the underlying innovation process mechanisms. We find new practical implications for innovation management and provide new insights about a new decentralized development process in communities.

Keywords

COVID-19 Pandemic; Open Innovation; Innovation Collective; Virtual Teams; Digital Innovation; 3D Printing.

4.1 Introduction

In 2020, the COVID-19 pandemic led to a significant increase in demand for medical ventilators (Corera 2020; HHS.gov 2020), which are needed to treat patients infected with COVID-19 who have a severe disease course (WHO 2020). Even before the pandemic, it was clear that the number of ventilators would not be sufficient for large-scale catastrophes – neither in the developed countries like the United States nor in the developing countries such as in Africa (Al Husseini et al. 2010). This very short-term increase in demand led to a rise in orders for ventilators that existing manufacturers could not meet in such a short time (Kliff et al. 2020). On top of that, many of the manufacturers' supply chains were not operating as usual, as the pandemic led countries to close their borders and shut down or limit their national industries (FDA 2020b). At the same time, 3D printing and overall digital technologies opened the potential for several organizations and consumers to address this shortage by innovating on new designs of ventilators. This crisis led governments to call on organizations and consumers to see if they could help with their expertise, e.g., the "Ventilator Challenge UK" (GOV.UK 2020) in Great Britain. As a result, online communities joined together to develop ventilators, and multiple initiatives were formed around the world.

The COVID-19 pandemic impressively illustrates how the innovation process has changed in an increasingly digital world (Nambisan et al. 2017): forming innovation collectives via online platforms involving various actors, turning their ideas into digital designs, and producing physical versions of them utilizing new digital infrastructures. Given the importance of better understanding the mechanism behind digital innovations, there is a growing interest in new theories of digital innovation management (Baskerville et al. 2020; Fichman et al. 2014; Nambisan et al. 2017). Moreover, the impact of digital technologies on the innovation process is not yet clearly defined and remains a research topic (Bstieler et al. 2018; Felin and Zenger 2014; Yoo et al. 2010), as does the question of how firms will organize for innovations in the future (Baldwin and Von Hippel 2011; Browder et al. 2019; Quinlan et al. 2017; Rindfleisch et al. 2017; Yoo et al. 2010).We want to address this field of research by our study. From our perspective, the COVID-19 pandemic fits this research theme because, within a short period, many new, diverse actors enter the ventilator market, using digital technologies to coordinate and create, trade, and integrate knowledge to develop a new product in a short time.

In this work, we investigate the ventilator developments of various initiatives to understand their innovation processes better. Our research addresses the research question, *to what extent digital technologies and the integration of partners in an innovation process influence the* *innovation process and its outcome*. With this, we shed new light on the relevance of corporate innovations in the future concerning innovations of crowds of users organizing within communities and virtual teams.

To answer our research question, we are conducting a case study research of newly founded initiatives between January and July 2020 that aim to develop ventilators using a mixed-methods design (Dubé and Paré 2003; Eisenhardt 1989; Yin 2014). We focus on initiatives around 3D printing technology as it is characteristic of digital innovation through users and open collaboration (Baldwin and Von Hippel 2011; Yoo et al. 2010). First, we throw light on the development descriptively, being able to better understand the phenomena by analyzing 118 individual cases of such initiatives. Second, we give insights into which factors facilitated the successful development of ventilators, paying attention to several factors like the organizational forms (*innovation collectives*) and the role of digital technologies. Based on these results, nine exemplary cases are selected to perform a qualitative analysis in-depth to further support or refute the findings.

Our research work is structured as follows. Next, we introduce relevant literature in the field of digital innovation and open innovation and describe the context of our work, the COVID-19 pandemic, and medical ventilators. We then present our research approach, followed by our results. Our paper wraps up with a discussion of our results and a brief conclusion.

4.2 Theoretical Background

4.2.1 Digital Technologies and Innovation

Digital technologies are increasingly closing the gap between digital and physical products. For instance, 3D scanners allow the transformation of a physical into a digital product and 3D printers allow the transformation vice versa (Rindfleisch et al. 2017). Furthermore, physical products increasingly consist of digital technologies such as software or communication technologies. With these technological developments, the clear distinction between physical and digital products fades, the so-called digital revolution (Rindfleisch et al. 2017). These technologies are affecting the products themselves, as well as the development of these products. By adding digital capabilities to physical products, they inherit characteristics of digital technologies. The emerging product is then characterized by its modular layered architecture, in which the individual layers can be connected by interfaces (Baldwin and Von Hippel 2011; Yoo et al. 2010). As these layers are decomposed into loosely coupled components, they allow a separate development. These layers form their task, with an individual problem formulation that can be approached by a solution specific to a layer and not an entire product (Nambisan et al. 2017).

As increasingly more products gain digital components, digital technologies affect the development of such products and the orchestration of partners within the innovation process (Nambisan et al. 2017). Thus, digital technologies also affect innovation management. Digital innovations affect the structure and processes within an organization and the usage of the corporate IT infrastructure (Yoo et al. 2010). These digital technologies also allow a wider field of actors to participate in innovation that do not need to be located within organizations' R&D departments (Baldwin and Von Hippel 2011). For instance, digital process technologies such as additive manufacturing allow consumers to produce their own products, and digital design software allows them to reshape their products according to their needs (Hopp et al. 2018). If orchestrated correctly and efficiently using the layered architecture of products, these consumers can develop their own innovations in a decentralized process within online communities (Baldwin and Von Hippel 2011; Yoo et al. 2010). Furthermore, IT tools supporting the innovation process need to adapt to handle heterogeneity and discontinuity in knowledge (Yoo et al. 2010) and support new organizational forms like virtual teams, open innovation, or crowdsourcing (Lyytinen et al. 2016). Against this background, Lyytinen et al. (2016) highlight two ways digitalization shapes product innovation: First, reducing communication costs and increasing the speed of innovation through digital connectivity, and second, increasing knowledge heterogeneity and combinability through digital convergence.

4.2.2 3D Printing

3D printers make it possible to produce a physical product from a digitally designed model, a so-called 3D model, without having to deal intensively with the manufacturing process (Rindfleisch et al. 2017). As a result, 3D printing is very popular with end-users, as it allows them to realize their own ideas without requiring a great deal of prior knowledge (Bstieler et al. 2018). New modeling tools are much easier to use, making 3D printing accessible to more and more consumer groups and a more comprehensive range of applications (Rindfleisch et al. 2017).

Nevertheless, 3D printing also offers decisive advantages for organizations. Traditional manufacturing processes usually require a separate, often costly production tool for each product and variation of a product. This is not the case with 3D printing, where a change in the product's digital design is enough to create a product variation. In this way, a high degree of product diversity can be achieved with comparatively low additional costs (Baumers and Holweg 2019), which enables so-called mass customization for end-users, e.g., to build patient-tailored medical devices such as hearing aids (Quinlan et al. 2017). Also, this product diversity supports product development to a high degree and is used for rapid prototyping. Here, 3D printing enables the rapid development of prototypes, which in turn enables short iteration processes in development. For these reasons, 3D printing is increasingly used in organizations, especially for pilot projects such as product testing (Quinlan et al. 2017).

4.2.3 Innovation Collectives and Open Innovation

In recent times, there has been a shift from closed innovation approaches, where the goal is to acquire the most talented workers and have them develop inside local internal R&D departments, to a more collaborative form of innovation (Baldwin and Von Hippel 2011). This is the case with open innovation, where an organization tries to establish relations with other actors in the market and its business environment instead of focusing on internal research and development (Wynarczyk et al. 2013). Chesbrough et al. (2006), p. 1) define open innovation as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively". Felin and Zenger (2014) see the core of open innovation as being the fact that a firm gains access to knowledge beyond organizational borders. This flexible knowledge exchange of open innovation between different actors can occur in different ways, at varying intensities, and over variable time periods. Thus, there is no predefined development approach that defines open innovation; instead, various development approaches are covered by the term, such as contracts, partnerships, contests, or communities (Felin and Zenger 2014). For our research work, we distinguish between three innovation collectives in the following: (1) *project innovation* within a single non-collaborating organization, (2) *cooperation* involving at least two federated organizations, and (3) *community innovation* consisting of a dynamic pool of individual actors without common organizational affiliations.

On the one hand, open innovation offers firms the opportunity to explore new growth opportunities at lower risk and potentially lower cost by sharing development costs among multiple partners (Bstieler et al. 2018). On the other hand, firms are reluctant to embrace open innovation as managers see the loss of internal know-how and higher coordination costs as the principal risks of open innovation. Loss of control over the innovation process, increased complexity, and internal hurdles are also cited as difficulties of open innovation (Enkel et al. 2009).

Cost is the key driver of many business decisions, just as it is in the choice of the innovation collective, i.e., how to organize for innovation (Baldwin and Von Hippel 2011). Innovation costs can be divided into design costs, communication costs, production costs, and transaction costs. The fact that communication costs have fallen drastically in recent decades due to the rise of digital communication technologies such as the Internet means that collaborative open innovation is associated with even lower costs (Baldwin and Von Hippel 2011). In addition, as already described, the digital revolution also has a significant impact on the development process (Nambisan et al. 2017): More and more designs become digital and can therefore be communicated more easily (Baldwin and Von Hippel 2011). Hence, using digital technologies alongside open innovation approaches can reduce development time and development costs significantly.

4.2.4 The Need to Revisit the Power of Innovation Collectives Beyond Organizational Boundaries from the Perspective of Digital Innovation

Current literature argues that new forms of decentralized innovation processes will increasingly compete with corporate ones. In addition, various decentralized innovation collectives have demonstrated their ability to successfully develop products that lead to new ventures (Browder et al. 2019)and thus challenge the products of traditional firms. This trend is further facilitated by the diffusion of digital production technologies (Rindfleisch et al. 2017) and the consideration of the modular layered architecture in the development process (Yoo et al. 2010). However, the extent to which they pose a threat to firms and their products remains unanswered (e.g., Baldwin and Von Hippel 2011; Quinlan et al. 2017; Rindfleisch et al. 2017). With this theoretical background, we focus on (1) how an initiative is composed as an innovation collective to develop the ventilator, (2) the role of digital technologies such as 3D printing, platforms, and communication tools in the innovation process, and (3) the importance of modular architecture in such initiatives. In doing so, we seek to understand the extent to which these different initiatives with different goals, such as open-source or commercial solutions, can compete with one another.

4.3 Empirical Context

To conclude rigor case study research, an understanding of the context in which the research is concluded is essential (Gibbert et al. 2008; Yin 2014). To draw meaningful conclusions and understand the limitations of our research, we present the context of our case study research in this section: the COVID-19 pandemic, and the ventilators.

In severe cases, an infection with SARS-CoV-2 can lead to respiratory issues and patients need to have breathing support through artificial respiration. This artificial respiration is provided through ventilators, which can cost tens of thousands of dollars. As they are very costly, countries only have a limited number of ventilators that cannot cope with the high demand in a pandemic (Al Husseini et al. 2010). In less severe cases, less technical ventilators can also be used (Phua et al. 2020). Even if the specialized manufacturers increased their production of these ventilators, many governments feared it might not be enough and asked non-specialized firms to assist in producing or developing ventilators and initiated various hackathons (e.g., FDA 2020a; GOV.UK 2020). In this environment, many initiatives were founded to develop a ventilator within a short time frame. The objective of many initiatives has been to develop ventilators for less severe cases that apply to the lowest requirements. This should help to keep ICU free for patients who need them more urgently. As described in Mora et al. (2020), our investigated projects also come up with a wide range of functionality for their ventilator types, ranging from minimal functions up to hospital-grade ventilators. Our study distinguishes the *scope of the project* of the initiatives between *emergency ventilators* with smaller project scope, *intensive ventilators* with larger project scope, and *nonspecific* ones.

Due to the pandemic and the countermeasures to prevent a wider spread, these initiatives faced certain challenges. To prevent the virus from spreading too quickly, governments introduced border restrictions and closures that largely affected the movement of goods (FDA 2020b; Miller and Pollina 2020). This, in turn, meant that supply chains were affected to a large extent. Thus, there was a higher demand for medical equipment, such as ventilators, but exceptionally low supply (Kliff et al. 2020). These supply bottlenecks also pose challenges for the initiatives, as they may not have all the materials they need for development. Aside from the effects on the movement of goods, governments have sought to reduce both contacts and travel by individuals. In turn, many firms increased their use of digital technologies to switch to virtual work and keep their operations running.

Success Criteria of the Initiatives. In addition to the general characteristics of an initiative, such as the *country of origin* or the *lead organization*, we also assess the success of the projects. Typically for new product development, technical or financial success is suitable for evaluating products (Griffin and Page 1996). However, as most ventilators of the initiatives we collected are not yet distributed, the financial success could not be measured. Therefore, we use the assessment of official authorities as a measure of success. In most countries, they must grant *regulatory approval* to be allowed to distribute the ventilators.

Further, we determined whether an initiative reported *completed development* (Turner 1999) of the ventilator. For example, initiatives self-report whether development is complete, either through a press release, by starting production, or by obtaining *regulatory approval*. Since we do not cover the market introduction phase of the initiatives in our data, which is neither our focus, we cannot say whether the ventilators are or were used in real-world scenarios.

4.4 Mixed-method Research Design

Our positivist case study research consists of two parts that were conducted sequentially and built upon each other. First, we examined initiatives to identify correlations between project characteristics, project outcomes, and innovation processes. After identifying these relationships in our quantitative data, we gathered additional qualitative data to take a closer look and examined specific initiatives to gain insight into how digital technologies and innovation collectives influence project outcomes and the innovation process. We decided to use a combination of qualitative and quantitative data as recommended by Keutel et al. (2014) to gain more insight into the cases, as both data types are mutually informative. Following Yin (2014), case study research is especially suited to answer "how" questions. However, it can also be used for hypothesis testing (Eisenhardt 1989), whereas the inclusion of multiple cases increases the robustness of our research work (Barratt et al. 2011). In the following sections, we address the issues of validity and reliability by strictly following the framework of Gibbert et al. (2008) on rigor case study research as well as documenting the research process to achieve the principle of transparency (Sarker et al. 2013).

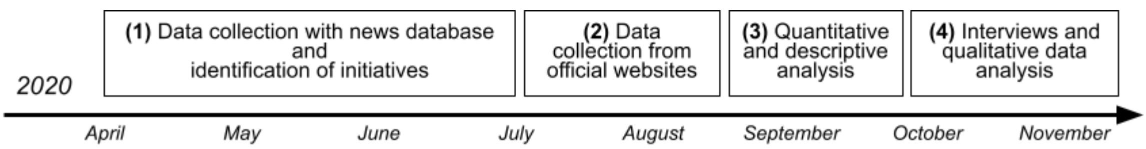

Figure 3. Timeline of the research process

4.4.1 Quantitative Method

Case Selection and Data Collection. We identified our cases based on the initiatives mentioned in news articles in the search engine provider *Lexis-Nexis* (*Nexis Uni,* academic search engine), which has also been used in other studies (e.g., Aggarwal et al. 2012) as well as especially in event-studies (e.g., Zhang and Nault 2019). We searched the database for news articles in the period from 01.01.2020 - 30.06.2020 (see Figure 3), using both English and German search strings (keywords: English: (3D print OR 3D printing OR 3D-print OR 3D-printing) AND (ventilator OR ventilators), German: (3D Druck OR 3D-Druck) AND (Beatmungsgerät OR Beatmungsgeräte OR Beatmungsgeräts OR Beatmungsgeraete OR Beatmungsgeraet OR Beatmungsgeraets). All the identified initiatives were used for the study without further sampling. To identify the initiatives, we screened more than 2000 news, from which we compiled a dataset of 118 initiatives based on the provided restrictions (see Figure 4). The set of identified initiatives is constrained by our search terms (e.g., always containing "3D") and the language of the articles (i.e., English and German). The amount of over 100 initiatives allows us to use quantitative methods to analyze the data set. We used different sources of evidence to fill the data set with information to achieve rigor (Barratt et al. 2011; Yin 2014). We used the official websites of these initiatives or the official website of the organizations participating in these initiatives to gather further data in July and August 2020. To this initial database, we added the data with information from the previously identified news articles and official government websites that provided information regarding the approval of the ventilators (FDA and Health Canada). While screening the websites (especially the press releases and news section), we added information to our dataset if it provided information to one of the data table attributes.

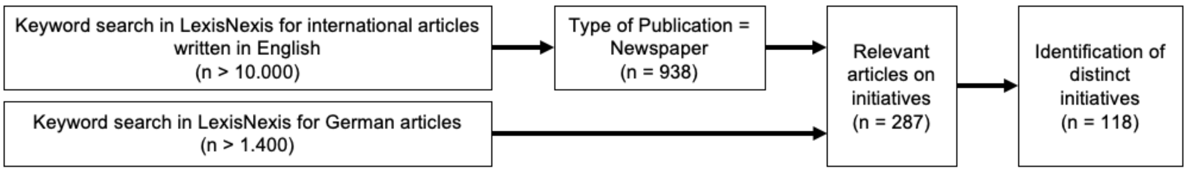

Figure 4. Identification and selection of relevant initiatives

Data Coding and Data Analysis. To allow for sufficient analysis, we structured our data table according to specific attributes and categories based on assumptions from our theoretical background. In Table 5, we present the relevant collected attributes, their definitions, and their values that were used in the quantitative analysis. In addition to the listed attributes (see Table 5), we collected further information such as *development duration, partnering companies,* or financial data. However, these could not be analyzed quantitatively or were unavailable in too many data samples and were excluded from quantitative analyses. We documented the data collection, coding, and analysis in a spreadsheet shared between both authors. Next, we analyzed the data using quantitative methods to find relations between attributes and project outcomes and used the exact Fisher-Test to test the direct effect of an attribute on the project outcome (Taillard et al. 2008).

Attribute	Values	Definition
Innovation collective (adapted from Felin and Zenger 2014 and Mora et al. 2020)	Cooperation	Union of organizations
	Community	Union of individuals who are not explicitly associated with an organization
	Project Innovation	Organization developing with no explicitly stated union with other organization
3D Printing (adapted from Mora et al. 2020)	Yes	The initiative stated that 3D printing is used or supposed to be used in the development or production
	No	The initiative did not state to use 3D printing in development or production
Scope of Project (adapted from Mora et al. 2020)	Emergency Ventilator	Ventilators not intended for long term use or invasive use
	Intensive Ventilator	Ventilators intended for long term use or invasive use
	Nonspecific	Ventilators not fitting in the two other categories
Usage of existing Designs	Yes	The initiative stated to use existing designs of ventilators
	No	The initiative did not state to use existing designs of ventilators
Commercialization	Commercial	Distribution of designs or ventilators either by selling or by licensing
	Non-commercial	Distribution of designs or ventilators either open access or by donation
Start of Initiative	Date	Stated date of formation of the initiative
Publication of product	Date	Stated dates of finished development, approval, publication, or production
Regulatory Approval (adapted from Mora et al. 2020)	Approval	Ventilator approved and certified by any national authority
	No Approval	Ventilator not approved and certified yet, even if already sent in for approval
Completed Development (adapted from Howsawi et al. 2011)	Yes	The initiative stated explicit or implicit that the development is fulfilled
	No	The initiative did not state explicit or implicit fulfillment of development

Table 5. Explanation of the collected attributes of the initiatives (n=118)

4.4.2 Qualitative Method

In our qualitative part of the study, we followed a theoretical sampling based on selected cases which "are particularly suitable for illuminating and extending relationships and logic among constructs" (Eisenhardt and Graebner 2007, p. 27). We identified 24 cases that differed in their characteristics and contacted these initiatives or their respective managers. We were able to conduct eight interviews between September 2020 and November 2020 with experts of the initiatives and one interview with an established manufacturer (see Table 6). We conducted the interviews via video calls, using semi-structured interviews that lasted about an hour on average. Six of the interviews were held by both authors, three of the interviews by one. The interviews were recorded, transcribed, and then analyzed. Thereby, we followed the steps of content analysis based on Hsieh and Shannon (2005): Given our theoretical background, we conducted the interviews along three main categories (*organizational structure and processes*; *use of digital technologies*; *modularity of tasks and product*) along with their assumptions and research questions for digital innovation. Our semi-structured guideline ensured that all interviews addressed our theoretical background, and it allowed us to elaborate on the specifics of each case. We then paraphrased the transcribed material, doing sequencing of the text by semantic units. In this, we used a deductive approach since we had theoretical assumptions in the context of our research. Based on the technique of content analysis and the rules of the reduction code, the data material was reduced into an abstract form to paraphrase and generalize the data material by keeping only the parts with substantial content. We used this extracted data to analyze each case separately and performed cross-case analysis to compare the cases with each other. After a certain number of interviews, no further findings were added so that after the ninth interview, the search for further interview partners was interrupted as theoretical saturation was reached (Flick 2004).

4.5 Results

Around two-thirds of the identified initiatives originated from Europe (33%) and North America (31%), 15% in Asia, 7% in Australia and Oceania, and 6% in Africa. The remaining 8% were cross-continental or could not be assigned to a founding country (3%). No initiatives from South America were found in the news articles. We can probably explain this by the search term since we used the term “ventilator[s]”, but in Latin America, “respirator” is commonly used instead. However, we did not include “respirator” as this is commonly used for masks outside of Latin America, which would have resulted in many articles being irrelevant to our search. Most initiatives came from the United States (22%) and Germany (11%). India and the UK each accounted for one-tenth of the initiatives and Canada for 7%. In total, the study found initiatives in 27 different countries.

In addition to the geographic distribution of initiatives, we also observed the volume of news articles over time. The LexisNexis news database provided 64% of all relevant news articles within one month of the first relevant entry. We were unable to determine an exact timeframe of the foundation for each initiative (only for n=46), with 80% of those we could determine were launched in March. About one-third of all initiatives that had completed their development had completed it in March, and the second third in April.

About two-thirds of all initiatives were classified as either cooperation or community innovation collectives. They thus pursued a collaborative approach: 48% cooperation, 32% project innovation (within a single organization), and 20% were community innovations. Almost three-quarters of the initiatives published their design documents or at least planned to do so. 18% of the initiatives reported that they built on existing models or designs, the remaining 82% developed the ventilator from scratch – or at least did not report using existing designs. Half of all initiatives stated that they were using or planning to use 3D printing in development or production. This is a relatively low percentage even though 3D printing was explicitly searched for. However, it can be explained by the fact that some news articles mentioned multiple initiatives, some with and some without 3D printing technology in use. 59% of all initiatives dealt with emergency ventilators. In contrast, 18% of the initiatives dealt with intensive ventilator development, while the remaining 23% could not be assigned to either of these categories.

#	**Country of foundation**	**Position of the interviewed person**	**Type of innovation collective**	**Goal of Project**	**Success measure**
A	Germany	Project founder, Project lead	Project Innovation within a single organization	Emergency ventilator	Project finished; no approval obtained
B	Germany	Project lead	Community	Emergency ventilator	Project not finished; no approval obtained
C	United States	Technical development coordinator	Project Innovation within a single organization	Emergency ventilator	Project finished; approval obtained (bought by medical firm)
D	Italy	Project founder	Community	Emergency ventilator	Project finished; approval obtained
E	Great Britain	Steering committee	Cooperation	Emergency ventilator	Project not finished; no approval obtained
F	Germany	Project founder, Project lead	Cooperation	Intensive Ventilator	Project not finished; no approval obtained
G	Australia	Project founder, Project lead	Community	Emergency ventilator	Project not finished; no approval obtained
H	Poland	Official spokesman	Community	Emergency ventilator	Project not finished; no approval obtained
I	Germany	Product development / Innovation department	Project Innovation within a single organization	Intensive Ventilator	Established manufacturer ramps up production and refurbishes old equipment

Table 6. Overview of the nine interviewed cases (A-I)

60% of the initiatives provided information about their commercialization strategy. Of these, 73% were non-commercial (open access), and 27% were commercial (licensing or sale). 46% of the initiatives reported that they finished their development. 24% of the initiatives published their designs. 14% of the initiatives received *regulatory approval* from a national authority.

Many initiatives were founded after the UK government called out for new ventilators and announced the national “Ventilator Challenge UK”. For example, a vacuum cleaner firm developed an emergency ventilator (“Gtech Ventilator”). However, the “Ventilator Challenge UK” board decided to use other ventilators, so the firm did not continue its ventilator project. The committee also rejected another initiative by a university (OVSI). OVSI nevertheless pursued the project after that, networking and cooperating with national and international organizations to develop and produce ventilators for low-income countries. OVSI will share their designs online for free. As a final example from our data, an initiative was founded in the U.S., where over 200 volunteers from across the country came together in a short period of time to develop a ventilator. This initiative has resulted in a start-up that aims to produce ventilators (The Ventilator Project Inc. 2021). We also collected initiatives of established ventilator manufacturers who tried to increase their production. They were partly supported by firms in the manufacturing and production sector. One established manufacturer "Medtronic" published the design specifications of one of their ventilators on March 30, 2020. However, during the course of the study, no initiative was identified that made use of this design. In contrast, the collaborative design of the UCL-Ventura ventilator was shared over 1800 times with teams from over 100 countries in approximately two months.

4.5.1 Quantitative Results

Use of 3D Printing. We compared the success rate for the given evaluation criteria of initiatives that reported to use 3D printing as a development or production technology with those that did not. Overall, 10.53% of all initiatives that reported using 3D printing gained *regulatory approval* compared to 16.39% that did not report the use of 3D printing. However, the difference is not statistically significant (p=0.2552, n=118). In projects targeting emergency ventilators, the difference is even greater at 20.69% compared to 9.76%, but not significant either (p=0.1732, n=70). Since we also found no difference in the analysis relating to the *completed development* criteria, we conclude that reporting on the use of 3D printing has neither a positive nor a negative impact on project success. Regarding *regulatory approval*, the opposite trend is even apparent.

Innovation Collectives. Cooperation and community initiatives had a marginally significantly higher approval rate of 17.28% than project innovation approaches with 5.41% (p=0.06653, n=118). Cooperation initiatives were the most successful, with an approval rate of 19.3%, compared to 12.5% for community projects and 5.41% for project innovations. We found cooperation is more successful than project innovation (p=0.0503, n=94). Comparisons of the other *innovation collectives* revealed no significant differences. This effect is also found in the projects targeting emergency ventilators (20% approval rate of communities, 20.69% cooperation, and 3.85% of internal innovations). There is a marginally significantly higher approval rate of initiatives having a collaborative approach than project innovation (p=0.05272, n=70) and a marginally significantly higher approval rate of cooperation than project innovation (p=0.06855, n=55). There is also a slightly better performance of community compared to project innovations (p=0.1303, n=41). This difference flattens out for initiatives targeting intensive ventilators, and only 4 of the 21 initiatives receive any *regulatory approval*. In general, and especially for initiatives targeting emergency ventilators, initiatives that take a more collaborative approach tend to have higher approval rates than project innovations within a single organization. We also found that community initiatives targeting emergency ventilators have a higher approval rate than project innovations. Given this, community innovations can compete with internal innovations. However, cooperation initiatives are those that have the highest approval rates across all projects. Regarding the success attribute of the *completed development*, cooperation has completed (57.89%) their development significantly more often compared to communities (29.17%, p=0.01644, n=81) and project innovation (37.84%, p=0.04531, n=94).

Commercialization. Lastly, we analyzed the attribute of *commercialization*. We found that commercial initiatives that pursue plans to either sell or license their ventilator products have a statistically significantly higher rate of obtaining *regulatory approval* (36.84%) than non-commercial projects with 9.8% (p=0.01309, n=70). For initiatives that reported *completed development*, this effect is even more pronounced, with an 84.21% completion rate for commercial projects compared to 41.18% for open access initiatives, and is significant (p=0.001248, n=70). This effect is also significant for initiatives targeting intensive ventilators with 100% compared to 42,9% (p=0.04895, n=13), but is no longer significant for emergency ventilator initiatives (62.50% compared to 38.89% with p=0.2044, n=44). Therefore, we argue that commercialization is an important factor in the success of the initiatives.

4.5.2 Qualitative Results

Table 7 shows the main findings of our qualitative analysis along with their categories. It lists mechanisms that the interviewed experts of the initiatives described (see Table 6; Cases #A - #I). For each row, the table indicates how many interviewees report the respective context (*total*). At the same time, the columns indicate whether and how often the mechanism has been classified as a *mandatory*, *facilitating,* or *hindering* mechanism (Gläser and Laudel 2009).

In total, all but one initiative consider digital communication technologies as important to the project's success. Case #C argued, "we were able to design and share designs and get parts made entirely virtually without ever having to, you know, meet some of these people". For Case #C, digital communication technologies were also mandatory to develop in short project iterations.

The same applies to the use of digital platforms like Github or Discord that support distributed collaboration and communications, "Discord got used a lot for channels for discussion and branching and connection of people. So, there was an incredible teaming up of people" (#G). However, a certain degree of physical contact was always necessary that was realized by makerspaces (#G), geographical proximity (#A), or even through sending physical parts by post (#B).

Category	The identified mechanism in qualitative content analysis	mandatory	facilitating	hindering	total
Use of digital technologies	*Digital communication → project success*	6	2	0	8
	Digital communication → short project iterations	1	4	0	5
	Digital platforms (e.g., Github, Discord) → project success	1	4	0	5
	3D printing → rapid prototyping	1	6	0	7
	3D printing → independence from the supply network	2	2	0	4
	3D printing as production technology	0	3	4	7
Modularity of tasks and product	*Modular ventilator → work separately on product modules*	0	3	0	3
Organiza-tional structure and processes	*Partnerships → project success*	2	5	0	7
	Existing private network → project success	3	4	0	7
	More participants in the initiative → Increased communication and coordination effort	0	4	0	4
	Active search for new specific partners → Project success	1	3	0	4

Table 7. The identified mechanism in qualitative content analysis

In addition, most of the newly formed initiatives (seven out of eight cases, excluding Case #I) used 3D printing more extensively during their product development, using the technology to shorten their development cycles and enable rapid prototyping. In half of the initiatives, 3D printing technology helped address crisis-related parts supply issues. In two of these initiatives, it was a prerequisite for undertaking the project in the first place. Nevertheless, the limitations of 3D printing technologies in the production of ventilators were also highlighted, being "too slow for mass production [...] and having issues with the roughness" (#F), "unfitted for scale-up [...] and pressure loss" (#E), having issues with "robustness and [...] degassing" (#I) of 3D printed materials as well as "serious concerns using it in the human airway" (#I) and "never in consideration for manufacturing" (#D).

When it comes to the modularity of tasks and products, there was a modular architecture of the ventilator in three cases. In three other initiatives, the distinction between the layers or modules was not clear. In most cases, the initiatives reported strict separation in the development of the physical and software components. Four initiatives reported an increasing coordination and communication effort as team size increased, which contributed to three initiatives deliberately conducting development in smaller teams. Four of the initiatives actively were looking for new partners to complement their existing expertise and thus contribute directly to problem-solving and project success. Case #A decided against this. They argued that this had to do with their smaller project scope.

In the organizational structure and processes category, an existing personal and professional network between participants and partners was cited as the main reason for the success of the initiatives. All the initiatives except the project innovation initiative Case #A consider their partnerships to be conducive to project success, and two of the interview partners even consider them to be a prerequisite saying the project “only worked because people knew each other, and certain structures already existed before” (#E). In addition, Case #G highlighted the availability of existing infrastructure on the network, saying, “the makerspace was instrumental to the project success”.

4.6 Discussion

Our results highlight the increasing importance of partnerships and cooperative development, especially in light of the digital revolution (Rindfleisch et al. 2017), in which products increasingly require different expertise in development due to the combination of physical and digital components. Our findings show that non-specialized innovation collectives can form in closed markets – here, the market for ventilators – and effectively accumulate knowledge. The fact that such a highly complex product as a ventilator can be developed in a short period, even though many economies were in a phase of shutdown and social distancing, underlines the potential of these innovation collectives and the importance of digital innovation as a whole. Thereby, our case study research contributes to the field of digital innovation (Nambisan et al. 2017) and addresses the role of digital technologies in the innovation process (Bstieler et al. 2018; Felin and Zenger 2014; Yoo et al. 2010). Analyzing our cases, we found several empirical insights to enrich the ongoing discussion.

First, our descriptive results show that the identified initiatives predominantly originate from developed countries, which various circumstances might have favored, e.g., existing innovation ecosystems, accessibility to technologies, or government support. Among these, collaborative types of innovation collectives were the most common form of innovation, and three-quarters of all initiatives published their designs or planned to do so, underscoring the great importance of open collaborative innovation (Baldwin and Von Hippel 2011). However, initiatives with a commercial objective have been significantly more successful, i.e., have completed their development and received regulatory approval more often. Thus, in our case, while we see an overall increase in the variety of innovations offered to the public (e.g., Rindfleisch et al. 2017), they tend to be less extensively implemented than commercial innovations which leaves us with the question to what extent it will be possible for communities to market their developed designs. Second, although most initiatives took an open collaborative approach, comparatively few initiatives (18%) reported building on existing open designs. While the experts interviewed stressed the importance of sharing with other initiatives, we also observed that some initiatives did not know about each other, even if both were in the same city or belonged to the same universities (e.g., Case #A). Similarly, one initiative did not know that a second initiative had built on its designs (e.g., Case #D). Therefore, on the one hand, we were amazed by the great willingness of the initiatives to share their knowledge and innovations (inside-out process). However, on the other hand, we were surprised that the initiatives reported little about the uptake of knowledge and innovation (outside-in process). Third, although we were unable to quantitatively show the impact of 3D printing on the development process, in many cases, 3D printing proved to be particularly useful for the development process, according to the experts. At its core, its importance lay in rapid development cycles, prototyping, and especially for resolving supply bottlenecks. Nevertheless, it became clear from the interviews that 3D printing as a production technology still has significant weaknesses, and therefore wasn't used for wide scale production. Forth, many initiatives, such as Cases #A and #E report being held back by circumstances such as challenges of legislation, financing, manufacturing, commercialization, and intellectual protection of new products, which is a challenge even for open designs (Hopp et al. 2018). This could also speak to the comparatively low approval rate of non-commercial approaches. The cooperation model, in turn, had the highest success rate. This invites further research to see how the different actors of cooperation could better complement each other regarding innovation costs, more specifically in terms of production and transaction costs (Baldwin and Von Hippel 2011). Lastly, non-collaborative initiatives had the lowest approval rate. As indicated by our qualitative results, we conclude that digital technologies have helped to lower communication costs dramatically, making collaborative innovation viable across a broader range of innovation activities than before (Baldwin and Von Hippel 2011). Concerning the innovation process, digital technologies and collaboration platforms played a central role through networking, communication, and decentralized development. Nevertheless, the possibility to physically meet and organize was seen by some participants as crucial for the success of the project. Therefore, the different kinds of community organizations, either in purely online communities, local makerspaces, or mixtures of both have different implications for the innovation process that remain to be researched.

Our insights are also relevant for practitioners. Our findings support the idea that external partnerships have a positive influence on the innovation process. In this context, the characteristics of digital innovations can be exploited. A precise analysis of the product's layered architecture, which connects both digital and physical aspects in the product through interfaces, should be a basis for selecting partners. Furthermore, the layered architecture of the products offers firms the opportunity to transfer their services and competencies to other products. For instance, the control technology of ventilators, which in many initiatives could be docked onto the product by external partners via interfaces. It is also noticeable that competencies in physical components can increasingly be supplemented or even replaced by digital technologies such as 3D printing.

At the same time, the involvement of communities by firms in their innovation process can offer benefits. The qualitative results showed that philanthropic aspects of the product influenced participants' willingness to participate in such initiatives. This may therefore be specifically suitable in projects where the focus is on social rather than economic benefits. Concerning decentralized development in online communities, the question arises as to what extent quality processes and certification of such distributed developments are even possible. The certifications of the innovations we have looked at show that these innovation collectives can meet the high-quality requirements of complex medical products. This clearly shows the disruptive potential of such community innovations. Our observations should encourage firms to focus on incorporating open innovation into their innovation process, as the number of open collaborative innovations is growing, and innovation collectives beyond organizational boundaries become more valuable as a source of innovation. In doing so, the companies should play to their strengths, which lie, for example, in the transaction costs and production costs of innovations. Thereby, our study further contributes to the emergent discussion on the future relevance of firms both as a whole and in the innovation process (Baldwin and Von Hippel 2011; Browder et al. 2019; Quinlan et al. 2017; Rindfleisch et al. 2017).

4.7 Conclusion

In this work, we investigate how digital technologies constrain or enable the innovation of ventilators in response to the COVID-19 pandemic. Overall, we collected secondary data from 118 initiatives that developed ventilators from 01.01.2020 - 30.06.2020. This extensive database was supplemented with primary data from expert interviews. Our research work highlights the relevance of digital innovation. Our findings show that through the effective use of digital technologies, even complex innovations are no longer developed only in large organizations but also by innovation collectives with different objectives, motives, and capabilities. In addition, established organizations are increasingly confronted with community innovations that offer complex solutions based on a modular architecture.

Of course, our study is subject to limitations. Because of the exploratory nature of our study, future research should validate and contextualize our findings under different boundary conditions across heterogeneous contexts and domains other than the COVID-19 pandemic and the development of ventilators. Although we have tried to maximize the quality of our observations by including a high number of cases as well as drawing on multiple sources and types of data, there are certainly aspects that we have not been able to observe but that could still influence the emergence and collaboration of the initiatives as well as the innovation processes and success. At the same time, our research also gives impetus for further research in this area since the impact of digital technologies on the innovation process is not yet fully understood.

5 Paper C: Digital Service Innovation in Plant and Mechanical Engineering: Exploring Contextual Factors in the Innovation Process

Title

Digital Service Innovation in Plant and Mechanical Engineering: Exploring Contextual Factors in the Innovation Process

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Publication Outlet

Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS 2021), Online Conference

Abstract

In recent years, the transformation from pure product businesses to data-based service innovation in various industries has intensified. This paper extends previous studies on "servitization", i.e. the transition from product manufacturer to service provider, focusing on digital service innovations. We develop an integrative model to examine the technological, organizational, and environmental context as prominent components of the initiation, adoption, and routinization of digital service innovations. Drawing on the Technology-Organization-Environment (TOE) framework, different factors are identified and then validated by conducting ten expert interviews regarding their relevance to the innovation process of digital services in the plant and mechanical engineering industry. The results strongly suggest that the general TOE framework needs to be revisited and extended to be used in this specific context. The extended TOE framework can serve as a basis for studying contextual factors in digital service innovations and guide managerial decision-making.

Keywords

Making Digital Transformation Real; Digital Transformation; Industrial Internet; Qualitative Study; Servitization.

5.1 Introduction

The digital age is hallmarked by modern technological developments. Especially, Internet of Things (IoT) and Artificial Intelligence (AI) enable service innovations (Barrett et al. 2015) as well as innovative business models around access to and use of data (Bilgeri et al. 2017). In the meantime, these technologies have also reached traditional industries, e.g., plant and mechanical engineering. It has been widely noted that technological innovations are a primary driver for the implementation of the industrial internet or "Industry 4.0" visions (Gölzer et al. 2015; Lasi et al. 2014). To prepare for this new era, incumbent firms are modernizing their IT landscape, implementing IoT platforms (Shim et al. 2019) or data science platforms (Schiller et al. 2015), and changing their organizational structures (Bilgeri et al. 2018; Haffke et al. 2017). In addition, new actors and startups from other industries are entering the market and are competing with the incumbents. New industry IoT platforms (e.g. Siemens' Mindsphere, GE's Predix) or e-commerce platforms (e.g. Thyssenkrupp's Steel Online, Alibaba Group) are competing between the product business and after-sales services of established industry suppliers. A corresponding shift in revenue shares towards digitized product-accompanying services is expected (Sebastian et al. 2017).

To fully realize the business value of digitalization in the plant and mechanical engineering industry, the innovation of digital services stands out as an important research topic (Bilgeri et al. 2017; Tim et al. 2017). Companies see new opportunities for doing business by digitizing existing processes and services. In addition, they also see new opportunities to generate new business by implementing new digital services such as object self-service (Fleisch et al. 2015), condition monitoring, predictive maintenance or other data-based services (Bulger et al. 2014).

As far as business models are concerned, these services may be linked to products and offered as Product-Service Systems (PSS) or hybrid value bundles (Jaspert and Dohms 2020; Veit et al. 2014). Recent studies already indicated the value of B2B service and product innovations. Managers should leverage PSS innovations where possible (Dotzel and Shankar 2019). In doing so, the focus also shifts from the customer perspective from the product to the utility value. The manufacturers change into the role of a service provider. The pricing strategies adapt to the ownership model and change to a usage-dependent or performance-dependent calculation (Gebauer et al. 2005a).

Although PSS and business model innovations based on life cycle and service orientation are not a new phenomenon in the industry, they gain new relevance in research and practice. In fact, they now seem to be favored by technological advances. As a well-known example of success, Rolls Royce (a worldwide leading manufacturer of engines) has demonstrated the potential of digital service innovations as a supplier of aircraft turbines. The turbines are no longer simply sold to the customer and thus become the property of the customer. Instead, the customer pays for the performance of the machines in a "power-by-the-hour" business model (Selviaridis and Wynstra 2015; Shim et al. 2019). These services are enabled by digital technologies such as Big Data Analytics, Machine Learning and IoT to achieve intelligent real-time performance monitoring.

The transformation from a product business to a service provider rarely takes place in a smooth and linear manner. It is often risky and traditional businesses do not seem to achieve the expected value from their investments in services (Gebauer et al. 2005a; Neely 2008). Prior studies show that digital service innovations in plant and mechanical engineering are still in their infancy. There are major difficulties for companies in initiation, adoption and routinization of digital services before it can generate significant business value. Digital service innovation becomes a significant research topic whereas the role of digital technologies can have a significant influence on the success of those services (Dotzel et al. 2013). Further, it is important to understand the key factors that influence digital service innovation. There is a need for research on the impact of servitization and the dynamics of technology shifts in a broader environmental context (Bilgeri et al. 2017; Tim et al. 2017). Yet, these (technological, organizational, environmental) factors were examined separately in different models. This motivated us to develop an integrated model in order to investigate the contextual factors. Against this background, we seek to investigate the following research question: What specific factors affect digital service innovations in the plant and mechanical engineering industry? To answer this question, a qualitative study was conducted, which is presented in this research work.

The paper is structured as follows: In Chapter 5.2, we provide an overview of the theoretical background and related work to define the field of research. In Chapter 5.3, we describe how the qualitative study was designed, which experts were interviewed and how the interviews were executed. Then, we will present the empirical results and integrate our findings by utilizing the TOE framework in chapter 5.4. Furthermore we discuss our empirical results based on theoretical insights of innovation diffusion theory (DOI) and integrate the key findings to expand the TOE framework. Finally, in chapter 5.5 we describe the limitations as well as the contributions to research and practice.

5.2 Theoretical Background and Related Work

5.2.1 Progress of Servitization in the Manufacturing Industry

The plant and mechanical engineering sector is traditionally characterized by physical goods (Buse et al. 2001). For a long time, services were seen merely as an extension of the physical offer. The term servitization can now be observed in almost all industries and was first discussed by Vandermerwe and Rada (1988b). Similar terms used in research are “Product Service Systems” or “Remote Product Servicing” (Sharma and Singh 2017; Vandermerwe and Rada 1988b). In the 1990s, the trend initially received little attention in mainstream engineering and management literature. Today, servitization is attracting even more attention as the service business has increasingly become the focus of many organizations, alongside the product business. There are various motives for this: First, many manufacturers from industrial nations struggle to compete on price. The declining profitability raises questions about the sustainability of the business models (Neely 2008; Sainsbury 2007). Besides economic motives, there are various strategic (e.g. customer lock-in, market barriers) reasons for the expansion of the service business. On the demand side, customers tend to focus on core activities and avoid investments. Furthermore, the need to own production factors decreases as resources are shared more often (Belz and Wuensche 2007; Gustafsson et al. 2010).

Besides these motives, servization can be favored by technological advances. There is an increase in generated data from machines and production, increased sensor technology and actuators directly on the equipment. Networking with new access options through industrial internet technologies is leading to a growth in the potential of new and innovative services (Herterich et al. 2016a; Huxtable and Schaefer 2016). Various practical publications and white papers push newly developed digital business model patterns into the manufacturing industry (Fleisch et al. 2015). However, strictly speaking, “-as-a-service”-models, as we know them from cloud computing (Stuckenberg et al. 2011), have been already existing in the manufacturing literature before. For example, the concept of Performance-based Contracting (PBC). PBC means that products, plants or technical systems are no longer sold to the customer, but are provided and operated by the provider or supplier itself (Belz and Wuensche 2007; Buse et al. 2001; Kim et al. 2007). The literature on PBC also contains research and models on common characteristics with a morphological box (Gustafsson et al. 2010), PBC-component services and a typology for the classification of PBC (Belz and Wuensche 2007). Lastly, there is research on how PBC is changing the business model of the pure manufacturing company, including the boundaries between product and services as well as implications on the provider and customer relationship. This includes core characteristics of PBC in ownership, maintenance and operational responsibility, and payment structures. Performance-based pricing models such as pay-on-availability or pay-per-unit are replacing traditional pay-per-equipment (Gustafsson et al. 2010).

Nowadays, digital technologies provide the opportunity for service innovations that become more efficient, are expanded or are even made possible in the first place (Shim et al. 2019). These include predictive maintenance and prognostics and health management (PHM). Here, IoT technologies enable the monitoring and collection of machine data (Wortmann and Flüchter 2015) and algorithms analyze the health status of the machines to enable IT-based predictions about the basic maintenance and optimization of these machine components in production (Lee et al. 2013).

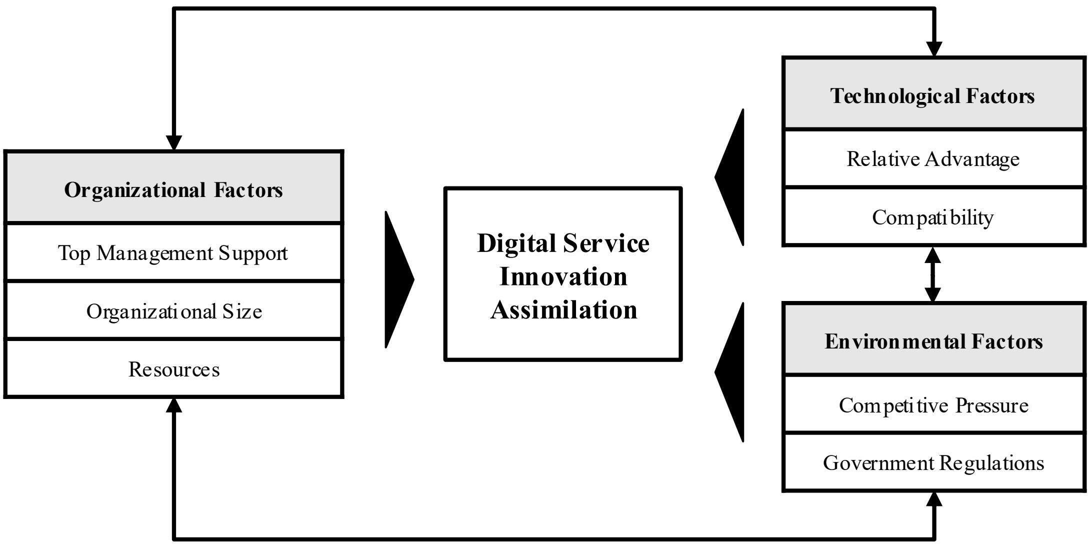

Figure 5. TOE framework as conceptual base (based on Depietro et al. (1990); Rogers (1995))

5.2.2 TOE Framework and DOI

In general, the TOE framework provides a useful and flexible basis for the exploration of contextual factors, as it provides a generic theory for the diffusion of technologies (Zhu and Kraemer 2005). It has therefore been widely used across different contexts and technologies suchas cloud computing adoption in hospital industry (Lian et al. 2014) or the e-business usage in the financial services sector (Zhu et al. 2004). In a nutshell, the TOE framework comprises three main elements that influence the adoption process of technological innovations: (a) Technological context outlines current technologies in use as well as new technologies that are relevantto the company. (b) Organizational context refers to descriptive measures about the organization suchas scope, size and management structure. (c) Environmental context describes the area in which a company conducts its business - its industry,its competitors and its government relations (Depietro et al. 1990). This framework is consistent with Rogers' (1995) innovation diffusion theory, where he stressed the technological characteristics and both the internal and external features of the organization as drivers of technology diffusion (Zhu and Kraemer 2005). Applying this view to digital service innovations in the plant and mechanical engineering industry, the assimilation of an innovation starts with the initial awareness and evaluation of the innovation. Next, the organization needs to decide to use technologies and further resources to deploy the innovation. Lastly, the new digital service innovation must be accepted, adapted and established within the organization. As we already know from servization literature of manufacturing companies, the transition to increased servization create both value and risk. Since there is little research on service innovation focusing onnew digital technologies, a general TOE framework, asdescribed above, is used as a first conceptual starting point (see Figure 5), which will be expanded in the course of our study.

	Position	**Number of employees (2018)**	**Turnover in million € per year (2018)**	**Firm position in value-chain**
A1	Head of Technology Management			
A2	Head of Product Management			
A3	Sales Employee	201 - 500	10 - 50	Components and System Suppliers
B1	Head of Marketing and Sales			
B2	Head of R&D			
B3	Program Management Digital Business (R&D)	501 - 1.000	50 - 250	Components and System Suppliers
C1	CEO	21 - 100	10 - 50	Mechanical Engineer
D1	Head of Corporate & Digital Business Development	5.001 - 15.000	1.000 - 5.000	Mechanical Engineer and provider of an industrial platform
E1	Business Unit Manager Marketing & Sales	100.000 - 150.000	10.000 - 50.000	Supplier, solution & system provider and provider of an industrial platform
F1	Member of the Board of Management, and Head of the Industry Division	100.000 - 150.000	10.000 - 50.000	Supplier, solution & system provider and provider of an industrial platform

Table 8. Overview of interviewed experts

5.3 Research Design, Data Collection and Analysis Process

The goal of this research is to gain an understanding of the key factors that influence digital service innovation in a broader environmental context. In order to gain qualitative knowledge despite the rapid changes in the industry, the method of expert interviews in this field are particularly suitable, since they have quick access to current trends and changes in the industry (Bogner et al. 2009). This approach also allows us to analyze data material in areas in which only limited knowledge exists (Neuendorf 2002; Yin 2009). In Table 8 the interviewed experts are presented. All expert interviews were conducted in September and October 2018. Eight of the ten expert interviews were conducted by telephone and two interviews at a personal meeting. The average duration was about 45 minutes. All interviews were recorded and transcribed for easier analysis.

The research work follows the steps of content analysis based on Hsieh and Shannon (2005): Based on the TOE framework, which serves as a conceptual framework, seven initial categories were derived from relevant literature (e.g., factors compatibility or top management support in Figure 5). These were used as a semi-structured guideline for our interviews. This guideline ensured that all interviews covered the main conceptual framework, and it allowed us to address the peculiarities of the respective firms contexts. The general questions that each interviewee was asked included questions about the company, the industry and existing expert understanding of “industrial internet and Industry 4.0”, as well as knowledge of the company’s strategic approach. Subsequently, further questions were individually selected from the following areas in each interview, depending on the course of the interview and expertise. If the companies had already started concrete initiatives with digital service innovations or had even used them, these contents were deepened in the discussion. Next, the transcribed material was paraphrased, a sequencing of the text according to semantic units. Thereby, we have used a deductive approach, as we have had theoretical assumptions in context of our research. Based on the content analysis technique and following the reducing code rules, the data material was reduced into an abstract form in order to paraphrase and generalize the data material by maintaining only the parts of substantial content, which was finally divided into categories (Corbin and Strauss 2014) within the TOE framework. For instance, the quotation of an interviewee “We have tried to exchange with other companies (...) There is no partner who can deliver what we need off the shelf. And it is too tailor-made for that, what we have to implement here in the company.” - (expert interview D1) was coded after a paraphrasing and generalizing process to factor “Strategic Collaboration and Cooperation”. As required, corresponding points in the material were assigned to the categories. To achieve reliability in our analysis, multiple people (two in total) coded and analyzed the data material by using a software tool (Richards 2014). During the interviews, hints or recommendations regarding other potential interviewees were followed up. Furthermore, an attempt was made to supplement the contents of the interview partners with another interview partner who is directly upstream or downstream in the value chain. After a certain number of interviews, no further findings were added, so that after the tenth interview the search for further interview partners was interrupted as theoretical saturation was reached (Flick 2004).

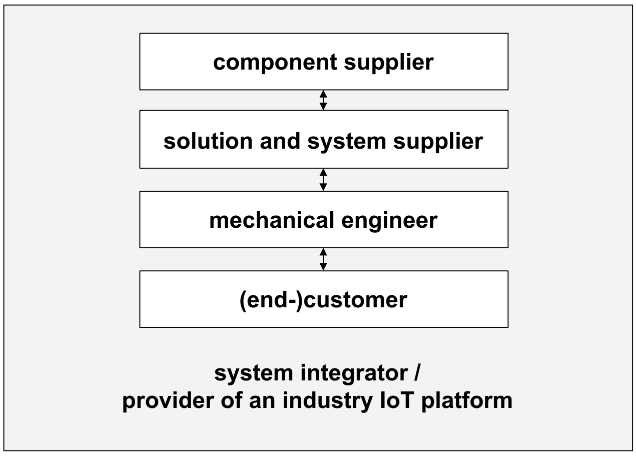

Figure 6. Relationships between the companies of interviewed experts

5.4 Results

In validating the proposed TOE framework for assimilation of innovation in digital services, we found evidence that the factors identified do not fully reflect the circumstances that companies face in initiating, integrating and establishing digital services within their organizations. Aspects that complement or contextualize the original framework (see Figure 7) are examined in more detail below. The results are presented below according to their respective contextual dimensions and associated factors.

5.4.1 Environmental Factors

According to the experts, the positions in the value-chain of plant and mechanical engineering are simplified: Component supplier, solution and system supplier, mechanical engineer, system integrator / provider of an industry IoT platform and the (end-)customer (see Figure 6). The (end) customer is characterized by the fact that he uses the machine or systems in his own production. All companies (A - F) indicate to be concerned with the industrial internet technologies for internal (own production and processes), as well as external purposes (products and services). In addition, two companies also provide their industrial internet platform as technical solution on the market which they originally developed for internal purposes.

Market Characteristics and Economic Situation. The plant and mechanical engineering sector is characterized by its “handicraft”, specialized intermediaries and technical complexity. Expertise is tied to people who have the necessary experience in the selection of components. Long availability, warranties and the reputation of the manufacturer create trust and signal a promise of quality. After the sale of components and systems, suppliers and component manufacturers have little insight into the end customer's use and customer's processes, except in service and warranty cases. In addition, intermediaries have important application know-how. They know the requirements and complexity to be considered when designing components, right through to installation and integration in systems and plants. According to the experts, missing uniform standards, safety concerns and a long-lasting installed base are challenges to be mastered.

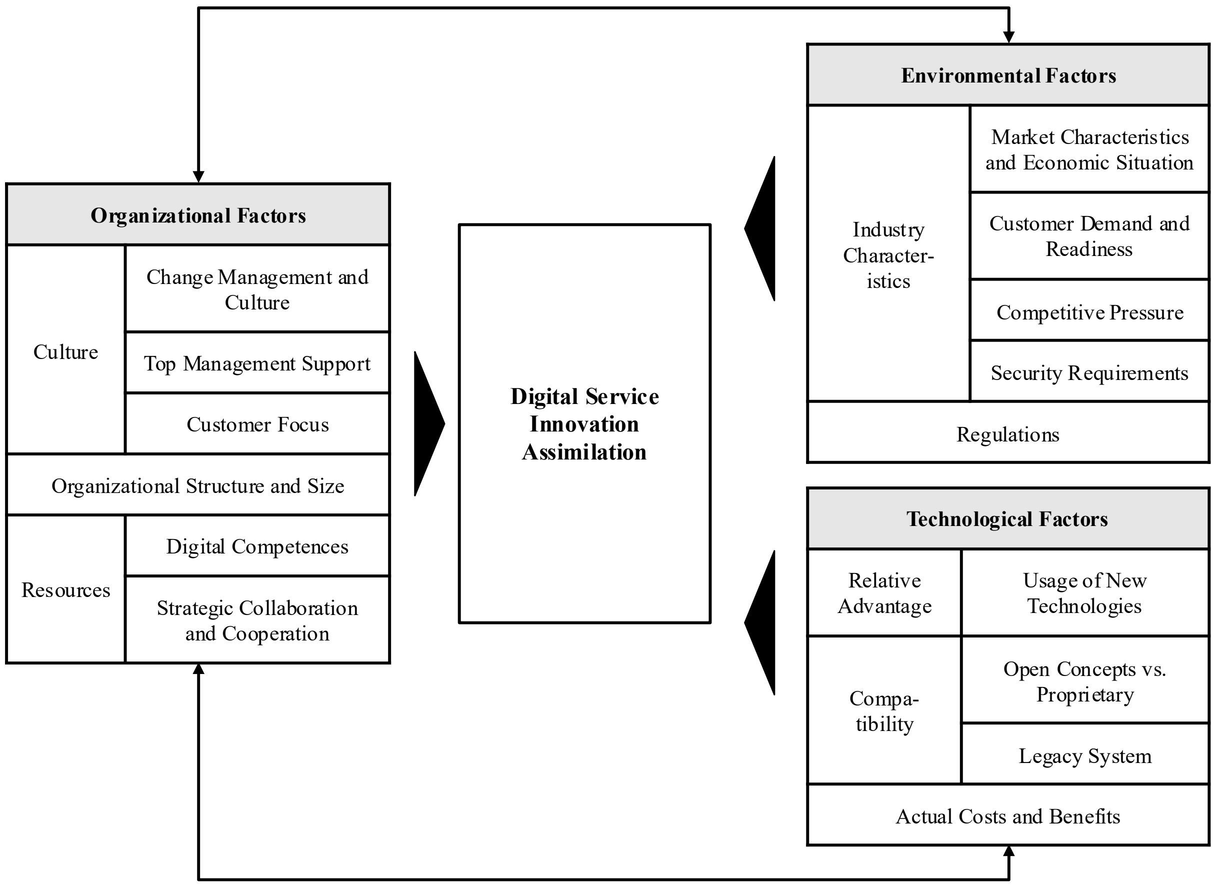

Figure 7. Extended and deepened framework for digital service assimilation

All experts report that digitalization and industrial internet have become a dominant topic. However, there is much skepticism and uncertainty about the concrete changes in the industry as a result of digitalization. Both small and large industrial companies describe the market as very immature regarding new technological standards. Actors in the market are experimenting a lot. New industrial internet technology platforms, like industrial IoT Platforms, are emerging and various concepts of operator models are tested. Some new business models are emerging, which, however, do not completely replace the old ones.

”In five years we plan to make 10% of our total turnover with the new subscription model (...) We don’t want to compare the new world with the old world - the old world will still make up a large part of our turnover.” - D1

Some suppliers with a large installed base in the market are using the hyped “Industry 4.0” as a sales argument and are already offering the first successful digital business models. So far, it cannot be observed that partners and dealers are dropping out of the value chain It is assumed that especially the system integrator will become more important in the future and offer more services. The dealer feel secure due to their specific application knowledge in the respective industry.

Customer Demand and Readiness. All of the interviewed experts work in companies that already have been established in the industry for many years and serve international markets. Although an existing customer base with a large installed base creates advantages in many respects, the experts also reported about disadvantages in terms of the deployment of new technologies: ”Certain technology developments we simply cannot do because of market penetration, so we have to go for established solutions because our customers confront us with a minimum availability of 10 years (...) usually we have 20, 25 years. This of course also slows down developments.” - C1

Over many years, a large number of different suppliers has led to a multitude of interfaces, different norms, and standards. Due to customer requirements for a high minimum availability, long warranties and long-lasting conventional technologies, systems and components have been used by customers for several decades.

With regard to the initiation of new digital service innovations (e.g. more sensors with digital value-added functions), experts report a lack of customer feedback.

”Of course we try with all our efforts to think more in the direction of the end customer and to get in contact with them, to pick up the requirements (...) but I have the feeling that the end customers do not really know that yet.” - A1

Important requirements and feedback on innovations mainly come from the end customer, who ultimately consumes the services. This is a challenge for all actors involved, especially those with no direct (end-)customer interface. Companies C- F can observe more customer requirements for new digital services on the market than companies A - B.

Concerning the customer requirements, experts say that their customers are looking for integrated services to either achieve the same output with less input, or increase output with the same input. Ultimately, the customer goal is to improve design, engineering, operation and maintenance of machines, increase productivity and performance, and reduce total cost of ownership. Further objectives are automated supply chains and the implementation of interfaces for partners and suppliers in order to have consumables even more precisely on site. However, all customers and suppliers in the machinery and plant industry are still very reticent about the opportunities and risks of digitalization.

”We see a growing need to get this data. However, we do not yet see at the moment where exactly the added value has been created.” - B2

Although customers want more data and digitization, they themselves often don’t know what to do with it.

”Both our customers and end-customers - they are asking what can we do with all this data?” - B3

Security Requirements. Security requirements for the adoption and utilization of new digital services in customer processes are another important factor within the industry.

”Firewall and Cloud, many customers have hell of a respect for it because they are afraid that they will be hacked and that you will have to open the firewall.” - B1

The availability of data derived from the use of PSS is a central prerequisite for digital service innovations. At present, the topics of data handling and ownership have not yet been clarified in industry. In addition, there is a need to embed production and process data from the customer application, especially in cases of holistic analyses and optimizations. However, this information often represents the customer’s intellectual property. Therefore, the customer usually blocks access to such data, especially if it is a permanent connection in real-time transmission. First approaches (e.g. isolated data connection, industrial gateways) try to address this issue. However, there is still a lack of experience or trust in such solutions.

Competitive Pressure. So far, experts report a watchful eye on the market, technical standards and new digital business models. Some actors in the industry fear that if trends are missed, the only thing left to do is to supply mechanics and others will become the “application know-how” carriers.

”At the end of the day, I then only concentrate purely on the mechanics, because we are then unrolled on the software side, i.e. on the interface side.” - A2

The currently high growth figures and high demand in the industry are also confronting organizations with the decision either to build up personnel resources, expand their machine park or expand digitalization to increase efficiency.

Regulations. In particular, the experts highlighted the warranties, data protection and intellectual property protection, and product warranties as important criteria factors for digital service innovations. These factors are often still unclear in the definition of service offerings, are subject to country-specific differences and slow down innovation.

5.4.2 Technological Factors

Usage of New Technologies. The term Industry 4.0 is understood in different ways by the interviewed experts and is often circumscribed by examples. For some, the addition of a controller and specific software to the product already counts as Industry 4.0, for others, it is about the use of augmented reality in the assembly of the machine. What all the experts have in common is that Industry 4.0 deals with data acquisition over the entire life cycle, starting with planning, production, and use till the end-of-the life. The use of new industrial internet technologies as well as connected and integrated data footprints constitute a central element for new business models. These new opportunities concern every area and activity, from marketing, sales, R&D, purchasing, production, customer operations to after-sales services. Especially by accessing data during the use of their products and components, manufacturers can offer their customers services such as analysis, predictive maintenance, scheduling of maintenance intervals and performance improvements.

Open Concepts vs. Proprietary. New technologies, on the other hand, may be very immature and challenge manufacturers to change familiar patterns and criteria when selecting suppliers, partners and standards. In addition, manufacturers see risks in protecting their core competencies if they open up their interfaces and systems:

”Every player in the market has different ideas about business models and if you focus on an open interface (...) you will certainly reveal your own added value or core competencies.” - A2

Legacy System. Experts report that customers expect the manufacturer to continue to support the older systems. One problem of services like predictive maintenance is, that their “machines, they all live much too long” (Expert B1). These challenges also mean that many manufacturers already have very different degrees of digitization maturity.

Actual Costs and Benefits. Organizations use industrial internet technologies to equip their products (from equipment parts to entire technical infrastructures) with more intelligence and functionality through software, sensors, and actuators. Subsequently, these products are often referred to as Smart Products. The experts have identified various goals, requirements, and challenges regarding digital service innovations. Six goals were identified:

- Improvement of service quality and efficiency through remote monitoring and over-the-air maintenance
- Increased process control, ease of use, product functionality and product flexibility through software components (digital add-ons) for configuration and free programmability
- Improved product development through knowledge of weak points and usage scenarios
- Increased reliability and reliability through predictive maintenance and product self-service
- Advanced asset management and energy optimization to increase operator efficiency
- Enable new business models such as “lot size 1”, sensor-data-as-a-service, analytics-as-a-service, pay-per-availability and pay-per-result.

However, it is also reported that developments of industrial internet technologies are perceived as risky and costly.

5.4.3 Organizational Factors

Change Management and Culture. Since the expected transformation from industrial internet technologies is taking place in all business areas, experts see that these are still inadequately prepared and thus hinder successful implementation. Examples include sales employees who have recently been involved in IT-specific customer discussions but lack the technical know-how to do so.

As already introduced, digital business models with new revenue models affect the provider’s entire product portfolio. Every corporate function as well as customer and supplier relationships change according to the experts. The transactional business model is replaced by recurring payment models. The sale will never be concluded through beneficial and needs-oriented life cycle services such as performance-based contracting.

”This is a disruptive change here in the company and a company that in the past was clearly focused on a transactional business, i.e. from all processes starting with sales to the systems behind them. (...) I have a product that I price through whatever approach and I sell the product once, customer pays, process completed. (...) Now when you get into a model (...) where we are going in the direction of recurring revenue, where we simply have a recurring business that is based on the output of the customer, it naturally changes the whole company." - D1

Departments have to control the monitoring of machines at the customer's site. The necessary infrastructure for lifelong product support must be in place and in operation. The systems are continuously further developed in the R&D of the manufacturer through data and customer feedback and constantly improved in the production of the customer. Finally, service teams must guarantee reliability.

The new world is generating numerous resistances. Even if a company wants to introduce less disruptive business models, "smart products" or data-driven services, a lot of internal convincing and coordination work is necessary. Not only the employees, functions, or departments in the company have to adapt, but also the application software or IT systems in use must be designed to map out the necessary service provision. All experts agree that current structures and cooperation within the traditional manufacturing organization have not yet been designed for this.

"Oh collaboration, thats also a very difficult point. In many many companies I see that between sales and innovation it is very hard. Like two sides of War. So when Digitalization comes up where you kind of have to work together, and this creates a lot of conflicts." - B3

Top Management Support. Companies that use new technologies to drive digital services innovation must adapt organizationally. New staff positions for digitization are introduced and top management is being involved. However, some experts report on a lack of management capacity for everything together.

Customer Focus. In addition, customer requirements in the development of PSS and digital service innovations are often unclear or even unknown. These may be based on individual assumptions and prejudices, without knowing the actual willingness to pay and without obtaining the customer's requirements. However this is highly valued by the experts and should be considered as critical KPI in the initiation and evaluation of the innovation:

"One difficult thing with digitalization and changing your business models and everything: You cannot say - Okay that's my ROI [...] in exact numbers. So I have tried other ways. So I'm looking for example into KPIs of customer engagement." - B3

Organizational Structure and Size. Larger companies that have already successfully implemented digital initiatives have built cross-functional competence centers. They are equipped with decision-making and instruction powers. Furthermore, the departments need to be well integrated with the existing organization through representatives in each area. The goal is to create synergies between the digital projects, to promote digital understanding within the company and to prepare the company to offer new business models in the future:

"(...) first started as a project (...) then said, we have to place it somewhere in the line-organization, as a central and independent unit in a division of the board (...) with interdisciplinary staff (...) and equipped with decision-making powers. (...) You have to imagine it like this, we are organized into product divisions. (...) then I say I am building a service that covers all products. That means that I am automatically involved in the discussion of all products and product areas. I have to change support and reporting structures, I have to adapt the IT system, which is geared towards transactional business (...). This means that my team will then create many small task forces, you have to imagine very agile speedboats that will then eat their way into the organization and tackle the corresponding topic areas as soon as they have been identified." - D1

Digital Competences. Emerging industrial internet technologies such as data mining, analytics, AI or the Industrial IoT require specialist knowledge. Sales and marketing of the manufacturer must be trained to better communicate the value generated and benefits gained through digital services.

"Suddenly, Sales is no longer talking to the engineers, but to the IT department, and we realize that our employees are not at all prepared for this." - B1

Furthermore, there is a lack of competence in the further areas of business models, e.g. with regard to new types of contracts, sales processes and tax aspects.

Strategic Collaboration and Cooperation. According to the experts, manufacturing companies must continue to encourage the establishment of new ways of working and collaboration. Individual hurdles in the disclosure of information and specialist knowledge within the company must be overcome. More proactive corporate communication and top management support is needed. In most areas, there are still too many gaps in knowledge and too little interest in digitization and IT. "Hardly any company in the industry has the complete know-how in this interdisciplinary field" (Expert F1). Therefore, it is necessary to work in partnership with customers and suppliers, even if some of them are competitors.

”An AI expert company alone lacks the domain knowledge. When you automate something it is important to understand the process, the equipment and what it means to increase productivity.” - F1

5.5 Conclusion, Limitation, and Outlook

Over the last 40 years, global competition from developing countries has put organizations in industrialized countries under great pressure. Not least for this reason, the expansion of the service business is increasingly moving into the focus of industry. In the meantime, this industry, as well as other industries, has been affected by the ongoing digitalization. As we know from other industries, such as the information and communications technology industry with cloud computing, new providers with digital business models are threatening existing business models or are even bringing them to a standstill. Still, there are major difficulties for established organizations in initiating, introducing and routinizing digital services before they can generate significant business value. In this area, the innovation of digital services is an important research topic.

Our qualitative study extends previous studies on servitization, i.e. the transition from product manufacturer to service provider, focusing on digital service innovations. Moreover, the study illustrates challenges of industrial organization in their transition to a service provider. The results of the study were presented as an extended TOE framework with consideration of the DOI theory which can serve as a basis for further research and guide managerial decision-making. Altogether, a framework for the assimilation of digital service innovation is proposed. This enables companies to carry out a structured analysis of their status quo and identifying areas of improvements in the assimilation of digital service innovations.

As any study, our qualitative research underlies several limitations. However, at the same time, these limitations provide interesting avenues for further research. Due to the interpretive nature of our research, the results we described represent the sense-making process of the researchers. Subjective personal judgments cannot be ruled out completely, even though we took great care to reflect the subjects opinions as correctly as possible. Despite the limitations, our study makes three contributions: Firstly, by using the TOE framework with consideration of the DOI theory, we have illustrated insights what factors are relevant in the context of digital service innovation assimilation. Therefore, analysis was carried out considering all players in the value chain. Secondly, we have emphasized that the transformation process to a service-oriented provider and organizational change will be critical to success, so further research and practice is needed in this field of research. Against this background, we have outlined an approach for future work and provided our identified factors as a basis for the research discussion. Thirdly, for practitioners, we have shown the potential of digital service innovation in frame of transformation process and are offering some guidance to the further development of transformation process of industrial companies in plant and mechanical engineering into a service-oriented provider.

6 Paper D: Cloud-based ML Technologies for Visual Inspection: A Case Study in Manufacturing

Title

Cloud-based ML Technologies for Visual Inspection: A Case Study in Manufacturing

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Publication Outlet

Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS 2021), Online Conference

Abstract

In recent years, cloud-based Machine Learning services have received much attention for promising fast and cost-effective deployment. At the same time, manufacturing companies are beginning to evaluate and implement these new technologies in their production processes. This paper adopts the design science research approach to demonstrate the use of cloud-based Machine Learning services to implement a visual inspection system in the manufacturing industry. As a result, our developed IT artifact can correctly classify all of the given parts in a dataset consisting of 363 images, outperforming the current manual inspection. Thereby, it addresses the various challenges faced by the industry when introducing cloud-based Machine Learning technologies, evaluating return on investment (ROI), and how this can facilitate further digital transformation in production.

Keywords

Case Studies of Artificial Intelligence, Business Intelligence, Analytics Technologies for Industry Platforms; Artificial Intelligence; Cloud Computing; Computer Vision; Design Science.

6.1 Introduction

Artificial intelligence (AI) and specifically Machine Learning (ML) approaches are on their way to becoming the key technology for numerous business applications. One area where ML methods are particularly successful is the field of computer vision (Ren et al. 2015). Since the advent of deep learning several years ago, those methods have dominated all important computer vision benchmarks (Krizhevsky et al. 2012). On top of that, they have also become much more efficient in regards to system resources (Tan and Le 2019). Among the best-known examples in everyday life are self-driving cars and the face unlock feature on smartphones. Beyond that, computer vision has the potential to have a high impact on industry and manufacturing. Potential applications in industrial production lines include identifying and localizing parts, detecting material defects on conveyor belts, and real-time analysis of materials (Yang et al. 2014). Although visual monitoring systems using conventional image processing techniques have already been used for several decades, conventional techniques usually come with several restrictions which could not be automated yet, especially when it comes to human flexibility, background knowledge and intuition.

In the course of global market trends, individualization of products, the need for more efficiency, shorter time-to-market cycles (Lachenmaier et al. 2015), and growing customer specifications, demands exceed conventional systems' capacities and capabilities. There is a growing need for more flexibility in these industrial processes.

Simultaneously, advances in computer vision promise to ease some of the restrictions of conventional visual inspection systems. Vendor cloud platforms promise a distributed adoption and use of ML and AI using Machine Learning as a Service (MLaaS). MLaaS simplifies the development and use of cloud-based off-the-shelf AI technologies and the adoption of pre-trained neural networks (Carvalho et al. 2019; Rai et al. 2019a). It eventually supports the entire development process, from the raw data set to the operational machine model, even with smaller training data sets. On top of that, cloud technologies continue to promise payoffs in reduced costs, increased efficiencies and provide business model transformation opportunities (Stamas et al. 2014).

Despite advances in computing, there is still much speculation about the use of ML for real applications, and the published benchmarks are often not realized (Baier et al. 2019). In this respect, the literature criticizes that the current ML research has lost touch with the "real world". It rarely includes an assessment of whether quantitative performance improvements are relevant in practice. More research is needed to evaluate the solutions developed under real conditions (Wagstaff 2012) and the corresponding economic implications (Baier et al. 2019).

This paper addresses this gap by developing and evaluating an ML-based visual inspection solution in the manufacturing industry using cloud-based ML technologies. Specifically, we address the following research questions (RQ): How can MLaaS facilitate the development of ML-based visual inspection in a production process? What are further potentials and challenges when introducing ML-based visual inspection into a production environment?

The remainder of the paper is structured as follows: The second section provides an overview of visual inspection techniques for quality control in a production environment. The research approach based on pertinent Design Science literature is introduced in Section 6.2.1. It is followed by the description of the designed artifact and design search process. Section 6.3 discusses the results and contributions to research and practice followed by concluding remarks and a description of future research directions in Section 6.4.

6.2 Theoretical Background

Product quality inspection in manufacturing is about comparing the properties of a product with its specifications (Newman and Jain 1995). If we specifically refer to visual inspection, we imply visually perceptible criteria, which is also called an optical inspection. Visual inspection is used in many areas such as industrial manufacturing processes (Chin 1988), food production (Maire et al. 2016), transport infrastructure maintenance (Cha et al. 2018), or the production of nuclear weapon parts (See 2015). As part of quality control, the aim is to ensure that faultless products with reliably consistent quality reach the customer. Products that are incorrectly sorted out, although they are acceptable, increase the scrap rate. Conversely, if a defective product is not recognized as such, it impacts customer complaints. Directly related to this are, among other things, customer satisfaction and loyalty (Čater and Čater 2010), a strong corporate brand (Van Riel et al. 2005), and ultimately the competitiveness of the company. Due to its great importance, quality control is one of the four major management functions alongside planning, organizing, and leading (Kujawińska and Vogt 2015).

6.2.1 Manual and Automated Optical Inspection Systems

Compared to other inspection methods, visual inspection is characterized by the fact that it is not only contact-less but also completely non-destructive, allowing 100% of manufactured products to be tested (Luo and He 2016). In the simplest case of manual optical inspection

(MOI), it is often possible to operate without special equipment and thus without a high initial investment. Nevertheless, a higher resolution compared to most other non-destructive testing methods can be achieved. Apart from a few technical gadgets (microscopes, better lighting and more ergonomic workplaces), MOI's core has hardly changed over time. Most efforts in recent years have been aimed at making MOI more reliable: With the advent of quality management procedures such as Six Sigma, the quality of human inspection was put under the microscope for the first time. It showed the error rate can range from 2-10% for simple inspection tasks to up to 30% for more complex tasks (Kujawińska and Vogt 2015; Swain and Guttmann 1983). This outcome is also difficult to reduce by multiple inspections, a fact known as the ”Two-Inspector Problem” (Drury et al. 1986). The error rate depends not only on the difficulty of the inspection task: Work results are influenced by numerous other factors. In addition to psycho-physical factors, such as the age and gender of the inspectors, the design of the workplace and social and organisational factors also have an influence (Kujawińska and Vogt 2015).

At the end of the 1990s, a quantum leap in quality control took place with the advent of digital sensors and the associated automation of visual inspection. Automated optical inspection (AOI) systems operate using conventional image processing techniques, such as a reference comparison (Thomas et al. 1995). In order to be able to install systems for AOI, several necessary restrictions have to be met (Demant et al. 2011). The inspection task to be solved must be described in detail and precisely in a technical manner, using the “language of image processing” (Beyerer et al. 2016), i.e., signal processing, edge detection, morphological image processing, and segmentation. Complex tasks are solved by combining these building blocks. For example, to count the number of pores in an object, the image is pre-processed so that the pores can be clearly distinguished from their background. Afterwards, the edges of the approximately circular pores are detected, fitted by circles, and counted in the last step. Furthermore, AOI systems require that all possible variants of test parts and defects must be known. In addition, the environmental conditions must be designed so that defects and objects can be detected at all. These environmental conditions must be kept as stable as possible (Demant et al. 2011).

If these prerequisites are given, automated visual inspection has some distinct advantages. It is efficient to a high degree and, once installed, has low operational costs. The inspection process is highly objective and detailed logs can be generated, from which the production process can be improved (Yang et al. 2016). However, some aspects of visual inspection can not be automated, especially in terms of human flexibility, background knowledge, and intuition.

Therefore, most literature suggests using so-called hybrid approaches, where the bulk of the task is automated, while humans perform mostly supervision tasks and decide in ambiguous cases (Beyerer et al. 2016).

6.2.2 ML-Based Visual Inspection

Machine Learning eases some restrictions for the use of an AOI system using conventional image processing techniques. First, the inspection task no longer needs to be described in a detailed and precise technical manner. Instead, ML automatically detects meaningful patterns in data (Shalev-Shwartz and Ben-David 2014). For instance, surface defects are not formally described, but only provided as labeled example images for ML algorithms. By that, the implicit knowledge of the inspectors is contained in the training data. Second, not all variations of components and errors need to be known in advance. ML systems are, to a certain extent, able to react to previously unknown or partly challenging to describe or parameterizable error types. ML systems can also exhibit greater robustness to changing environmental conditions, e.g., by simulating such fluctuations in training data during data augmentation (Fawzi et al. 2016; Yin et al. 2019).

In general, ML algorithms can perform various tasks during visual inspection. These include image classification, which classifies a test image into several categories, and object detection, which locates objects of interest in an image (Forsyth and Ponce 2011). For this purpose, early ML algorithms used a two-stage approach: Feature descriptors were used to extract useful features from images. These were then used as input to a classification algorithm. However, the quality of the output hinges on the quality of those hand-crafted features (LeCun et al. 1998). With the rise of deep learning in the last decade, manual feature extraction is no longer necessary, as it is also learned (Rawat and Wang 2017). Among those deep learning models, Convolutional Neural Networks (CNNs) are now used almost exclusively for image classification tasks. They work best when provided with data in the form of multiple arrays, such as images or linear signals (LeCun et al. 2015).

6.2.3 Machine Learning as a Service

In addition to the progress in the field of computer vision, new tools and libraries, standard algorithms, and pre-trained neural networks facilitate the development process from raw data to an operational ML model (Carvalho et al. 2019) – even with smaller training data sets, e.g., by using transfer learning techniques (Gopalakrishnan et al. 2017). Finally, these techniques and technologies have already been provided via several cloud platforms as Machine Learning as a Service. Cloud technologies enable rapid on-demand deployment of single use cases up to large-scale deployment throughout the company. Its advantages include on-demand computing power with quick implementation, fewer IT staff, low maintenance, and lower cost (Yang and Tate 2012). Despite these promising conditions, cloud computing is subject to some limitations in an industrial context. These comprise, among other things, the requirements for real-time processing and interactions, the comparatively limited computing power of industrial sensors and controllers, and last but not least, security and privacy considerations (Matt 2018). These restrictions must be addressed to foster the use of cloud technology in the industrial environment.

6.3 Research Design and Case Description

The Design Science Research Methodology (DSRM) applied in this case study has been described by Peffers et al. (2007). They identified six activities performed in an iterative loop as the creation process of a Design Science artifact. Such an artifact can, for example, be a piece of software or an ML pipeline, as is the case in this research work. Additionally, the authors adhered to the guidelines for Design Science Research by Hevner et al. (2004).

The case study was conducted within a German technology group. Although the individual divisions of the group pursue business in different markets, a central organisational unit enables cooperation across all areas concerned with digital transformation. One of the business units is active in the mass production of electronic sensors and actuators. For one of its products, surface inspection of production flaws and dirt particles is performed manually at a production throughput in the order of magnitude of several hundred thousand parts per month. In the context of this case study, this process should be automated by ML-based visual inspection. Further, the current manual inspection only could perform binary classification, i.e., sorting the produced actuators into two categories (OK and not OK). Thus, the case study's primary goal was to provide an algorithm that could outperform the human inspectors in that dimension. Beforehand, the performance of each human inspector was evaluated individually using the F1 metric, which resulted in the failure rates for simple inspection tasks (2-10%) (Kujawińska and Vogt 2015; Swain and Guttmann 1983).

However, improvements in other dimensions were needed to justify the investment and the risk associated with adopting this new approach. So, a secondary goal was to provide new insights into the production process, which could improve the manufacturing process and detect deviations from the defined standard conditions before those deviations could manifest themselves in errors. Thus, investigation was not only focused on algorithms for binary classification, but also for multilabel classification (determining the kind of error) and detection (localizing the error).

Since this case study shall demonstrate how ML can be incorporated into an already established production environment within a company, particular focus lies in communicating the artifact to support decision-making for the stakeholder. Therefore, the demonstration and evaluation of the artifact include an analysis of the financial feasibility and visualizations of the performance and capabilities of the ML system.

Lastly, proprietary data was used for this case study. Therefore, no original images can be shown. Figure 9 depicts an anonymized version of the device.

6.4 Results

The following section describes the designed artifact and the design process. Since a large focus of the DSRM lies on communication and demonstration, the artifact will be explained extensively to the stakeholders of the production process, as shown in Section 6.4.2. In Section 6.4.3, the algorithms' performance will be evaluated and compared to the manual visual inspection, in the domains of prediction accuracy and financial feasibility.

6.4.1 Design and Development

The structure of the design and development phase follows the flowchart shown in Figure 8. In the following, the individual steps are outlined in greater detail.

Image Capturing. The device under inspection is a small thermal sensor, which is shown in Figure 9 as a simplified version. It consists of multiple different precious metals, screen-printed on a ceramic substrate, and covered by a protective glass layer. Different errors can be introduced during the production process, e.g., dust particles underneath the glass layer, scratches on the surface, or cavities in the printed metal parts. Due to the variety of those errors, they can not be made visible within a single image. In order to capture the full breadth of errors, four images under different lighting conditions (incident light with different amounts of dark-field illumination as well as transmitted and coaxial light) are captured for each of the 363 specimens of the sample dataset. A simplified depiction of the resulting images is shown in the top row of Figure 9. Since position and orientation of the camera are kept constant during the capturing of the image series, the resulting images can be stacked on top of each other.

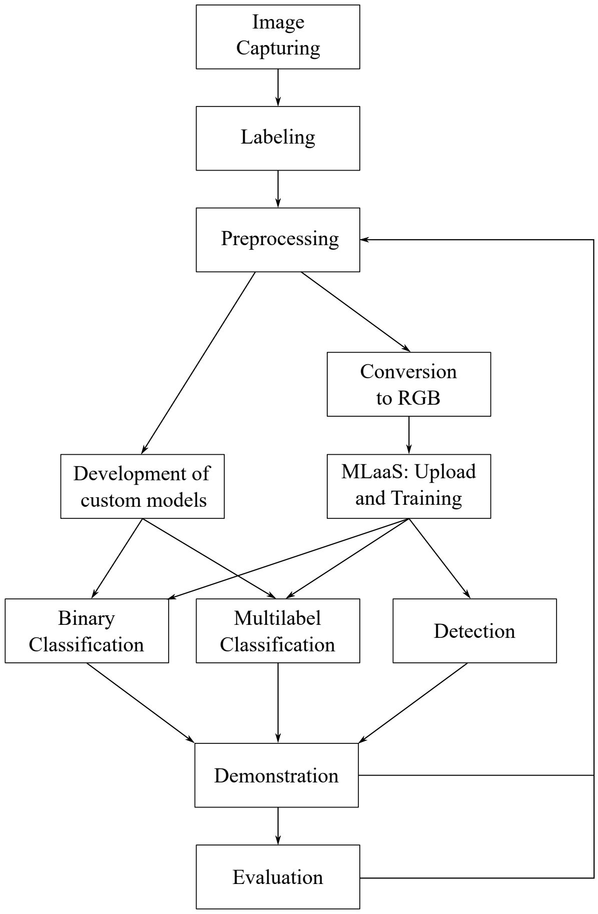

Figure 8. Flowchart showing the development process of the artifact.

Labeling. A production engineer labels each of the four illuminations for every image in the dataset, based on the error catalogue that is also used for the current manual visual inspection. They mark each error with a rectangle and further annotate the category of the error. This allows to additionally deduct the labels for the simpler binary and multilabel cases, where the location detail is irrelevant.

As a labeling software, IBM's *Maximo Visual Inspection* (formerly *PowerAI Vision*) (Ibm 2020a) is used. The images of the different illuminations are labeled independently from one another. This way, only errors that are actually visible in a certain illumination are marked as such. This procedure will become important when combining these information in the red, green, and blue channels of an RGB image.

Preprocessing. For preprocessing, we use OpenCV's Template Matching to crop the labeled microscopic images to only show the device (OpenCv 2020). Next, we perform image augmentation in accordance with the device's actual properties: Since it shows mirror symmetry, the size of the dataset can be doubled by creating vertically f lipped copies. Since the substrate may come from different suppliers and may have a slightly deviating color, thickness and density, we can create additional images for training by changing the colors for the substrates.

Conversion to RGB. One of the strengths of MLaaS is its ability to work with pre-trained models. However, there is no out-of-the-box solution to handle the information contained in the four different images we have of each specimen in this use case. To overcome this limitation, we selected the three illuminations containing the most information about errors. We copied each illumination to the red, green, and blue channels of a new color image in the next step. Further, we discarded the illumination with the least information content. This newly created color image is then used as input to the pre-trained models. In order to determine the information content of an illumination, three metrics are computed for each image and then aggregated over all images of one illumination:

- Total number of labels
- Unique labels: As mentioned above, one actuator's four illuminations are labeled independently from one another. Often, errors can be detected in more than one illumination, resulting in bounding boxes at similar positions in these images. A label is considered unique if its bounding box does not overlap with another bounding box on another illumination.
- Essential labels: If an actuator only has errors detectable in a single illumination, the removal of this illumination would make an otherwise rejected part undetectable.

Taking these three metrics into account, we are able to keep most of the information while removing one illumination. This process is visualized in Figure 9.

Upload and Training. We use two MLaaS providers in this case study: IBM's *Maximo Visual Inspection* and Google's *Cloud AutoML Vision* (Google 2020). Both work in a similar manner: The images for training are uploaded, in addition with a specification file describing the labels. Afterwards, we can train a ML model in the cloud. After the training is completed, we can perform online predictions using the vendor-supplied APIs or download the model for use on an edge device.

For all training processes, a split into training (70%), validation (15%) and test set (15%) is performed. In all cases, the test set is never uploaded into the used tools to preserve its independence. IBM's tool allows for some adjustments to be made: For the first task (binary classification), we choose GoogLeNet (Szegedy et al. 2015), pre-trained on the ImageNet dataset, as the model architecture. Multiple other pre-trained models are available within the tool (Ibm 2020b), none however were fit for the specialised use case at hand. Next, we perform a grid search over learning rate and weight decay to find the best model based on the F1 metric. At the time of the case study, the service did not offer a feature to solve the second task (multilabel classification). However, we could exploit a property of the device to reduce the task of multilabel classification to a binary classification task for each label: The different errors labels correspond to the material classes on the device, e.g., “Substrate Error”, “Gold Error”, and “Glass Error”. With one small exception, these areas do not overlap. We can then create one binary classification task for each class of material, by cropping out the rest of the device and training only on the area of the selected material. Again, a pre-trained GoogLeNet is chosen, grid search over learning rate and weight decay is performed and the best model for each error class is determined. For the third task (detection), the faster R-CNN algorithm (Ren et al. 2015) is available through the platform.

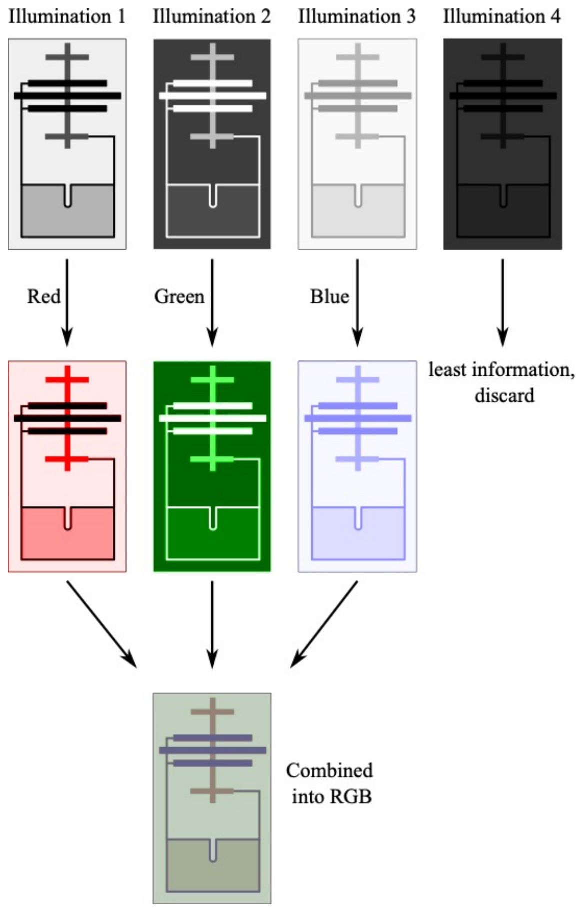

Figure 9. Visualization of converting four illuminations to one RGB image.

Google’s service allows only to set a budget of node hours for training. We train the models with the same images as on IBM’s platform. Here, the only parameter to choose from is the amount of node hours the training should be performed with. This value is set to 100 hours. This way it is high enough, so that convergence is reached in every training. Again, the multilabel classification is reduced to a binary classification task using the same blacked-out data. Even though this service is able to perform multilabel classification, this approach lead to better results and comparison between platforms.

The training duration ranges from a few minutes for the classification tasks to one hour for the detection models on both platforms. The training process is performed completely transparent for the user, who will have no further influence on the process until the completion of training. Furthermore, cross-validation can not be performed. At the time of experimentation, the used tools did not have the option for cross-validation, instead it would have had to be performed manually.

Development of Custom Models. To further evaluate the performance and use of MLaaS we decided to develop a custom model.

MLaaS, especially in the field of computer vision, uses powerful, but very generic algorithms to solve a wide variety of use cases. To potentially improve upon the performance of those MLaaS providers, we develop a custom model that is free of the restriction of the cloud platforms. This approach took advantage of two properties from our special application:

First, our custom model will use the information of all four illuminations. This is an improvement over the MLaaS platforms, where only three illuminations could be used in the three channels of an RGB image. Second, each image is taken under the same orientation and lighting so that each time there is a fixed structure that does not change drastically from image to image. The only differences are potential production flaws.

Both of these facts can be exploited by implementing a variation of an established facial recognition algorithm (Turk and Pentland 1991). The images within each illumination are normalized by subtracting the mean of the images and then scaling the data to unit variance. Each normalized image is then flattened into a vector and arranged into a feature matrix. Of this feature matrix, the eigenvalues and eigenvectors are calculated using principal component analysis (PCA). This decomposition has some interesting properties: First, the mean of the images which was subtracted in the normalization step shows a device without flaws. Second, the eigenvectors belonging to the biggest eigenvalues represent the most significant flaws present in the test data.

This eigendecomposition can now be used to classify the devices. We could show that the eigenvectors belonging to the 800 biggest eigenvalues contain 99% of the variance of the original data. We can now project the images into this lower-dimensional space, spanned by the corresponding eigenvalues, and use these coordinates as new feature vectors. Classification is performed using a Support Vector Classifier (SVC). This approach is capable of performing binary and multilabel classification. However, detecting the location of production flaws is not possible.

6.4.2 Demonstration

Both MLaaS providers allow for online as well as offline predictions. For this case study, the evaluation was performed using online prediction, since no additional setup was required. However, when used in production, the models need to be downloaded onto edge devices: Preprocessing, creating the RGB image, upload and inference take around 270 ms in our calculations. This additional latency would already impact the throughput of the production line. Additionally, online predictions would make the whole production process reliant on an internet connection.

For the further demonstration of the design artifact and showing how ML can be used in our case study, we designed two ML-based visual inspection systems aligned to our business environment. In the first system design, we only replaced the MOI bythe MLcomponent and appropriate hardware. However in this design, product handling is still done by the production staff, as it had been done when parts where taken to MOI and back. In the second design, the handling of the product parts is automated by a pick-and-place machine. This system design therefore requires more modifications to the production process by introducing a new machine into the process. These two new system designs were presented to the business.

As a further communication instrument, we presented some exemplary visualizations. These visualizations show how additional quantifiable information obtained through the ML model can be used in the production process. The first visualization shows a Pareto chart, which depicts the frequency of different error types as a bar chart. The diagram allows the viewer to quickly compare the current AI predictions with historical predictions to detect changes. Secondly, we designed a heat map of the product. The heat map uses color concentration to indicate a concentration of defects in certain areas of the product within a certain time. This tool can also be used to monitor the running production and to react to deviations.

Lastly, a graphical user interface (GUI) demo was implemented, which served to communicate the ML model's functionality. The GUI allows users to use the AI to analyze their sample images of products. The output then displays the analysis (error classification) and a detection as a bounding box over the corresponding area of the image.

6.4.3 Evaluation

The created artifact, i.e., the trained Machine Learning model, needs to be evaluated in terms of several criteria:

First, the performance of the different models in the testing environment is determined. For this, a suitable metric needs to be found. Accuracy, which is the percentage of correctly classified parts, can hide bad prediction performance on underrepresented classes. When the production process is running as intended, the fraction of faulty parts is going to be small, making accuracy an ill-suited metric. From a business standpoint, high precision (a small number of undetected faults) and high recall (a small number of erroneously discarded non-faulty parts) were decided to be equally important. Thus, the F1 score, which is the harmonic mean of precision and recall, is chosen to compare the different models. Table 9 shows the best performances under this metric for the two MLaaS providers and the custom model. In multilabel classification and detection, the average F1 score over the types of errors is reported. In all cases, the test set that was not used during training is used to determine these metrics.

	AutoML Vision	**Maximo Vis. Insp.**	**Custom Model**
Binary Class.	0.90	1.00	0.86
Multilabel Class.	0.85	0.90	0.71
Detection	0.75	0.78	-

Table 9. Comparison of F1 scores of the two MLaaS providers and the custom model. Note that the latter is not able to perform detection tasks.

Several clear trends can be seen: In the two classification tasks, the custom model has the worst performance of the three approaches, even though it is able to exploit the most information from the data. This shows the supremacy of the pre-trained models used by the MLaaS providers, especially on such a small dataset.

Of the two MLaaS platforms, *Maximo Visual Inspection* performs better in all three categories. In the case of binary classification, it can correctly predict all samples from previously unseen images, even with different data splits. However, since training and evaluation are based only on a small labeled dataset, it remains to be seen how this model will behave in a production environment. The higher performance of the *Maximo Visual Inspection* platform can be attributed to two factors: First of all, it allows the user to adjust some settings and parameters. This is in contrast to Google's platform, which just allows the user to only define a training budget and leaves the rest to the automated ML system running in the background.

Additionally, further insights and metrics from the training process are provided, making a continuous improvement possible.

Another goal of the Case Study is to analyzes the economic implications of switching to the new ML-based visual inspection system. First, the costs of the current manual inspection are evaluated. For most factors, numbers are available from the business unit or through interviews, e.g., labor costs, office space, and equipment. Furthermore, manual inspection performance is taken into account for the cost calculation, which is derived from a measurement system analysis. This leads to the cost of “false negatives” classifications in quality inspection. False negatives are products that are incorrectly classified as defective. Second, the costs of the two different proposed automatic visual inspection system designs (manual handling and fully automated) are estimated. The costs divide up into three categories: Development costs, the initial investment into hardware, and running costs. Development costs include data labeling costs, labor costs, and cloud infrastructure costs. Next, initial investments include the costs for product handling, image sensors, and ML hardware. Lastly, the operating costs for the AI solution were calculated. This includes the costs for the False Negatives and costs for the operation and management.

Finally, the variable and fixed costs of different solutions can be compared. The case study showed that the costs amortize already within the second month. This analysis also helps to compare scenarios that may involve changes in the existing production process. Although the AI solution has a high initial investment, it has the lowest variable costs and is, therefore, the preferred option in the long run. This also satisfies the condition given by the business unit that a visual inspection system should be profitable within two years. A postimplementation review is nonetheless necessary and open for further research.

The above considerations are purposefully kept very simple. It is expected that higher costs and unforeseen difficulties arise during the actual implementation. However, in the long term, the automatic inspection based on AI is expected to have a positive return on investment, taking all previous considerations into account.

Finally, the developed artifact is evaluated in its business environment (Hevner et al. 2004). For this purpose, the solution is presented to the decision-makers in the company. The observations on the presentation show that the demonstration of the solution is well received. The functionality and decisions of the AI can be replicated and visualized through the GUI. In addition, the dashboards for statistical monitoring of the solution are considered to be a valuable tool. It was decided to use the ML solution in production.

6.5 Discussion

Commencing with the *theoretical implications*, our study contributes to the current "Develop" research stream of digital innovation (Kohli and Melville 2019) by showing how Information systems (IS) artifacts are developed and what adoption antecedents are. We showed that MLaaS can be used to implement a ML-based visual inspection system in the manufacturing industry. Further, we demonstrated which steps need to be considered during ML development (e.g., Labeling, Conversion to RGB, Upload and Training) in order to use MLaaS. The outcome of the system design relies on attention to all steps and new work routines, starting from capturing the training data up to addressing the challenge of introducing a ML black-box solution into a production process, embracing the central idea of socio-technical theory (Mumford 2003).

Furthermore, our study contributes to the discussion that the "best practice" design of a vendor-supplied IS may be a myth (Swan et al. 1999). On our way to find an optimal ML model for the different prediction tasks (binary classification, multilabel classification, and detection) the two vendor platforms performed quite differently in terms of configuration process (provided configuration and optimization options) and performance (overall F1-Score). Different vendors provided the best results for different parts of the solution. Therefore, this case study cannot be considered as an overall comparison between the providers, and it was not our intention to highlight a better cloud platform. However, the different performances can have a substantial financial impact, especially when it comes to high volume manufacturing. The advantages of cloud computing, among others, are rapid on-demand deployment, quick implementation, and fewer IT staff (Yang and Tate 2012). These advantages also became evident when using AI cloud technologies. MLaaS helps non-IT companies in the subject matter to build expertise in certain AI areas, like computer vision. A comparison with our custom-developed AI approach shows that the performance of the providers' black box solutions cannot easily be beaten by in-house developments. Therefore, these solutions provide a high potential for speeding up the development of ML products. Simultaneously, it also becomes apparent that MLaaS services do not (yet) make data science expert knowledge obsolete since challenges with the data, training or evaluation of the models remain. One example is the preprocessing of the available data into the three color channels of an RGB image explained in Section 4.1.

MLaaS helps especially with hyperparameter tuning or the search for an optimal architecture. Choosing the right tool for the right task, however, is still up to the data scientist. In addition, proprietary MLaaS aggravates the black box dilemma that is already known in the context of cloud computing services (Yang and Tate 2012), since the developed solutions are often black boxes again. This dilemma can lead to several problems, e.g., lower acceptance and user's trust of model predictions (Wanner et al. 2020) as well as challenges in clarifying the accountability for such a system (Martin 2019). In turn, MLaaS makes the development of such AI solutions more accessible and promote their widespread use within a company, contributing to the democratization of AI tools in the company (Rai et al. 2019a).

Our final IT Artefact consisted of the ML model and a software (including a user interface) that allows the production staff to upload sample images of the products to review the AI's decisions, as explained in Section 6.4.2. Its use indicates that the models are able to generalize even to previously unseen error patterns. In addition to the demonstration of several graphical ways to visualize the resulting data on dashboards, this led to a high acceptance from the responsible business unit. These dashboards, based on the AI output information, provide an outlook on how such a solution can create useful additional information for new process improvements (e.g., improved error detection) to facilitate further innovation. At the same time, the additional representations and feedback from the business unit lead to a better insight into the mechanisms and operation of the model, which also contributed to the question of the responsibility and ethical implications of such a system (Martin 2019).

Moving beyond theoretical implications, our study also has several *practical implications*. At first, all three technical challenges (binary classification, multilabel classification, and detection) could be solved with higher than expected performance. By combining the information contained in four differently illuminated images into one RGB image, high-performing models for each of these tasks were trained using standard architectures within cloud AI services. Furthermore, they outperformed a custom algorithm based on PCA, which was specifically developed to handle the information contained in all illuminations. In addition to technical feasibility, financial viability was shown as part of a case study. Estimates about the costs of the automated inspection were compared to the costs of the current manual inspection, showing a positive return on investment and, based on the concrete implementation, possible cost savings of several hundred thousand Euros per year.

6.6 Conclusion

In many manufacturing companies, the process of manual optical inspection requires considerable human and financial resources. Also, it involves various challenges that influence inspection quality. Here, ML-based visual inspection has emerged as a powerful technology to automatically monitor product quality and thus reduce the number of defective products.

Simultaneously, cloud services and the use of off-the-shelf AI technologies simplify the development and the adoption of pre-trained neural networks. In this paper, we demonstrated different approaches to the development of an ML-based visual inspection system in the manufacturing industry utilizing MLaaS platforms. Especially IBM's *Maximo Visual Inspection* could achieve excellent results in binary classification, multilabel classification and detection tasks, performing even better than a custom model based on PCA. We demonstrated the value of this artifact to the involved business unit, fostering understanding in AI and showing how they can use the data from these models to improve their production processes. Further research can combine the findings from this and several similar use cases into a framework for automating visual inspection problems using Machine Learning.

7 Paper E: Exploring Service Innovation in Manufacturing Firms Through the Lens of Service Systems: A Structured Literature Review

Title

Exploring Service Innovation in Manufacturing Firms Through the Lens of Service Systems: A Structured Literature Review

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Publication Outlet

Proceedings of the 25th Pacific Asia Conference on Information Systems (PACIS 2021), Dubai, UAE

Abstract

Industrial firms in the manufacturing sector are increasingly expanding their product range with services. The continuous innovation of such services plays a central role. Digital technologies such as the internet of things, cloud computing, big data technologies, and data analytics, which are gaining importance in the context of the industrial internet, enable the development of intelligent and networked product-service systems. This research work presents a structured literature review in which 75 relevant publications with high-ranking were identified. Through the theoretical lens of work system theory, we analyze service innovations driven by digitalization and their impact within industrial firms, between firms and their customers, and within product/service offerings. The resulting model provides a basis for further research and supports practitioners with a systematic analysis of their service transformation.

Keywords

Service Systems; Digital Service Innovation; Literature Review; Work System Theory.

7.1 Introduction

Services are becoming increasingly important for formerly product-oriented industrial firms as a means of attracting new customers, retaining existing customers, or creating a competitive advantage (Vandermerwe and Rada 1988a). Most recently, this trend has intensified further in the context of digitalization. Industrial products and machines are equipped with industrial internet technologies, like the internet of things (IoT) and artificial intelligence (AI), providing connectivity and intelligence and enabling new service innovations (Allmendinger and Lombreglia 2005; Porter and Heppelmann 2014). In research, this development is being studied under the term ‘servitization’ (Baines and Lightfoot 2014) or, more recently, ‘digital servitization’ as a combination of digitization and service transformation in the industry (Paschou et al. 2017). Companies see new opportunities for doing business by digitizing existing processes and services. However, companies often struggle to successfully implement industrial internet technologies and assess the potential of these digital technologies in service innovation (Ardolino et al. 2018; Frank et al. 2019a).

To fully realize the business value of digitalization in the plant and mechanical engineering industry, the innovation of digital services stands out as an essential research topic (Baines et al. 2017; Bilgeri et al. 2017). In this context, the role of digital technologies in the service transformation of industrial companies is still under-investigated (Ardolino et al. 2018). Although the number of research has increased significantly in recent years, there is a lack of a holistic view and a common understanding about the roles of digital technologies and especially the use of data and analytics to innovate digital services (Hunke et al. 2019). Overall more research is needed on the use of advantages brought by digital technologies in the context of service innovation (Schüritz et al. 2017). Against this, we seek to investigate the following research question: *How do digital technologies influence service innovations in the manufacturing industry, and what specific roles do they play in the service system?* To answer this research question, we conducted a literature review. We use the work system theory (WST) (Alter 2013) as a theoretical lens to structure our findings and analyze them through the lens of work systems (service systems). This helps us “visualizing operational impacts and service management challenges related to increasing digitization and automation within firms, between firms and their customers, and within product/service offerings” (Matzner et al. 2018, p. 12).

The remainder of this paper is structured as follows: The following section provides an overview of the theoretical background and related work to narrow the field of research that served us to conceptualize, analyze, and synthesize our literature review. Next, we describe the research approach used to compile and analyze the publication data from our literature review. Findings are presented in the subsequent section. We then discuss these findings, and the last section concludes our research work and provides recommendations for future research.

7.2 Theoretical Background and Related Works

7.2.1 Digital Technologies for Service Transformation in Manufacturing

The increasing adoption of digital technologies by industrial companies represents a fundamental first step of their digital transformation efforts (Frank et al. 2019b). This is also described by digital servitization, which is defined by Kohtamäki et al. (2019) "as the transition toward smart product-service-software systems that enable value creation and capture through monitoring, control, optimization, and autonomous function." Digital servitization represents a transformation of industrial companies' processes, capabilities, and offerings and the value networks connected to them. The goal of digital servitization is to create increased service value (Sjödin et al. 2020).

In this transformation, companies are beginning to equip their products with sensors, microprocessors, and data storage devices to enable digital networking with other products and information systems. Together with the ability to analyze data, these formerly analog, physical products are becoming smart products. These products pave the way for the provision of digital services, so-called smart services (Beverungen et al. 2019; Kammler et al. 2019; Porter and Heppelmann 2014). Moreover, systems of smart services are described as technology-supported, continuous, and routinized interactions because they offer the possibility of combining resources and activities at service providers and consumers (Beverungen et al. 2019). A variety of other terms and synonyms for smart products, smart services, and smart service systems are represented in the literature, such as 'smart devices' or 'cyber-physical systems' (Beverungen et al. 2019) as well as 'data-driven services' (Schüritz et al. 2019), 'analytics-based services' (Hunke et al. 2019), or 'smart product-service systems'('smart PSS') (Zheng et al. 2018). Zheng et al. (2018) address the concept of 'smart PSS'. They define smart PSS as a business strategy that focuses on IT-driven co-creation of digital services to meet individual customer needs in a sustainable way. The main components for this strategy are the various stakeholders, intelligent systems, and smart and networked products. Digital services derived from these are at the core of smart PSS business strategy. Schüritz et al. (2017), in turn, examine digital servitization specifically from the perspective of data analytics. In doing so, they describe data analytics capability as an advanced development of servitization and introduce the term *datatization*, which can be defined as the "innovation of an organization's capabilities and processes to change its value proposition by utilizing data analytics" (Schüritz et al. 2019, p. 4). All approaches have in common that formerly physical products are equipped with hardware and software systems that can network digitally with other products or the internet. They are based on data and analysis methods, enable innovative services, and generate added value for the customer.

		Relation to technology		
Capabilities	**Description**	**IoT**	**CC**	**BDA**
Identification (user)	Identification of a system user in every phase of use.	X	X	
Identification (product)	Identification of the product and functional configuration.	X	X	
Geo-localization	Locating moving objects.	X	X	
Timestamping	Establishing a time reference of an occurring event.	X	X	
Intensity assessment	Measuring the level of product usage or units produced.	X	X	
Remote monitoring (usage and condition) and prediction	Remote monitoring of the product condition and operating parameters allows triggering signals when critical values are exceeded and ensures service quality. Subsequent analysis and interpretation of the most current data can predict future behavior.	X	X	X
Control	Remote control and/or maintenance activities to configure products and prevent malfunctions.	X	X	X
Optimization	Optimize product performance through real-time data analysis combined with predictive models and decision support models.	X	X	X
Autonomy	The product autonomously handles the management of functions and connections to other products.	X	X	X

Table 10. Capabilities of combined digital technologies in service innovations in manufacturing, adapted from Ardolino et al. (2018)

In this transition, the literature identifies digital technologies, which are also referred to as the "new IT" (Tao et al. 2018): the internet of things, cloud computing (CC), big data, and big data analytics (BDA) (Ardolino et al. 2018; Frank et al. 2019a). This is further supported by Paschou et al. (2017), who, through a literature review, identify IoT, CC, and BDA as the most prominent technologies in digital servitization. Implementing these technologies will achieve connectivity and intelligence and enable advanced front-end technologies such as smart products or smart manufacturing (Ardolino et al. 2018). The capabilities of an organization to leverage digital technologies for data collection and storage, data access, and data analysis are prerequisites for services to be adopted by digital technologies. Here, the IoT enables data collection and transmission. Data storage is enabled by CC technology and forms the basis for subsequent BDA applications. In combination, the three technologies - the IoT, CC, and BDA - can take on additional capabilities and new purposes (see Table 10). In this way, they enable a digital service offering and influence service innovations (Ardolino et al. 2018).

7.2.2 Theoretical Integration

We chose to use the theoretical lens of work systems theory (Alter 2013) to analyze, synthesize, and integrate our findings from the literature for the following reasons: From an IT perspective, WST links services and service systems and gives an essential insight for organizations in adopting a service orientation (from business to technology). Thereby, according to Alter (2010) "a service system is a work system that produces services for customers" (Alter 2010, p. 202). Since it involves social and technical aspects, it helps us visualize operational service transformation impacts and challenges related to increasing digitalization (Matzner et al. 2018). With this, we want to investigate the influence of digital technologies in service innovations in the manufacturing industry.

In general, the WST distinguishes between technologies and work routines as different components of work systems. In a work system, human participants and/or machines perform work to produce specific products/services for internal or external customers. In doing so, the processes and activities encompassed by the work system use information, technology, and other resources (Alter 2013). The work system is a general way of thinking about systems within or between organizations, which is widely used in different contexts and technologies. This approach has been used, e.g., for the analysis of work systems on crowdworking platforms (Mrass et al. 2018), mobile-learning initiatives of educational institutions (Krotov 2015), or in business process management (Alter and Recker 2017). Although the idea of work systems goes back more than two decades (Alter 2013), it has gained popularity in recent years. It has increasingly come into play in consideration of service systems (Alter 2010) and increasing digitalization. This is shown, e.g., by studies in financial institution services (Marjanovic and Murthy 2016), open data services (Lindman et al. 2013), and service management (Matzner et al. 2018).

WST comprises three components shown in Figure 10: The definition of work system, work system framework, and the work system lifecycle (WSLC) model. While the work system framework represents a snapshot at a point in time, the WSLC model describes how a work system evolves over time. In addition, it can cover both planned changes initiated by projects that move through the cycle and unplanned changes (e.g., adaptations, workarounds) primarily during operation and maintenance (Alter 2010).

1) Definition of work system: A work system is a system in which human participants and/or machines perform work (processes and activities) using information, technology, and other resources to produce specific products/services for specific internal and/or external customers.

2) The work system framework | **3) The work system life cycle model**

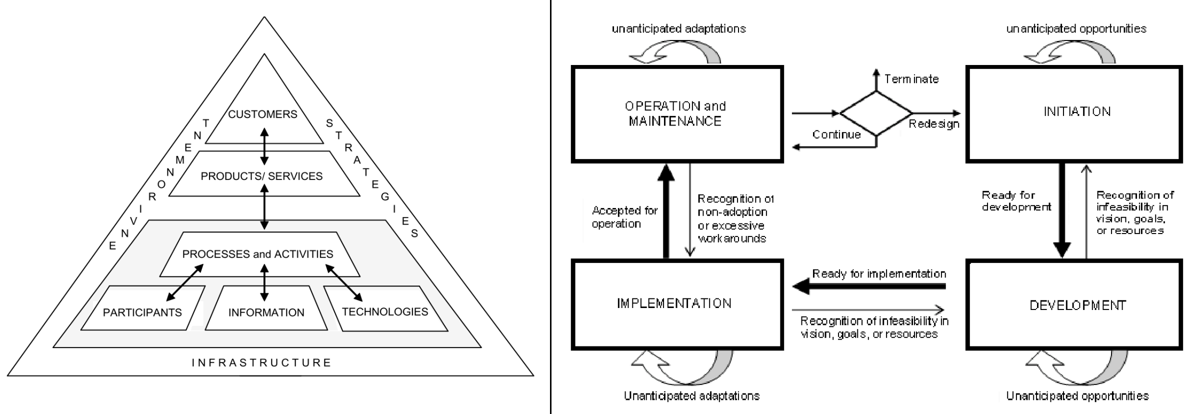

Figure 10. Three components of work system theory (Alter 2013)

Following Alter (2010), the WSLC model consists of four phases. In the *operation and maintenance* phase, the service system is managed and continuously improved. Business and IT coordinate on the system's needs and capabilities. The *initiation* phase is generally driven by problems and goals to be pursued by business and IT and the evaluation and initiation of projects to improve the service system. In the *development* phase, business and IT analysts determine how the improved service system should run by evaluating requirements and appropriate system components. The goal is to ensure that the technology developed or acquired fits the operational plans and goals for the service system. In the *implementation* phase, business professionals manage the implementation in the organization. This also includes the associated change management (e.g., training, address acceptance, and resistance in organizations). At the same time, old systems may still need to be operational.

7.3 Research Method

To gain a better current understanding of the impact of digital technologies on service innovations in the manufacturing industry and their role in service systems, as well as to identify future research needs, we conducted our literature review according to the five phases of Brocke et al. (2009): (1) Definition of the review scope using a taxonomy table, (2) conceptualization of the topic, (3) identifying relevant literature in different databases, (4) analysis and synthesis, and (5) identification of future research needs.

In this respect, we first outlined the scope of the literature review using Coopers's (1988) taxonomy table (see Table 11): Our review focuses on literature that represents research results and theories and pursues the goal of integration and criticism. In the context of integration, the existing literature is summarized and based on this synthesis, central statements are made about our specific field of research. Next, existing research is compared with each other based on a previously established criterion in the context of criticism. In doing so, we take a neutral position. The topic is presented from different perspectives based on existing literature and integrated into theoretical lens of service systems. We also chose to review the literature with exhaustive selective coverage, analyze it thoroughly, and then report our findings with selective references so that a selection of the literature is used in detail to answer the research question. Our organization is conceptual, as articles with comparable content are compared with each other. With our results, we address both specialized scholars and practitioners/politicians (Brocke et al. 2009).

Characteristics	Categories			
Focus	Research Outcomes	Research Methods	Theories	Applications
Goal	Integration	Criticism		Central Issues
Perspective	Neutral Representation		Espousal of Position	
Coverage	Exhaustive	Exhaustive and Selective	Representative	Central/Pivotal
Organization	Historical	Conceptual		Methodological
Audience	Specialized Scholars	General Scholars	Practitioners/ Politicians	General Public

Table 11. Taxonomy of our literature review (Brocke et al. 2009), following (Cooper 1988)

7.3.1 Conceptualization of the Topic of the Literature Review

Second, following Rowley and Slack (2004), we outlined the initial, overarching topic of our research using a mind-map, which served as the basis for defining the key terms in the database search. The final mind-map (see Figure 11) is the result of an iterative process in which we first jotted down all terms, synonyms, and associations related to the topic area. We used an initial review of the literature in our topic area as a basis for this.

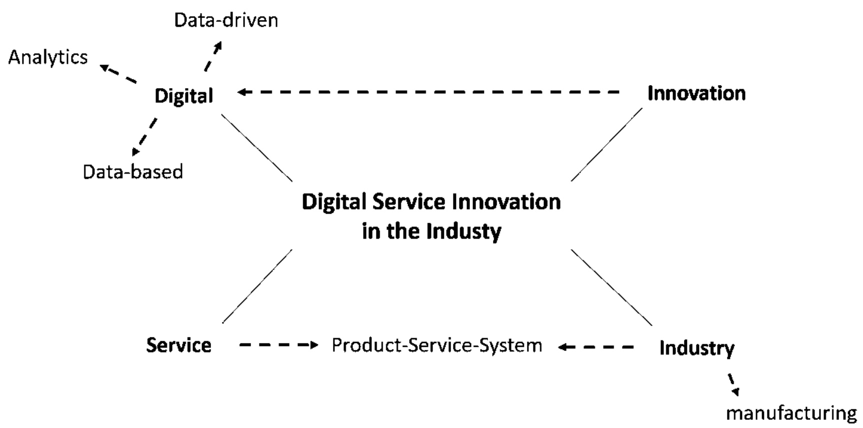

Figure 11. Overview of key terms in database search on digital service innovations in industry

After several iterations, we filtered out overlapping content and trimmed the topic to a manageable size. As a result, four areas can be identified in the field of digital service innovations in the industry: (1) digital technologies (‘Digital’), (2) ‘Service’, (3) ‘Innovation’, and (4) ‘Industry’. We conducted the literature review using a keyword search of terms from three of these topic areas.

We covered digital technologies in the first topic area using the terms ‘digital’, ‘data-based’, ‘data-driven’, and ‘analytics’. We have chosen these synonyms to address the different functions of digital technologies in more detail. Data-based services are generally built on the use of data and include services that are enabled or enhanced by data. Further, data-driven innovations represent stand-alone services through a high degree of autonomy or independence that transform the value proposition (Hunke et al. 2019). Since the analysis of data is a crucial feature of digital innovations, we included the term ‘analytics’. Analytics-based services characterize a particular form of digital services (Hunke et al. 2019). The search terms ‘service’ and ‘product-service-system’ cover the second subject. The term ‘product-service-system’ is included as a search term alongside the central term ‘service’ to emphasize the link to the manufacturing industry and make the search more efficient. Since, in many cases, the combination of digital technologies and services is already considered as an innovation (Hunke et al. 2019), the term of innovation is not included as a search term in order not to limit the results too much. This is indicated in the mind map by a dashed arrow from ‘Innovation’ to ‘Digital’. Finally, the last topic area covers the industry, which is restricted to manufacturing. The term ‘manufacturing’ is therefore included in all searches.

	OR			
AND	digital	data-based	data-driven	analytics
	service		product-service-system	
	manufacturing			

Table 12. Search term for the structured literature search

7.3.2 Identifying Relevant Literature

Third, as proposed by Brocke et al. (2009), we conducted a literature search across databases based on our key terms. In order to meet Webster and Watson's (2002) standards for a complete literature review, we searched in the databases ‘EBSCOhost’, ‘AIS electronic Library’ (AISeL), and ‘Science Direct’. We narrowed down the literature to results awarded with a rating of at least 'C' of the VHB-JOURQUAL3 (JQ3)[1] ranking of the German Association of Business Administration Professors. This list is also used in other studies to screen high-quality literature (e.g., Hund 2020; Schmidt et al. 2021) and to balance the literature review's comprehensiveness and quality. For all searches, we linked the three topics with an AND condition and the respective synonyms with an OR condition (see Table 12). In addition, we conducted two searches on the topic of digital servitization using the keywords 'digital servitization' and 'datatization' to comprehensively cover the topic. This results in a total of ten searches, which are listed in a table (see Table 13) split between the three databases with the respective total number of hits and the number of relevant results.

		Searches		EBSCO total	EBSCO JQ3	EBSCO relevant	AISeL total	AISeL JQ3	AISeL relevant	ScienceDirect total	ScienceDirect JQ3	ScienceDirect relevant	All
1	Manufacturing	*digital*	*service*	1222	79	22	41	25	21	250	50	26	
2	Manufacturing	*digital*	*PSS*	26	3	0	7	4	0	74	12	1	
3	Manufacturing	*data-based*	*service*	66	9	3	32	22	1	23	7	1	
4	Manufacturing	*data-based*	*PSS*	15	4	3	9	7	1	133	30	7	
5	Manufacturing	*data-driven*	*service*	122	21	5	9	7	3	101	26	2	
6	Manufacturing	*data-driven*	*PSS*	6	2	0	3	2	0	25	6	0	
7	Manufacturing	*analytics*	*service*	494	86	5	20	9	4	275	73	8	
8	Manufacturing	*analytics*	*PSS*	11	1	0	3	1	0	46	13	0	
9	Manufacturing	Datatization		0	0	0	12	10	9	0	0	0	
10	Manufacturing	Digital Servitization		44	11	4	5	3	1	60	40	15	
			total	2006			141			987			**3134**
			JQ3-Rating		216			90			257		**563**
			relevant			42			40			60	**142**
			min. C			37			40			60	137
			duplicates			21			0			0	21
			unique per DB			16			40			60	116
			not available			0			0			1	1
			available			16			40			59	115
			JQ3: C			9			18			13	40
			JQ3:A/B			7			22			46	**75**
			Backward search										**27**

Table 13. Search term combinations and database literature search results

In total, the literature search resulted in 3,134 articles, of which 563 were screened based on their JQ3 ratings using their title and abstract. We classified 137 articles of these as relevant based on the following criteria: (1) All topic areas (digital, innovation, services, and manufacturing) are recognizable in either the title or the abstract. (2) Articles that are not written in English are not included in the analysis. (3) If the focus of the articles is too one-sided on one subject area or geographic region, or (4) if the articles have not been published in the period from 2000 to August 2020, the literature is not considered relevant. After removing duplicates and unavailable publications, we retrieved a total of 75 articles with VHB rankings A+ to B,

[1] Find the VHB-JOURQUAL3 list under: https://www.vhbonline.org/vhb4you/vhb-jourqual/vhb-jourqual-3/gesamtliste

which we fully screened and reviewed to answer our research question. In addition, we found 27 relevant articles during the reverse search following Webster and Watson (2002).

7.4 Findings of the Quantitative Analysis

To get a first glimpse of the literature, Figure 12 shows the 75 articles with A+ to B Rating, which we identified in the database search according to the time of their publications. We can see that the number of articles deemed relevant to answer the research question has increased since 2016.

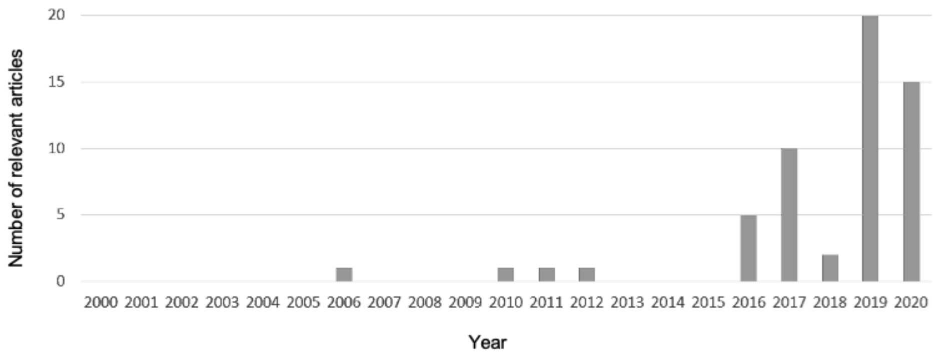

Figure 12. Time of publication of relevant articles from the database search

Overall, industrial companies have the opportunity to use the capabilities and functionality of digital technologies for product- or service-related innovations as well as for process-related optimizations (Bilgeri et al. 2019; Novales et al. 2019). It is important that digital services and digital technologies deliver added value for customers. In addition, the use of digital technologies brings advantages and opportunities for the manufacturer, from which customers can also benefit indirectly (Novales et al. 2019). Following the WSLC model (Alter 2013), we will next summarize our findings according to the four phases as follows: *Operation and Maintenance*, *Initiation*, *Development*, and *Implementation*.

7.4.1 WSLC – Operation and Maintenance

The data obtained from the operation process provides the basis for changes in the *operation and maintenance* phase. Information derived from this has a major influence on the changes, whether operation and maintenance are *continued*, *terminated*, or a new project is initiated in a structured way (*redesign* → *Initiation*). Decisions for the latter are, e.g., information about the use of the products and services that enables prioritization of product functions in respect of customer needs. As a result, it becomes transparent which product functions are essential and at which points the manufacturer can avoid over-engineering. The knowledge gained about usage behavior and malfunctions during operation enables the industrial company to further develop its products and services efficiently and adapt to actual operating conditions (Bilgeri et al. 2019; Novales et al. 2019; Porter and Heppelmann 2014). Among the less significant changes in implementing digital technologies in operations is adapting products to different regions with different languages and regulatory requirements realized through software components that can be varied much more cost-effectively than physical components (Porter and Heppelmann 2015).

The deployment of new digital user interfaces enables, among other things, remote control of the products and extends the modularity of the devices through customizable digital interfaces (Novales et al. 2019). Since smart services are based on smart products, industrial companies can still offer new service offerings through product innovation (Allmendinger and Lombreglia 2005). In addition, industrial companies can use product usage and performance data to optimize customer service and the after-sale process. These include offering maintenance services, procuring spare parts, and selling associated additional services and solutions. Moreover, the use of digital technologies can enable the performance of remote monitoring and diagnostics as well as fault identification through the determination of specific environmental conditions related to error messages (Bilgeri et al. 2019; Porter and Heppelmann 2014). This leads to a transformation of the formerly reactive after-sale process to offering preventive and proactive services and remote services (Porter and Heppelmann 2015), thus influencing the implementation phase of the WSLC model. Often, digital components of a smart product, much like a computer, can already be repaired via remote maintenance. These features help improve quality and prevent machine downtime for customers (Bilgeri et al. 2019; Porter and Heppelmann 2015). If problems cannot be solved remotely, experts will use detailed information provided by digital technologies to solve the problems on-site – at best before they occur. In that respect, Kammler et al. (2019) propose a system to transform sensor-based information into service staff actions. Here, smart service systems require the integration of environmental and process information, which in the future, the service provider will use to identify patterns by observing process flows automatically. Based on the information gained about the state of individual objects, the provider can trigger its service activities and thus contribute value in terms of avoiding unnecessary service operations. Thereby, service processes become less complex and take less time, enabling increased efficiency and performance (Kammler et al. 2019).

The new way of data-driven service delivery has the effect of shortening maintenance time, increasing the time between incidents, and improving the predictability of service activities by reducing unplanned repairs (Herterich et al. 2016c). For instance, continuous condition monitoring systems signal changes in condition and trigger short-term maintenance calls (Vössing 2019). In addition, the implementation of predictive maintenance activities leads to the early triggering of just-in-time maintenance and repair services and enables the replacement of regular maintenance schedules (Novales et al. 2019). After all, digital technologies take over the automatic evaluation of work orders for specific service activities, calculate their duration and determine the required skills of the professional who is performing the service. On the one hand, a data-driven planning process enables short-term workforce planning by prioritizing orders on an ongoing basis and making dynamic adjustments to plans in the event of deviations through an automated decision-making process (Vössing 2019). On the other hand, long-term staff planning is estimated by wear pattern models that capture the wear or fatigue of machines (Müller and Buliga 2019). Considered together, both types of workforce planning provide the basis for predictive decision-making when frequent updates to these are made (Vössing 2019). This also serves the purpose of detecting and preventing warranty issues (Porter and Heppelmann 2014).

7.4.2 WSLC – Initiation

The *initiation* phase of the WSLC model is about the identification of new projects to change the services in an articulated way. It is essential to select the proper requirements and initiatives for further innovation of the service system (Alter 2008). Potential triggers from the preceding operation and maintenance phase for a redesign of the services system are listed in the previous section, e.g., identification of faulty or over-engineered product functions; adjustment of product design and function (Bilgeri et al. 2019; Porter and Heppelmann 2014) by replacing physical parts with software-based parts (Porter and Heppelmann 2015). In the *initiation* phase, the new data sets and information available in the service system trigger a new set of opportunities in initiating innovation. For instance, while customer feedback or data from test products used to be the key to gaining information about how products operate, manufacturers can now do this through automated data collection. This allows the manufacturer to identify inefficiencies even in the absence of customer contact (Bilgeri et al. 2019). By identifying common product defects and usage patterns, manufacturers can improve the selection and prioritization of new requirements, thereby reducing defects in later phases of operations (Naik et al. 2020). In this context, Kühne and Böhmann (2019) present a scheme that industrial companies can use to establish a link between the data obtained and the value that can be derived from it to generate new ideas.

7.4.3 WSLC – Development

The goal of the *development* phase is to find the right resources for the implementation of changes in the service system. For technologies as resources, this means, among other things, that they must match the operational plans of the service system. Here, digital technologies can enable automated product validation in this phase, such as through virtual tests and simulation models. In addition to higher effectiveness, efficiency is also increased by accelerating the development process. As a result, development time can be shortened through early feedback and valuable information within an iterative innovation process. At the same time, this enables the timely launch of products and services on the market (Bilgeri et al. 2019).

An essential requirement of this phase is the consideration of the modularity of selected resources and a later modification of the products through software updates. First, digital components can be reused across different products, and software updates can change product functions during operation. Next, digital-enabled capabilities can be added to products and combined with complementary products. Finally, it is possible to build a network based on digital products (Novales et al. 2019).

Similar to the two previous phases, decisions in this phase become more data-driven. By collecting and analyzing prototype and/or product usage data, the process of product and service development can be optimized (Novales et al. 2019). At the same time, new competencies can also be extended to suppliers' systems to avoid quality problems and ensure uniform standards (Bilgeri et al. 2019). In this context, Frank et al. (2019a) present another industrial internet concept: The so-called smart supply chain, which allows for an increase in operational efficiency through the implementation of digital technologies. This concept establishes the link between internal activities in production and the external activities of suppliers through horizontal integration (Frank et al. 2019a).

7.4.4 WSLC – Implementation

Changes in the service system must be carried within the organization. Moreover, legacy systems often need to continue to be supported. The development and delivery of smart products are no longer based on mechanical engineering skills alone but will become an interdisciplinary task. The proportion of software engineers will be significantly increased in the development of smart products. In turn, digital technologies in smart products open new possibilities in product development. At the same time, offering customer-specific, individual products demands a high degree of adaptability and variability from the organization (Porter and Heppelmann 2015). Furthermore, digitized products favor the possibility of joint development (co-creation) of products and services with customers and external partners. After all, mutual data exchange can lead to an optimized, demand-driven innovation process (Novales et al. 2019).

The use of digital technologies is also changing the nature of production and manufacturing activities (Frank et al. 2019a), as the production of smart products involves new components, such as cloud-based software components. In other words, the industrial company must adapt its production to this new type of product composition. Smart products allow for extensive standardization of production, and the individualization of products only takes place late in the production process. In addition, the production process extends beyond the manufacturer's production site, e.g., when digital components are loaded and configured at the customer's site. In these cases, changes to the products can be adopted even at far advanced stages of production or even after completion. After all, by performing updates, the manufacturing process becomes a permanent process that extends over the entire product lifetime (Porter and Heppelmann 2015).

Smart products lead to a change in sales and marketing processes to maximize added value for customers (Porter and Heppelmann 2015). The sales process can be improved through targeted marketing based on product usage data (Novales et al. 2019). Product positioning, identification of different customer groups and customer types, and communication of the product's value proposition are, along with the proper pricing, critical success factors for an industrial company offering digital services and provide starting points for new sales opportunities. In addition, IoT data can help service providers with their data-driven market research. This involves combining existing market research with industry- and company-specific insights. Since individual customer needs are known through the analysis of the collected data, customers can be targeted with specific offers, which increases the efficiency of the sales process and the quality of communication (Bilgeri et al. 2019; Porter and Heppelmann 2014).

7.4.5 Field of Action According to the Elements of the Work System Framework

According to our findings, there are several new challenges and opportunities to consider when introducing digital service innovations in the context of digital servitization, which is illustrated in Figure 13 along with the elements of the work system framework and their field of action.

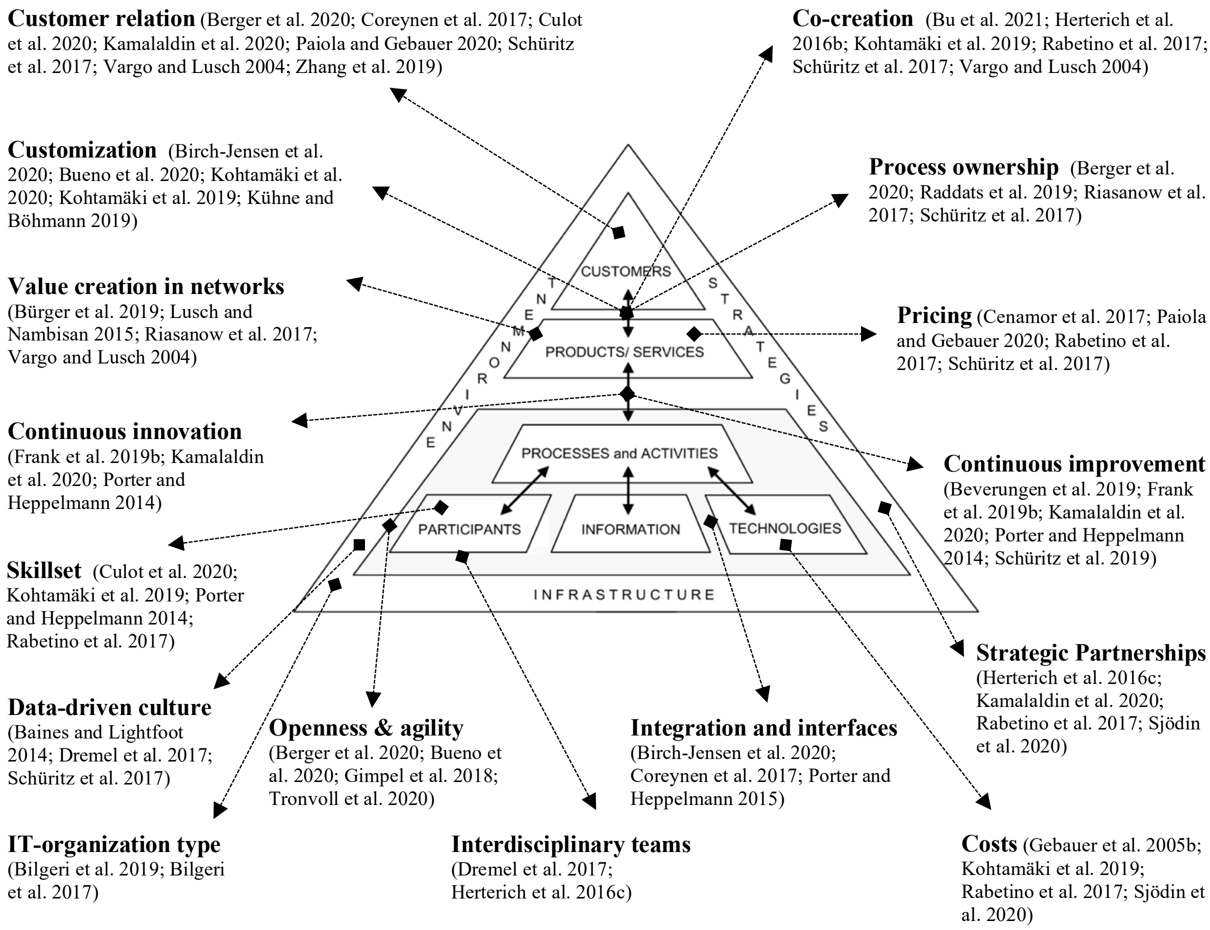

Figure 13. Field of action along with the elements of the work system framework (Alter 2013)

We can see that the *customer* is a core element of the service system and is intensively researched. Essential components of the customer relationship are trust, retention, and customer loyalty. In value creation at the customer's site, process responsibility is managed between customer and supplier, standardization and individualization are balanced, and value is jointly driven (co-creation). Regarding the *product/services*, a suitable payment model is further indicated, whereby the willingness to pay for services is a critical element in services exchange and represents an open challenge in the industry. It is also becoming increasingly important to consider products/services in their environment and value networks. Another focus is the adoption of continuous innovation and optimization processes in the alternation between products/services and *processes and activities*. The aim here is to act flexible and agile, to make optimized decisions, to act in a resource-efficient manner, and to take advantage of new value creation potential through new services.

Culture is another important field of action in the *environment* of the service system. Digital service innovations require a data-driven, open, and agile organizational culture for them to be successful. Simultaneously, this means that service system *participants* need new skills and must work in new organizational structures. On the one hand, interdisciplinarity and, on the other, the collaboration between IT and the business are emphasized (IT-organization type).

Next, the role of innovation units is also examined in this context. As the WSLC model has already shown, data and *information* are essential for digital service innovations. As shown, information flows into the processes and activities of the organization. In addition, the link with other elements is also emphasized in the literature. On the one hand, standardized platforms and components should be considered when selecting *technologies*. Initiatives in this area can quickly become expensive, which means that comprehensive reuse of the technologies will be better scaled and more economical. On the other hand, information management and integration are related to the organization's *strategies* (e.g., data strategy, partnerships).

7.5 Conclusion and Further Research

Our research examines the impact of digital technologies on service innovation in the manufacturing industry through the lens of service systems. Our results improve the understanding of the transition of service systems to a more service-oriented approach by structuring changes against the background of the work system life cycle model and the work system framework. We found out that the existing literature has mainly worked out the changes to the operation and maintenance phase, as well as intensively dealt with the customer and organizational challenges. At the same time, data plays a central role in all areas and phases of the service system. It becomes clear that the development of new intelligent services is affecting the entire service system. Many elements of the service system are becoming more linked and are accelerating through digital technologies. Through a service system perspective, it helps practitioners visualize the operational meaning of service transformation utilizing digital technologies and identifying related challenges.

In addition, our study highlights opportunities for further research. First, in the publications we reviewed, the technologies IoT, CC, and BDA are the main drivers for new digital services. This led to changes in the service system based on new data and information. Less of the focus was on concrete applications and technologies such as augmented reality or additive manufacturing, which offer opportunities for future research. Also, it would be of interest to measure how much share a digital technology takes in the service system compared to processes and activities performed by other participants and resources. Quantified data can help to further emphasize the importance and role of information systems, especially concerning the economics of new digital services. Finally, although research in the field has increased a lot in recent years, the initiation and development phases of the WSLC model still offer much potential for further research.

It is important to mention that this work is also subject to limitations. After using the initial literature to define the scope of this study and flesh out the research question, we used this as the basis for selecting keywords for our literature review. These keywords provided the basis for the subsequent literature search in the three selected databases, although it is possible that the keywords did not uncover all potentially relevant publications. In addition, the search was limited to three pre-determined databases. The selection of relevant literature was also limited to those articles with a JQ3 ranking of at least 'B' to obtain high-quality articles. Although the selection process of publications relevant to answering the research question was carried out using predefined criteria and as best as possible from an objective perspective, it is still subject to subjective judgment. Lastly, the embedding of our results in the WST is not without limitations. On the one hand, there are still few comparable applications in studies. On the other hand, it is noted in the literature that the theory as a whole is mainly based on the work of a single researcher and the theoretical positioning remains unclear (Niederman and March 2014). Nevertheless, we can show with our literature review that integrating the results into the WST helps represent, structure, and understand systems in industrial firms. Here we invite future studies to demonstrate the usefulness of the WST.

8 Paper F: The Case of Human-Machine Trading as Bilateral Organizational Learning

Title

The Case of Human-Machine Trading as Bilateral Organizational Learning

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Publication Outlet

Proceedings of the 42nd International Conference on Information Systems (ICIS 2021), Austin, USA

Abstract

In today's organizations, both humans and machine learning (ML) systems jointly form routines. Yet, we do not know much about the underlying reciprocal interplay between them, which complicates their effective coordination. Taking an organizational learning perspective, we study the dynamics of human learning and ML to understand how organizations can benefit from their respective idiosyncrasies when enabling bilateral learning. Drawing on a case of human traders and a reinforcement ML system trading productively at Allianz Global Investors, we apply human-machine pattern recognition on digital trace data to explore their (interconnected) dynamics. We find that bilateral learning can increase trading performance, which appears to result from an emerging virtuous cycle between humans and the ML system. Our explorative case study offers insights into how organizational learning depends on the coordination of both human learning and ML, which can help manage the collaboration between human and artificial intelligence within organizational routines.

Keywords

Machine Learning; Organizational Learning; Digital Trace; Human-AI Collaboration.

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[2] NOTE: Both Timos contributed equally to this paper | Shared co-first authorship

8.1 Introduction

In recent years, numerous breakthroughs in artificial intelligence (AI) have uncovered AI's potential to surpass human performance in various contexts (e.g., He et al. 2015; Vinyals et al. 2019). In the light of such breakthroughs, more and more organizations strive to use AI in their processes to improve their organizational performance (e.g., Bean 2019; Insights 2018). In doing so, today's organizations focus on how to use AI to automate (sub-)tasks within routines (e.g., Brynjolfsson and Mitchell 2017). To date, it is undeniable that the rise of such AI-enabled automation already transforms organizations' routines, especially when AI takes over tasks that were formerly performed by humans (e.g., Raisch and Krakowski 2021). To this end, existent discussions mainly deal with achievable cost savings and error reduction with AI-enabled automation (e.g., Kellogg et al. 2020), shifting humans to other 'higher-value' roles (e.g., Brynjolfsson and Mitchell 2017), or emerging social challenges such as ethical AI (e.g., Rhue 2019). Only recently, discussions began to stress the great importance of the reciprocal interplay between humans and intelligent machines for their coordination and its consequences within organizations (e.g., Leavitt et al. 2021; Murray et al. 2021; Rai et al. 2019b; Schuetz and Venkatesh 2020). While a few researchers have already begun to examine how human actions affect AI and vice versa and how organizations may coordinate this relationship, related research still remains in its infancy and emphasizes the need for further analyses (e.g., Grønsund and Aanestad 2020; Lyytinen et al. 2021; Seidel et al. 2019; Sturm et al. 2021). Surprisingly, one aspect has only received little attention although it is not only central to the technology behind modern AI but also to its relationship with humans and organizational routines: *learning*.

The technology that enables modern AI is machine learning (ML). AI systems based on ML—by us referred to as *ML systems*—use ML algorithms to derive patterns from data and then apply these patterns to new data in order to act (Mitchell 1997; Russell and Norvig 2016). By doing so, ML systems do not require us to manually solve and translate our solutions into code anymore but derive solutions on their own from given data (Samuel 1959). In other words, ML algorithms grant information systems (IS) the ability to learn autonomously to act intelligently (Brynjolfsson and Mitchell 2017). With their ability to learn, ML systems join the central process of *organizational learning* beside human learners (e.g., Ransbotham et al. 2020; Sturm et al. 2021). Organizational learning is the fundamental driver that controls how strongly an organization relies on and adapts established routines and how strongly it adopts new ones (March 1991). Organizational learning thus controls how an organization adapts itself to its environment and, by doing so, defines an organization's performance (e.g., Argote and Miron-

Spektor 2011). Organizational learning is based on a complex system of learners that interact with one another, which requires coordination (March 1991). Due to its high complexity, optimal coordination of organizational learning constitutes a difficult endeavor (e.g., Levitt and March 1988). Despite decades of research, however, literature has largely assumed the learner to be purely *human* (e.g., Argote et al. 2020). With ML being able to learn as well while differing significantly from human learning (as we will discuss), the rise of ML denies this assumption and requires us to fundamentally rethink organizational learning theory. Yet, we only know little about how ML systems actually affect organizational learning (Argote et al. 2020). As the result of organizational learning is more than only the sum of individual learning but also subsists of the individuals' interactions (March 1991), mutual learning that builds on humans' and ML systems' individual learning should not be neglected. Organizational learning thus constitutes a promising context for analyzing the bilateral relationship between humans and learning machines that collaborate within their organization (Sturm et al. 2021).

To help unravel the complex bilateral human-machine relationship in organizational learning, we conducted a case study at Allianz Global Investors, a global asset management firm that introduced an autonomous ML system for trading financial instruments next to its human traders. Trading constitutes a fruitful context to study organizational learning as learning lies at the heart of trading: organizations aim to learn about the complex causal structure of markets and related trading strategies in order to optimize their future investment endeavors. Moreover, such trading is executed in a purely digital world in which market states and trading actions are naturally tracked and are rich in information. By exploring digital trace data, we thus aim to answer the following research questions (RQs): *In the context of trading, (1) how does ML and human learning affect each other in organizational learning, and (2) how can organizations leverage their bilateral relationship to improve organizational performance?*

To answer the RQs, we rely on an abductive, pragmatist approach for human-machine pattern recognition to analyze the (interconnected) dynamics of the humans' and ML system's trading behavior. In doing so, we explore how idiosyncrasies of human learning and ML contribute differently to trading and how their synthesis affects the organization's trading performance. Our case study offers empirical insights about how organizational learning depends on the coordination of both human learning and ML, which can help organizations to craft effective human-AI collaboration designs and stimulate related research endeavors.

8.2 Theoretical Background

We first introduce organizational learning and ML along related work. Next, we compare idiosyncrasies of human learning and ML. We then combine both research streams to form our study's objective.

8.2.1 Organizational Learning

In their seminal work, Levitt and March view organizational learning "as learning by encoding inferences from history into routines that guide behavior" (Levitt and March 1988, p. 320). Individuals in organizations gather experiences based on their chosen actions and associated outcomes. Based on these experience-outcome pairs, they infer learnings (i.e., beliefs about the causal structure of reality) to guide future actions. Organizations store these learnings in their routines to make use of and further distribute the developed knowledge (e.g., Argote and Miron-Spektor 2011). By doing so, organizations form complex systems of interacting individuals who learn to make sense of the environment in which organizations act and to which they adapt to (Levitt and March 1988). The better organizations learn (i.e., the better they understand their environment to guide their actions), the better they can act and adapt to increase organizational performance (March 1991). Organizational learning marks therefore an essential process that organizations need to pursue continually in order to survive (e.g., Grant 1996; March 1991).

One of the most central and crucial concepts in organizational learning is that organizations need to balance explorative and exploitative learning (e.g., Gupta et al. 2006; March 1991). While explorative learning represents the search for new ideas with uncertain outcomes which shift away from an organization's current knowledge, exploitative learning refers to the use and incremental refinement of existing knowledge to obtain its immediate benefits (March 1991). Balancing both types of learning is important: If organizations overemphasize the short-term benefits they can gain by exploiting given knowledge, they can become trapped in a state of stagnation, ignoring new potentially useful directions. In contrast, if organizations neglect exploitation while extensively exploring new ideas, they will not survive in a competitive environment as they fail to refine and apply knowledge to develop specific competences (March 1991). Achieving this balance is, however, a difficult endeavor that has yielded decades of research studying how to overcome the various flaws of organizational learning to optimize organizational performance (e.g., Argote and Miron-Spektor 2011; Levitt and March 1988). Especially the so-called 'learning myopia', which is the tendency to favor exploitation over exploration, represents a major and versatile issue: Due to their distant and uncertain benefits, learners tend to avoid experimenting with new, yet unproven ideas and prefer to rely on established ideas that proved to be successful in the past (e.g., Levinthal and March 1993). Research has uncovered numerous factors known to either mitigate (e.g., high team diversity; March 1991) or intensify (e.g., incentives that reward successes and penalize failures; March 2010) a learner's myopia, further complicating the crucial balance of explorative and exploitative activities (Levinthal and March 1993). Despite decades of research on organizational learning (several fantastic overviews exist, e.g., Argote et al. 2020; Argote and Miron-Spektor 2011; Huber 1991), research on the impact of IS on organizational learning still remains in its infancy (Argote et al. 2020; Argote and Miron-Spektor 2011).

8.2.2 Machine Learning

One of the most widely accepted concepts of AI is the one of the 'intelligent agents', which is "anything that can be viewed as perceiving its environment through sensors and acting upon that environment" (Russell and Norvig 2016, p. 34). Here, intelligent behavior is defined as an agent function selecting actions based on context information. While various approaches exist to realize this function (e.g., specified rules or statistics; Russell and Norvig 2016), the one that largely underlies modern AI is ML; that is, learning with algorithms from data-based experience to infer models that capture derived data patterns. ML systems then apply these models to new data to guide their behavior (Mitchell 1997). ML systems are developed in an iterative process, in which humans select and prepare data, select and parametrize algorithms, and assess implemented alternatives to craft the best-performing ML system. By doing so, humans define the conditions under which the ML system learns to develop its own understanding of a problem solution (e.g., Amershi et al. 2019; Sturm et al. 2021). So far, IS research on ML has mainly focused on topics like adoption (e.g., Pumplun et al. 2019), automation of (sub-)tasks (e.g., Brynjolfsson and Mitchell 2017), or emerging social challenges like ethical or transparent AI (e.g., Rhue 2019). Only recently, scholars began to stress the great importance of the reciprocal interplay between humans and AI (e.g., Leavitt et al. 2021; Murray et al. 2021; Rai et al. 2019b; Schuetz and Venkatesh 2020). While a handful of researchers have begun to examine how humans affect AI and vice versa and how organizations may coordinate this relationship, related research remains scarce and emphasizes the need for further analyses (e.g., Grønsund and Aanestad 2020; Kellogg et al. 2020; Lindebaum et al. 2020; Lyytinen et al. 2021; Murray et al. 2021; Seidel et al. 2019; Sturm et al. 2021). Especially, work on the impact of ML on organizational learning is still limited and mainly provide only basic insights into potential setups and hypothetical consequences (e.g., Ransbotham et al. (2020) propose possible learning modes with varying human-machine autonomy, Balasubramanian et al. (2021) theorize and simulate potential consequences of ML). In doing so, the scholars primarily put forth one foundational, ongoing discussion: does ML amplify (e.g., Balasubramanian et al. 2021) or alleviate (e.g., Sturm et al. 2021) learning myopia, shifting organizations towards exploitation or exploration?

8.2.3 Strengths and Weaknesses of Human and Machine Learning

Organizational learning is generally far from perfect (e.g., Argote et al. 2020; March 2010). Reality itself complicates learning as its complexity renders its underlying causal structure difficult to discern: numerous variables interact and can change continuously, including actual random variations (March 2010). In an ideal world, a learner thus gathers extensive experiences (i.e., samples of reality) to construct a complete picture of reality and flawlessly sees through complex multivariate relations while ignoring random noise to infer accurate learnings about reality (March 2010). To assume such ideal circumstances is, however, rather lunatic than appropriate as learning is constrained by humans' limited experiences and learning capabilities (e.g., Levinthal and March 1993; Simon 1972). As ML systems differ significantly in their way of learning, often even viewed as a panacea to overcome human limits (e.g., Lindebaum et al. 2020), we now compare major idiosyncrasies of humans and ML systems. To this end, we focus the comparison on key elements of learning that are essentially shaped by a learner's capabilities (e.g., Argote et al. 2020; Levinthal and March 1993; Levitt and March 1988): (1) *learning base,* (2) *inference*, and (3) *learned model*.

a. Learning Base (Human vs. Purely Data-based Experience). A human observes reality through her/his unique sample of experience (Levitt and March 1988). This sample is gathered by the human choosing and performing actions from among action alternatives (e.g., making a specific decision) and observing associated action outcomes (e.g., the perceived success or failure of a performed decision) over the human's lifetime (Argote and Miron-Spektor 2011). To this end, human experience is far from being an optimal base for learning: our experiences usually comprise very small, incomplete samples of reality that are often skewed and erroneous (March 2010). That is, because a single one of us cannot observe the overwhelming breadth of reality in its entirety but is limited to her/his specific interests, social and organizational context, unique sequence of decisions, repeatability of actions and contexts, measurement errors and misinterpretations, cognitive memory, and attention—just to name a few factors (e.g., Argote et al. 2020; March 1991). A more comprehensive and correct picture of reality is therefore likely spread across multiple humans' diverse experiences (March 2010). Humans thus usually take part in a time-consuming social learning process to jointly share, evaluate, and combine individual experiences to some extent (e.g., March 1991). Yet, not everything is bad about human experience as a basis for learning. Human experience is not limited to specific media or domains per se. Humans can draw upon a rich amount of diverse integrable sources (e.g., knowledge repositories or human senses) to form their experiences and can transfer learnings and experiences between domains and contexts (e.g., Argote et al. 2020). Moreover, humans are able to contextualize learnings and craft hypothetical samples (i.e., thinking about 'what-if' scenarios), allowing them to enrich their small samples of reality (March et al. 1991).

In contrast, ML systems purely learn from data (e.g., Brynjolfsson and Mitchell 2017; Mitchell 1997). Indeed, organizations' data is also often skewed, erroneous, and incomplete, and is therefore often also far from being a perfect learning base. Yet, while organizations can only partly control and improve individuals' collected experiences used for learning (e.g., Argote and Miron-Spektor 2011), ML systems' data is usually actively assessed, enlarged, and cleansed, partly mitigating the issues related to the less controllable human experiences (e.g., Amershi et al. 2019; Domingos 2012). As an ML system can store and process large amounts of data, it can learn from a more comprehensive and diverse sample of reality, often covering multiple individuals' experiences (e.g., Brynjolfsson and Mitchell 2017; Jordan and Mitchell 2015). ML systems can therefore grant organizations the ability to craft and learn from larger and actively cleaned samples of reality. Yet, this can only be true for experiences described by ML systems' narrow frame (i.e., predefined goals and provided data; Salovaara et al. 2019). While ML systems' data-driven learning allows them to analyze larger samples of experiences, they are at the same time blinded by it: ML systems neglect any information outside their data frame, potentially overemphasizing aspects captured by data while ignoring aspects that are actually relevant but non-capturable with data—ML systems are unable to look outside the box (Domingos 2012; Salovaara et al. 2019). ML systems' learning can therefore even act restricting as many learnings must be contextualized and critically reflected before applying them naively (e.g., Raisch and Krakowski 2021). Moreover, ML systems usually require large amounts of data to learn reliably (Brynjolfsson and Mitchell 2017; Salovaara et al. 2019). If only small data samples are available, no learnings can be derived or the ones available may rather confuse than benefit others who learn from resulting ML models (e.g., Balasubramanian et al. 2021).

b. Inference (Bounded vs. Formal Rationality). In addition to human experience being a non-ideal basis for learning, humans themselves are no perfect learners either that always flawlessly derive the causal structure from experience (e.g., Levinthal and March 1993; March 2010). That is, as famously coined by Simon, because humans can only learn within their bounded rationality: "boundedly rational agents experience limits in formulating and solving complex problems and in processing (receiving, storing, retrieving, transmitting) information" (Williamson 1981, p. 553, quoting Simon). Humans simply struggle to untangle the complex relations of reality's numerous variables. Overwhelmed by reality's complexity, humans thus fall back on learning simplified heuristics to describe reality's causal structure instead of using complete optimization methods to derive an optimal representation of reality (March 2010). Humans are also no rapid learners. Humans are slow in processing large amounts of information and take part in the slow social learning process to enrich their own learnings with the ones of others (e.g., Levinthal and March 1993; March 1981). Human knowledge creation certainly takes its time, which further impedes the creation of sound learnings if time is limited (March 2010). Moreover, bounded rationality creates room for humans' irrational 'foolish' behavior (March 2006). While acting foolish (i.e., not doing the seemingly 'right' things; acting imprudent or playful) is largely detrimental to organizations as it mostly yields costly failures (March 2006), a small amount of foolishness can yet benefit organizational learning: Foolishness acts as driver for (unintended) exploration. Acting foolishly implies disregarding established beliefs about how things should be done, which often leads to trying out new (sometimes better) ways that would otherwise be overlooked, diversifying gathered experiences (March 2006, 2010).

In contrast, rationality is imperative to ML systems: ML systems are deliberately implemented as rational agents with the explicit goal to always act (and learn) rationally (Russell and Norvig 2016). Due to their high information processing capabilities and use of formal learning mechanisms, today's ML systems are even viewed as "supercarriers of formal rationality" (Lindebaum et al. 2020, p. 248), yielding hopes that organizations have finally crafted the perfect learners they have always hoped for (Lindebaum et al. 2020; Murray et al. 2021). As ML systems also rely on (indeed more profound) heuristics, they are, however, no perfect learners either—but indeed less bounded in their rationality: ML systems can analyze larger samples of experience and identify more complex relations between greater numbers of variables to derive more accurate heuristics than humans (e.g., Lindebaum et al. 2020; Raisch and Krakowski 2021). ML systems are also very efficient learners as they can process large amounts of data very quickly and can thus make new knowledge rapidly available as soon as new data exists (e.g., Kellogg et al. 2020; Lindebaum et al. 2020). Yet, having such increased rationality, ML systems may also alleviate foolishness. While this can be beneficial, ML systems also risk eliminating foolishness as an important mechanism to occasionally explore unorthodox ideas, which drive innovation (e.g., Balasubramanian et al. 2021).

c. Learned Model (Broad vs. Narrow). Humans learn mental models of reality (i.e., an individual's understanding of the world; Levitt and March 1988). Such models generally cross multiple domains and contexts (e.g., Argote et al. 2020). For instance, a single human can learn a model on how to play an instrument, speak a language, and diagnose diseases. Humans can use their models to transfer learnings from one domain or context to another, which enables them to assess whether existing learnings likely fit novel or changed contexts (e.g., Raisch and Krakowski 2021). In contrast to artificial general intelligence that aims to resemble the general focus of human intelligence, today's ML systems only enable narrow AI (e.g., Brynjolfsson and Mitchell 2017; Sturm et al. 2021): ML models are highly contextual models that purely focus on a narrow aspect of reality. While ML systems can adapt autonomously to changing contexts if the underlying concept does not change fundamentally, disruptive context changes or reduced information (e.g., through concept drifts, broken sensors) may confuse ML, leading to obsolete ML models that must be reevaluated and retrained by human experts that can look beyond its narrow frame (e.g., Lindebaum et al. 2020; Raisch and Krakowski 2021). In other words, due to their high contextuality, ML models thus tend to be less robust to contextual changes compared to humans' mental models.

8.2.4 The Need to Revisit Learning During the Rise of Machine Learning

Organizations already use ML systems next to their human employees to autonomously shape, perform, and collaborate in organizational routines (e.g., Brynjolfsson and Mitchell 2017). Yet, it remains unclear how humans and ML systems affect each other and how they should be coordinated as a whole. This is important: if done wrong, organizations may jeopardize organizational performance—and in the worst case their long-term survival if ML obstructs essential organizational processes (e.g., Raisch and Krakowski 2021; Sturm et al. 2021) by, e.g., exacerbating learning myopia (Balasubramanian et al. 2021) or spreading false beliefs (Sturm et al. 2021). Only recently, management and IS scholars recognized the great relevance of managing the reciprocal interplay between humans and intelligent machines in organizations (e.g., Rai et al. 2019; Schuetz and Venkatesh 2020). However, *learning*, although being a key aspect that blends human and ML systems' behavior, remains widely overlooked. This is surprising as focusing on learning allows to draw the discussions on human-machine collaboration back to its central driver and ML systems' specificity. Despite decades of research on organizational learning (e.g., Argote et al. 2020), the literature can only partly inform related studies as it has essentially assumed the learners to be purely *human*. Indeed, a few scholars already started to study ML's impact on organizational learning, but have still only scratched the surface and call for further research (i.e., Afiouni-Monla 2019; Argote et al. 2020; Balasubramanian et al. 2021; Lyytinen et al. 2021; Ransbotham et al. 2020; Seidel et al. 2019; Sturm et al. 2021). These studies are mainly theoretical work (exceptions: Ransbotham et al. 2020; Seidel et al. 2019), missing empirical insights and strongly suggest investigating human-machine learning empirically to enrich ongoing discussions. Although literature on ML in organizational learning is very limited, students of this topic can draw on widely established computer science and organizational learning literature to characterize human learning and ML (see previous sections). By doing so, focusing on learning allows us to ground analyses on the micro level (i.e., how human learning and ML function and differ) to contribute novel theory on the macro level (i.e., theorize human-machine dynamics). To this end, to provide empirical evidence, we now use the above-discussed characteristics of human learning and ML as a theoretical basis to explore 'macro-level' dynamics between humans and an ML system by studying a real-life case of human-machine trading.

8.3 Research Design

Below, we first introduce our trading case as a suitable empirical context to analyze organizational learning. Then, we outline our research approach and provide an overview of the collected data and its analysis.

8.3.1 Empirical Context

In our study, we examine the case of human-machine trading at Allianz Global Investors (AGI), a global asset management firm with over 500 billion euros in assets under management in 2021 and more than two thousand employees worldwide. AGI's investment routine follows two essential steps: (1) a portfolio manager requests an order (i.e., to buy a set of specific securities), and then (2) a trader executes this order on a best-efforts basis. Every month, AGI's traders execute transactions worth billions of euros. In our case study, we focus on the second part of AGI's process; that is, the actual execution of a given order. More precisely, we focus on the trading of futures contracts.[3] To this end, effective trading is an adaptive process that requires a trader to develop an understanding (i.e., learn a model) of the market environment and associated trading strategies to react purposefully. This is challenging as trading takes place in

[3] Futures are financial derivatives for a transaction of an asset at a predetermined price and date.

an extremely noisy, complex, and turbulent world: Financial markets change continuously and many factors affect the markets' development, rendering market comprehension and strategy development a very challenging endeavor. To be effective, today's traders choose from a large set of *trading algorithms*[4] that reflect execution sequences predefined by external brokers. Moreover, trading takes place in a world that allows to clearly monitor and evaluate trading behavior with every trading action and related market state being captured in data. Based on an industry-standard benchmark, each trading decision is evaluated with an associated (positive or negative) trading performance. The case of AGI's trading therefore represents a well-suited context to explore organizational learning empirically: First, learning lies at the heart of trading as its success depends on thoughtful trading decisions. Second, as the whole trading process is conducted digitally, drawing on this case enables us to observe the traders' experiences and learned propensities over time within naturally collected digital trace data—no matter whether the trader is human or an ML system.

8.3.2 Research Approach and Collected Data

Methodology. We conducted a descriptive case study (Yin 2011) based on big data analyses of digital trace data. Digital trace data captures individuals' actions within organizational routines, thus allowing to explore actual individual behavior within specific empirical contexts over time (e.g., Lindberg 2020; Pentland et al. 2020). We followed Lindberg's (2020) pragmatist approach for analyzing digital traces to demonstrate how patterns emerge from the idiosyncrasies of agents' actions in a particular empirical context (e.g., Lindberg 2020; Venturini and Latour 2010). The pragmatist approach emphasizes that actions can only be understood with regard to their specific context and associated meanings behind the different actions (Burks 1946; Lindberg 2020). Although pragmatists stress the importance of causation, pragmatism is less concerned with deriving universal patterns, but focuses on portraying contextually efficacious practices (Farjoun et al. 2015; Lindberg 2020). In its essence, pragmatism aims to evaluate an action's meaning in terms of its consequences, as Lindberg (2020, p. 93) puts it nicely: "It is hard to observe internal emotional or cognitive states, but it is possible to clearly observe actions and the consequences that such actions engender. Thus, when trying to understand how actors think about and interpret their worlds, it is necessary to also look at their actions and the consequences of those actions. [...] [T]he pragmatist approach posits that understanding causality is central to understanding meaning, since the meaning of

[4] Not to be confused with ML algorithms, trading algorithms are manually programmed buying/selling rules used to automatically manage the price, size, and timing of trades, thus executing a predefined trading strategy chosen by a trader (Kissell 2013).

an action (or utterance, i.e., a speech act) largely resides in its consequences". Considering this perspective, Lindberg (2020) proposed a method grounded in human-machine pattern recognition. Using abduction, the method does not start with the a priori formulation of hypotheses, but with the discovery of patterns from digital trace data: First, based on human or machine pattern recognition, inductive generalizations are derived from data. In our case, we rely on machine pattern recognition (i.e., computationally derived patterns, e.g., descriptive statistics and correlations, or other regularities, e.g., action categorizations; Lindberg 2020). The inductive generalizations function as 'working hypotheses' that are then justified using human or machine pattern recognition to explain inductive observations. In our case, we rely on human pattern recognition to explain identified patterns and reflect on our findings using extant literature and qualitative insights. Resulting inferences are "viewed as 'reasonable inferences' tempered by theoretical experience and intimacy with the data under scrutiny" (Lindberg 2020, p. 94) which do not have to be inductively or deductively true but presumptively follow from the analysis. By doing so, related studies embody the capacity of science to make new discoveries by contributing fruitful evidence and innovative ideas to inspire and create momentum for further research endeavors and discussions (Dougherty 2016; Lindberg 2020).

Data. We accompanied AGI's journey towards its adoption of a productive, autonomously trading ML system since the initial idea in January 2019. From its first rollout in mid-2020 until the end of November 2020, the ML system's initial knowledge base was formed and tested. We then collected data on its official productive use from December 01, 2020, to April 16, 2021. During this period, AGI enabled bilateral human-machine learning beginning February 19, 2021. As one of the authors was employed as a trader for the whole duration by AGI and was actively involved in the ML system's implementation, we were able to continuously gather first-hand insights into the adoption process, talk directly to the traders, receive access to internal documents, and attend internal meetings. We had full access to over 50,000 logged order events (i.e., data points capturing assignments, order routing, executions) with over 200 data fields per log entry. These logs enabled us to detailly review each step for every order from the initial request until completion for both the human traders and ML system. To study the digital traces, we focused our analyses especially on the execution price, benchmark price, chosen trading algorithms, and information about the given market state per trade. As can be seen in Figure 14, the captured traces include several orders (N) traded by either human traders (D_0, D_1) or the ML system (D_2, D_3) before (D_0, D_3) or after (D_1, D_2) the enabled ML system's advice. Moreover, to better understand the portfolio of over 190 trading algorithms, we had the chance to review algorithm manuals and talk to algorithm providers personally. We further had access to 52 meeting notes from AGI's weekly team meetings and 45 meeting notes from AGI's algorithmic trading reviews with the providers. We also received live demonstrations of the trading workflow, software, and ML system, and were able to talk to the traders directly about abnormalities that we identified in the data to gather further context information. After the observation period, we provided an anonymous online survey with open-ended questions in which the traders further reflected on their work with the ML system.

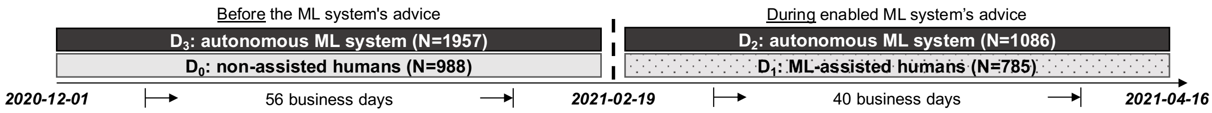

Figure 14. Collected digital trace data

Analysis: We ensured research rigor by strictly following Lindberg's (2020) seven guidelines for crafting mutable digital traces and conducting abductive analysis; that is, we enriched our continuously sampled quantitative digital trace data captured by the trading system with additionally gathered qualitative data, iteratively solved puzzles that emerged from derived data patterns, searched for explanations for surprises, and investigated identified patterns' correlation and causation. Moreover, we ensured to satisfy Lindberg's (2020) principles for evaluating the process (i.e., developing theory) and product (i.e., the developed theory) of abductive inquiry to assure our findings' quality: First, to ensure a high-quality research *process*, the research problem, data, and analytical techniques must be well integrated. As highlighted before, we identified the trading context as a suitable context for analyzing the conundrum of (coupled) human learning and ML as learning lies at the heart of trading. Trading's digital nature allows us to track each actor's decisions, enabling us to collect quantitative data capturing individual trading decisions and context information that we further contextualized with qualitative data (e.g., from attending meetings and interviewing traders) to enable a somewhat 360-degree view on AGI's trading process. We further ensured that the data pertains to the same individuals performing the same activities within the same organizational structures over time. Lastly, we also ensured the rigor of our analyses by enabling iterative cross-validation through continually exploring, confirming, and explaining patterns derived from quantitative data using machine pattern recognition in view of qualitative patterns deduced through human pattern recognition and vice versa. Second, to craft a high-quality research *product* with this method means to show "a process (consequences) that interacts with its environment (context), while at the same time also exhibiting the iterative dynamic between structure and agency (constitution)" (Lindberg 2020, p. 103). We ensured this integration by analyzing the evolving (interrelated) dynamics of human traders and a trading ML system (i.e., constitution) in relation to varying market states (i.e., context) in terms of in- or decreasing trading performance (i.e., consequences) at all times. This allows us to assure that we situate identified practices and causal mechanisms within particular contexts to enable the identification of causal consequences of social structures. To further evaluate our results, we also judged derived findings against existent theory.

8.4 The Case of Human & Machine Trading as Organizational Learning

We first show how human-machine trading translates to organizational learning. Drawing on these insights, we then analyze how human, machine, and human-machine learning affects AGI's trading performance.

8.4.1 Human Trading, ML-based Trading, and Bilateral Human-Machine Trading

Throughout the course of our study, AGI traversed three different phases with each phase representing a unique learning scenario: (a) purely human trading, (b) autonomous ML-based trading, and (c) bilateral human-machine trading. Figure 15 illustrates a conceptualization of the human learning, ML, and their interconnections that can be observed in the three trading modes as discussed below.

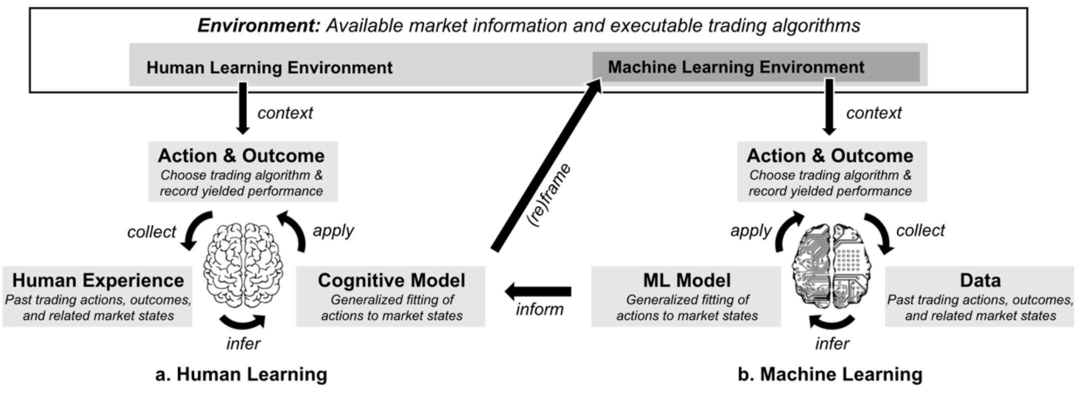

Figure 15. Conceptualized bilateral human-machine learning (in the trading case)

Illustrated in Figure 15a and Figure 15b respectively, both the human and ML system's learning cycle at AGI follows the same essential logic: A learner's *action* involves comprehending the current market state to choose the seemingly best fitting trading algorithm from a set of executable algorithms. Each trading algorithm is externally defined and provided by external brokers. The learner then indicates her/his/its choice in AGI's execution management system that applies the selected algorithm as a trading strategy to trade the given order. Hence, the action that is performed by a learner is the decision about a trading algorithm to fit the current market situation. Each trade yields some trading performance as an action *outcome*, defined as the margin between the trade's execution price and AGI's performance benchmark.[5] The higher a trade's performance, the more successful a trade is regarded. Through executing trades, a learner samples action-outcome pairs and contextualizes these with gathered information about the faced market states. This sample represents a learner's *experience*. The learner then tries to derive generalizable patterns from this experience by inferring heuristics about the success and failure of each trading algorithm within specific market states. Based on these heuristics, the learner adapts her/his/its *model* that the learner uses to guide future trading actions in the quest to optimize trading performance. Building on this first-order individual learning cycle, humans and the ML system can form a second-order mutual learning cycle: Human traders use their experiences and models to *frame* the ML environment by defining actions, context variables, and objectives that they consider relevant for trading. The ML system then acts and learns within this framed environment and *informs* traders about its experiences and inferred model. If done right, this can turn into a virtuous cycle: The better humans understand trading, the better they can frame the ML environment to improve its learnings. In turn, the better the ML becomes, the better the system can inform human traders to improve their understanding of trading. If done wrong, however, this may also turn into a vicious cycle, inhibiting individual and mutual organizational learning processes. While the humans and the ML system follow these learning cycles, we can observe the following differences in their (mutual) learning behavior.

(1.) Human Trading. For decades, AGI relied purely on human learning to guide its trading endeavors. Each of AGI's human traders develops her/his own unique propensities to act following the explained learning cycle (Figure 15a). Due to the discussed limits of human learning, human trading is far from being perfect: A trader's experience is limited to her/his unique course of trading; that is, no one trader can sample all trading algorithms across all imaginable market states but can only draw from her/his past trading choices, working time, and market developments during her/his career. Moreover, the traders can only perceive these experiences bounded by the context information they can gather. To comprehend the current market state, AGI's traders primarily rely on up-to-date data from financial data providers (e.g.,

[5] The benchmark ('arrival price') is the market price at the time that the order starts working (i.e., arrives at the market). The benchmark gets adjusted if the order has a high impact on the market or the market moves shortly after the order started working. In those cases, the benchmark price is an average price over a time period instead of a single point in time. The benchmark is normalized by the value of the smallest price increment in EUR to reflect the trading standard unit 'value per traded lot'.

Bloomberg) and market commentary and reports from Brokers that they mainly consume through visual analysis (e.g., charts showing insights about market developments). To enrich these insights, the traders also use information from various available media (e.g., financial news portals, Twitter) to set the observed trends into a broader context of potential impact factors (e.g., tweets with political relevance). Yet, they can only inform themselves within a limited time span as they must rapidly react to the ever-changing market to not miss any opportunities. To this end, a single trader's experience is far from sketching the full picture of current market states. Even though traders can view their historic performance in reports, the hundreds of executions performed every day paired with the extensive number of factors affecting market developments complicate human traders to generalize accurate heuristics to form reliable trading strategies.

(2.) Autonomous ML-based Trading. In addition to its human trading, AGI built an ML system for its trading executions. The ML system is implemented as a reinforcement learning agent that learns and trades autonomously without any active human involvement, mimicking the human trading process. Following reinforcement learning modalities, the ML system collects its own purely data-based trading experience by interacting with its environment (i.e., choosing trading algorithms within current market states). The ML system then uses the data-based experiences to infer heuristics about trading algorithms' success per market state which it uses to guide future actions (see also Figure 15b). Thereby, we refer to the *sample density* as the number of samples used by the ML system to learn about a specific state-action pair. In particular, AGI's learning agent is implemented as a Q-learner that continually learns a Q-table to compute heuristics about pairs of trading algorithms and market states (Watkins and Dayan 1992). Using Q-learning, trading is framed as a multiarmed bandit learning problem (Auer et al. 2002). Although the ML system acts and learns autonomously, its learning depends on human learning: To enlarge its own gathered experience, the ML system includes data of the humans' trades. AGI further relies on its human traders' expertise to frame the ML environment, including the executable actions, reward function, and representation of market states. The traders preselected 22 trading algorithms as the ML system's executable actions based on an analysis of algorithm providers' reliability, historical execution performance, completion mechanics, personal preferences, and experiences. By doing so, the traders aim to exclude trading algorithms that appear generally unlikely to be successful and also disable an algorithm's use for specific market states when they agree on an algorithm being unlikely successful in these. With this framing of actions, the traders aim to reduce the necessity for the ML system to explore algorithm-state pairs that are very likely to produce low trading performance. The traders also defined the above-explained trading performance as the ML system's reward function to align its optimization objective with their own. Lastly, the traders also frame how the ML system perceives the current market state. In its current version, the traders framed market states along four continuous variables which describe the market state during a short time period before an order arrives at the trading desk: *impact_measure*, *mean_spread*, *std_deviation,* and *trade_frequency*. The *impact_measure* indicates the impact of the order relative to the market liquidity. The higher its value, the stronger a trade generally impacts market development. *Mean_spread* is the average distance between the bid and offer price. The higher the distance, the higher the leeway for trading becomes since each level between bid and offer can be used for trading and quoting. The *std_deviation* is the standard deviation of bid and offer prices, where a higher deviation indicates greater volatility in quoted prices. *Trade_frequency* is the average number of trades per minute in the market, reflecting how frequently other market participants trade. As the impact of others' trades can be observed, a higher *trade_frequency* facilitates to comprehend and hide the potential impact of own trades. As perceived by human traders, a security is more difficult to trade with increasing value of the variables (for *trade_frequency,* the opposite applies). Besides these variables, the ML system cannot perceive any other information about the market and therefore only focuses on these market characteristics, disregarding any other insights. At the time of our study, the ML system learned from 5493 self-executed and a thousand human trades. AGI uses the ML system productively to trade an average amount of 10.2 billion EUR in notional per month.

(3.) Bilateral Human-Machine Trading. In the initial ML-based trading setup (as described above), the human trader's learning outcomes already affect the ML system as human expertise is used to frame the ML. To allow human traders to also learn from the ML system and thus to enable bilateral learning, AGI enabled its ML system to advise human traders: as soon as a human trader assigns a new order, the ML system applies its model to the human's order without executing the order. The results of the applied ML model are then visualized for the human trader in a pop-up window. Figure 16a shows an exemplary visualization of the ML system's advice. Executable trading algorithms (anonymized as 'trade_algo_x' for this publication) are ordered along the X-axis based on their performance and a bubble's size represents the respective sample density. The Y-axis represents the algorithms' average expected performance with regards to the current market state. Next to the chart, the market state is described in a simplified form[6] to share the ML system's perception of the current

[6] The ML system's four continuous market variables are converted to simplified nominal values (i.e., *low*, *low-med*, *med-high*, *high*).

market state. Human traders can also reopen all past advice from a centralized intranet website to revisit the ML system's advice without having to face a currently assigned order. To balance the trading allocation between the human and ML system, AGI now lets the ML system randomly skip one-third of the trades that it would have usually traded. This allows us to investigate bilateral learning between machine and human on comparable datasets.

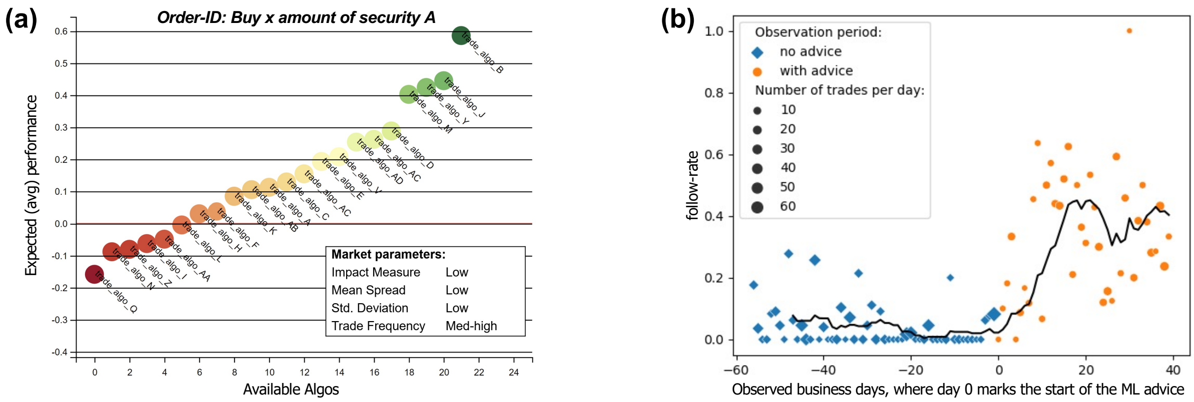

Figure 16. (a) Exemplary trading advice of the ML system and (b) daily follow-rate before and after enabled ML system's advice

8.4.2 The Impact of Human and Machine Learning on Trading Performance

To understand how bilateral learning between AGI's human traders and ML system affects trading performance, we now explore the behavior of AGI's human traders when receiving trading advice from the ML system as additional guidance for each trade they execute.

Advice Consideration. To understand whether AGI's human traders actually considered the ML system's trading advice, we compare the human trading decisions before and after enabled advice. We examine the *follow-rate* (i.e., percentage of trades where human decisions equal ML system's advice) to analyze whether the humans' and ML system's behavior became more alike after enabling the advice (we let the ML system give us post-hoc advice for all human trades prior to its enablement). We can cluster the data on the follow-rate into two categories: trading days prior to (56 days) and after (40 days) the enabled ML system's advice. Figure 16b shows the daily human follow-rate and a 10-business day moving average of the follow-rate to highlight the observable trend. The higher the follow-rate, the more the human traders took the ML system's advice on a given day. As implied by the point cloud in the upper right, human trading behavior tends to stronger align with the ML system's behavior after enabling its advice.

On average, human trading equaled the ML system's advice in 5.3% of trades prior to and in 34.0% after the enabled advice.[7]

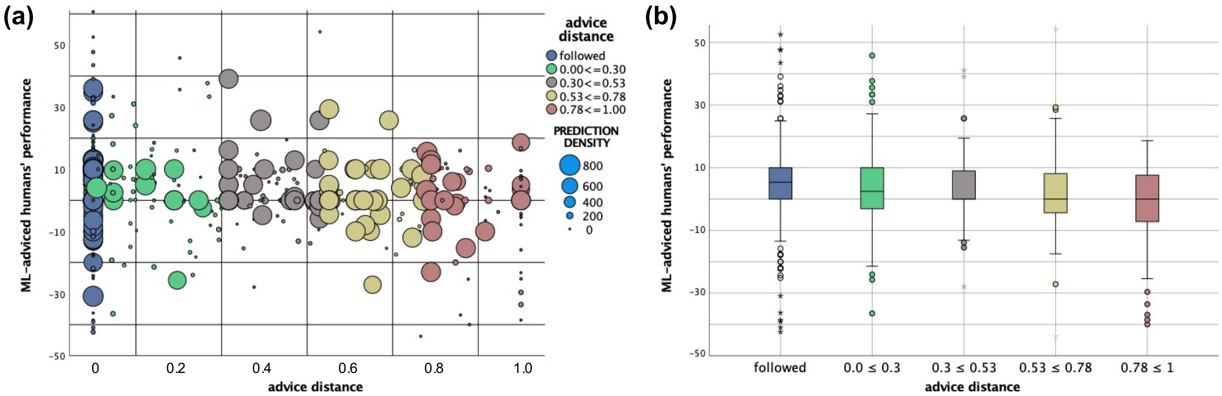

Figure 17. (a) Human trades (N = 561) plotted along performance and advice distance (b) boxplots of human trades clustered into followed and no-follow quantiles

Performance Impact. To understand whether the ML advice helps AGIs' human traders, we now nuance our analyses of the human follow rate. We calculated the *advice distance* for each advice, which reflects a normed performance difference between a taken decision and received advice in relation to the best and worst decision.[8] We use the advice distance as an independent input variable, which we compare against trading performance. A human trader may hold broader knowledge or intuition about market developments which the ML system cannot quantify with its narrow market view. If a human trader believes another trading choice to be more favorable, the trader will likely neglect the ML system's advice. If traders do this well, human trading decisions should not positively correlate with the advice distance. Figure 17a illustrates performance and related advice distances of the human trades. To highlight contained trends, we clustered the trades into five groups along the advice distance: in addition to trades with followed advice (i.e., advice distance = 0), we split the no-follows (i.e., advice distance > 0) into quantiles along the advice distance. Figure 17b shows that, with increasing advice distance, the boxplots of each group shift downward toward lower performance, as do their medians (i.e., 5.3, 2.4, .01, .0, .0).[9] While the effect appears small, it should not be neglected as such small improvements in trading already create large profit gains. In sum, the more the

[7] We also computed Kendall's tau-b correlation coefficient (Daniel 1990; Kendall 1945) between the provision of ML advice and the daily average percentage of humans following the ML advice for 96 days. We found a strong, positive association between providing ML advice to the humans and the humans following the advice, which is statistically significant with $\tau_b = .653$ and $p = .0005$.

[8] We defined the advice distance as $d_{Advice} = 1 - (score_{BestDecision} - score_{MadeDecision})/(score_{BestDecision} - score_{WorstDecision})$. Orders for which the selected algorithm was beyond the ML system's set of algorithms were not considered for this analysis.

[9] We also computed a Spearman's rank-order correlation (Daniel 1990; Spearman 1987) between advice distance and performance of an order. We found a weak negative correlation between advice distance and performance (i.e., performance decreases as advice distance increases), with $r_S(559) = -.176$ and $p = .0005$.

human traders follow the ML system's advice, the more effective their trading appears to become.

Yet, although following the ML system's advice tends to improve human performance, the ML system does not outperform the human traders; that is, on average, human traders and the ML system perform equally well after all.[10] However, if we regard the joint performance of the humans and ML system before (during the first 56 business days) and after (during the subsequent 40 business days) the enabled advice, we can observe that AGI's overall trading performance increased significantly.[11] The enabled bilateral human-machine learning appears to have improved AGI's trading performance.

8.4.3 Unveiling the Mutual Dynamics within Bilateral Human-Machine Learning

At first glance, our observations appear rather paradoxical: AGI's ML system does not outperform the human traders but the human traders improve their performance if they follow the ML system's advice more closely. To better understand the human-machine dynamics that underlie this conundrum, we now take a closer look into both actors' trading behaviors along different market scenarios.

The violin plots in Figure 18 show how human performance is distributed along four key market dimensions (i.e., the variables also used by the ML system), each with four different levels ranging from low to high. Each 'violin' is split into two colors: The orange area shows the performance distribution along the Y-axis of the humans when following and the blue area when not following the ML system's advice. At the same time, the bulge size of the colored areas indicates the underlying amount of data. When comparing the violins within each dimension, we can observe two tendencies: First, as the level increases from low to high, the amount of follows relative to no-follows decreases (exception: for *trade_frequency,* we can observe the opposite trend). Remember that with increasing levels of the variables, trading becomes more difficult for the traders (for *trade_frequency* the opposite applies). Thus, the more difficult trading becomes, the less the human traders appear to follow the ML system's advice. Second, for all levels, the orange distributions' peaks are skewed stronger towards the

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[10] We ran a Mann-Whitney U test (Daniel 1990; Mann and Whitney 1947) to assess differences in trading performance between ML-assisted humans and the ML system while the ML system's advice was enabled (N = 1871 trades). Distributions of the performance for ML-assisted humans and the ML system were not similar, as assessed by visual inspection. The performance for the ML-assisted humans (mean rank = 920.42) and the ML system (mean rank = 944.70) were not statistically significantly different, with U = 414028.5, z = -.962, and p = .336.

[11] We ran a Mann-Whitney U test (Daniel 1990; Mann and Whitney 1947) to assess differences in trading performance before and during enabled ML system's advice is statistically significant (N = 3797 trades). We found that performance distributions before and during enabled ML system's advice were not similar. The performance during enabled ML system's advice (mean rank = 1947.94) was statistically significantly higher than before (mean rank = 1851.61), with U = 1893097, z = 2.714, and p = .007.

top than the blue ones, indicating a better overall performance when humans follow the advice. This observation is consistent with our analysis in the previous section: when following the ML system's advice, AGI's human traders tend to improve their performance.

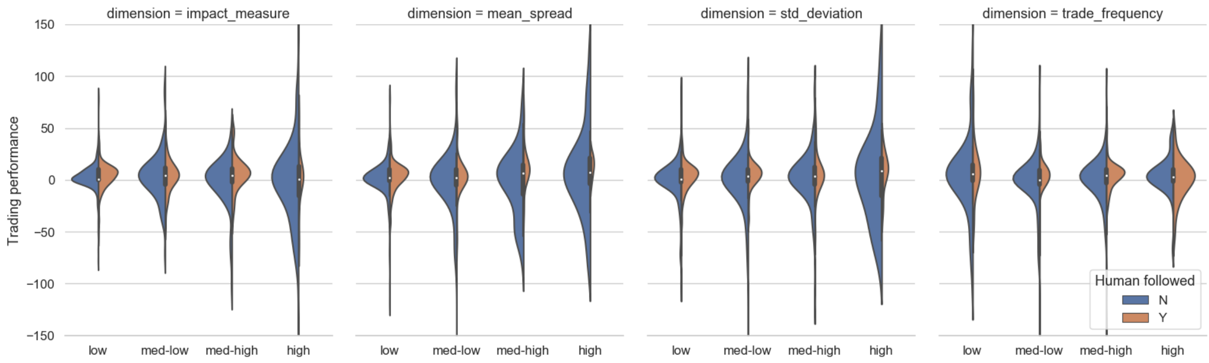

Figure 18. Performance distributions along different market scenarios

To better understand why the human traders do or do not follow the ML system's advice in certain scenarios, we talked to the human traders on how they utilize the ML system's advice. The traders agreed that, when receiving such advice, they essentially try to reflect on their own and the ML system's gathered amount of experience with the faced scenario. Note that simple scenarios also reflect scenarios that are traded very frequently at AGI. Both the human traders and the ML system have therefore already gathered related experiences extensively, and, due to the great sample combined with the relatively limitedly faced difficulty, already developed their own strong beliefs about how to trade such scenarios. While they mostly favor their own developed trading strategies that appear most reliable in the face of their past experiences, AGI incentivizes its human traders to keep improving their trading through exploration of new trading strategies, as their bonus is coupled with increased trading performance. As the ML system's advice represents approaches that were successful in the past and condenses its and multiple traders' experiences, it grants human traders the possibility to occasionally explore different but equally reliable alternatives, reducing the risk of costly failures that exploration of new approaches usually comes with. By doing so, the ML system helps to break open solidified (potentially suboptimal) propensities, helping humans to reevaluate and nuance their own developed strategies. This is in contrast to more difficult, rarer scenarios, where the human traders and the ML system have so far only gained limited experience to develop robust trading strategies. In such scenarios, the human traders still explore extensively to uncover more reliable strategies. Here, deliberately reflecting on experiences is especially relevant to not only identify promising opportunities but to also bypass ominous actions as flawed or needlessly repeated explorations can accumulate several million euros in trading costs. Thus, to better guide their exploration, human traders utilize the ML system's advice to not simply follow the so-far most promising approach but primarily to reflect on organization-wide experiences. This allows them to either further explore seemingly promising approaches or identify unexplored 'blind spots' that might yield further beneficial directions. Consequently, the human traders tend to follow the ML system's advice less frequently in more difficult trading scenarios.[12]

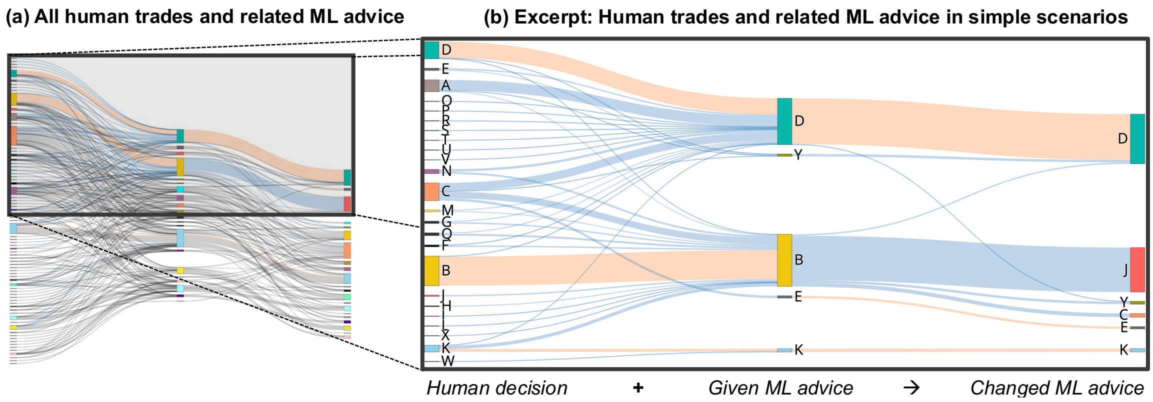

Figure 19. (a) All human trades (left) linked to given (middle) and eventually changed (right) ML system's advice; (b) excerpt of trades in simple scenarios

While this shows how ML affects human trading behavior, we now explore how human trading affects the ML system's learning over time (remember: the ML system also learns from human trades). The sankey diagrams in Figure 19 outline the ML system's behavioral changes in relation to the humans' trading behavior: Both diagrams consist of three segments, respectively showing the aggregated decisions regarding individual trading algorithms by the human traders (left), the accordingly received ML system's advice (middle), and the changed advice that the ML system provides for these human trades at the end of the observation period when this human data is used for retraining the ML system (right). Each node (represented by a letter and a color box) groups trades where a specific trading algorithm (e.g., *'D'*) was used or advised. The links between the nodes connect single trades across all three segments. The larger a node, the more frequently the respective trading algorithm was used or advised. The thicker a link, the more frequently respective connections appeared. Consequently, paths between the left and middle segment represent whether a human followed an advice or not, while paths between the middle and right segment represent changes in the ML system's advice when being retrained with all human trading choices. While the left diagram (a) bases on all observed trades, the right

[12] We also computed Kendall's tau-b correlation coefficient (Daniel 1990; Kendall 1945) between following the ML system's advice (Yes = 1/No = 0) and the sample density of the advice (*N* = 766). We found a positive association between humans following the ML system's advice and a higher sample density, which is statistically significant with $\tau_b = .170$ and $p = .0005$.

diagram (b) shows an excerpt covering only trades in simple scenarios (i.e., frequent trades for which the ML system learned from a high sample density).

In Figure 19, the higher number of nodes in the human segments demonstrates that the humans used a larger variation of trading algorithms. When focusing on trades of simple scenarios (Figure 19b), we can clearly observe that human trading affected the ML system's trading behavior in several ways: The ML system revised its strongest strategy from using trading algorithm *B* to *J* and diversified it with the use of the additional algorithms *Y* and *C* in certain scenarios. Although in 65% of trades the human traders used a variety of other algorithms (blue links) instead of following the advice *D*, the ML system reinforced and extended its use of the superior algorithm *D*. While the human traders increasingly explored algorithms *A* and *C* in various scenarios, the ML system figured to keep both in most cases. In complex scenarios (the nodes with grey connections in Figure 19a), comparable patterns can be observed that, due to an even greater diversity in human trading and less experience of the ML system, yielded more changes in the ML system's advice. To this end, the vibrant human trading helps the ML system to enrich its experiences which stimulates a broader assessment, revision, and extension of its inferred trading strategies.

8.5 Discussion

With the increasing use of ML systems in organizational routines alongside human counterparts, enabling effective human-machine collaboration becomes ever more important. Only recently, scholars started to stress the great importance of managing the bilateral relationship between humans and ML systems (e.g., Rai et al. 2019; Schuetz and Venkatesh 2020) and increasingly acknowledge the great potential of organizational learning research to analyze this relationship (e.g., Lyytinen et al. 2021; Ransbotham et al. 2020; Seidel et al. 2019). Yet, despite decades of research on organizational learning, scholars have largely assumed the learners to be purely human (e.g., Argote et al. 2020; Argote and Miron-Spektor 2011). So far, only a handful of scholars have studied potential impacts of ML on organizational learning but mainly remained on a theoretical level and call for further research (i.e., Afiouni-Monla 2019; Balasubramanian et al. 2021; Lyytinen et al. 2021; Ransbotham et al. 2020; Seidel et al. 2019; Sturm et al. 2021). With our study, we aim to help answer these calls by drawing on a case in a real-world organizational context. We provide empirical insights to enrich ongoing discussions, hoping to inspire further research endeavors and help organizations design effective human-AI collaborations.

Our study contributes to theory in multiple ways. First, given its impact on organizational performance, our study emphasizes that an organizational learning perspective should not be neglected when managing the emerging bilateral human-AI dynamics. With our case, we demonstrate how scholars and organizations can adopt this perspective to empirically identify and explain actual (interrelated) behaviors of humans and ML systems within organizational contexts. Second, hoping to inform such studies, we condensed key idiosyncrasies of human learning and ML from existent literature to help recognize potentials for change when human learning is being replaced or augmented with ML. Moreover, drawing on these theoretical idiosyncrasies and insights from our case, we proposed a conceptualization of the fundamental learning processes and linkage between humans and ML systems. As shown in our case study, both can be used to theoretically ground agents' characteristics and relations to guide empirical analyses of reciprocal human-AI dynamics and explain their (unintended) consequences. Third, as we based our analyses on a novel method of human-machine pattern recognition ourselves, our study demonstrates how human-AI collaboration can also benefit research endeavors. Scholars interested in leveraging this potential can rely on our study to stimulate comparable research designs. Our study further illustrates how especially digital trace data analyses can thereby act as a powerful and context-rich tool to help unravel complex behavioral dynamics, allowing to (1) leverage machines' high information processing capabilities for recognizing fruitful patterns in extensively tracked activities and (2) humans' broader contextualization capabilities for finding explanatory patterns through inquiries with involved actors and contexts. Our case exemplifies that one must be careful with isolated analyses when aiming to unravel ML's complex consequences, urging scholars to consider varying temporal or spatial foci when studying human-AI relationships.

Fourth, our study adds empirical insights to the ongoing automation-augmentation discussion on whether humans should be taken 'out of the loop' as soon as ML systems can reliably replace them in their routines (e.g., Brynjolfsson and Mitchell 2017; Raisch and Krakowski 2021). Although AGI's ML system enables successful autonomous learning, our observations suggest that AGI can benefit from keeping its human traders 'in the loop' as their broader contextualization adds value to the whole learning system. Due to its reliance on a preselected subset of trading algorithms and market variables, the ML system can explore and infer trading strategies only within its narrow frame. Despite its less bounded information processing, an increased reliance on the ML system's trading would therefore come with the risk of restricting AGI's trading strategy innovations to the limits of the ML system's framed view. With their holistic market view and less rational behavior, the inclusion of humans helps AGI to actively counteract this risk as they help to look ‘outside the box’; that is, while the ML system grants AGI the ability to learn reliable strategies within its boundaries, AGI requires its human traders to learn about promising algorithms and pivotal market conditions beyond the system’s frame. Only if AGI’s human traders keep actively learning through their own trading experiences, they can translate the complex, ever-changing trading environment to a substantiated, fruitful frame in which the ML system can unfold its preeminent learning capabilities.

Lastly, our study further contributes to the emergent discussion on whether ML amplifies (e.g., Balasubramanian et al. 2021) or alleviates (e.g., Sturm et al. 2021) organizations’ learning myopia (i.e., the tendency to favor exploitation over exploration; Levinthal and March 1993). In the case of AGI, we can observe that the human traders take a more explorative role while the ML system tends to act rather exploitatively. For AGI, increasingly shifting trades to the ML system thus appears to come with an increased risk of stagnation when ML outcomes remain isolated. However, when enabling humans to also learn from the ML system (i.e., enabling bilateral learning), we can observe an opposite effect; that is, human exploration benefits from the ML system’s increased exploitative behavior as its shared learnings allow humans to better reflect on past organization-wide experiences and help to rationally uncover blind spots and promising strategies. Depending on the maturity of the developed beliefs, ML thereby either helps the humans to break open solidified propensities or better guide ongoing explorations of so-far uncharted areas. In contrast, the human traders’ boundedly rational trading behavior adds larger variations to the ML system’s experience which would have been neglected within its narrowly focused formal exploration, helping to overcome potential convergence towards suboptimal strategies. To this end, our findings point to a potential virtuous cycle between human learning and ML, in which humans improve ML through diversifying experiences for the ML system’s exploitation and ML benefits human learning through informing human exploration. These insights demonstrate that well-coordinated bilateral human-machine learning can act as an effective mechanism for organizations to counteract myopia. To make use of this potential, future research could explore organizational designs on how to unite both learners’ idiosyncrasies to mutually enhance and effectively balance explorative and exploitative behavior and focus on more detailed analyses of how different contexts (e.g., varying amount of experience or faced complexity) affect learning myopia in human-machine collaborations. Especially with myopia’s broad context dependency, future research can help uncover the extent to which observed effects are unique to the trading context’s specific decisions, objectives, and incentives, and how they can be translated to divergent contexts, such as more subjective, more ambiguous, or less competitive domains (e.g., the health care or public sector). We also encourage scholars to explore conditions and mechanisms that sustain the identified dynamics in the long term or impede them, in the worst case even turning bilateral learning into a vicious cycle.

Our insights are equally relevant for practitioners. Organizations can use our results to inspire and design future AI initiatives beyond ML-based automation of routines. To leverage ML's full potential, our study demonstrates that practitioners are well-advised to consider potential human-AI collaboration designs already at an early stage of their ML development. Our observations should encourage organizations to rethink whether integrating ML within their routines gave birth to new knowledge silos, how they can make this ML-based expertise available to human experts, and how they can maintain human-AI knowledge transfer in both directions to enable synergy effects. In its essence, this is not only a matter of organizational design, but reflects a new managerial issue that requires organizations to deliberately reflect on both actors' idiosyncrasies to effectively coordinate their emerging dynamics.

Of course, our study is subject to limitations. Due to our study's exploratory nature, future research should validate and contextualize our findings under different boundary conditions across heterogeneous contexts and domains. As we relied on a single case, our observations must be interpreted within the limits of its peculiarities. It is not clear that similar dynamics emerge in comparable routines, especially if other ML types, human-AI collaboration setups, or observation periods are used. Although we aimed to maximize the breadth of our observations by drawing on a rich and diverse set of data, there are certainly many aspects that we could not observe but could still influence human-machine dynamics since they were not trackable in digital traces or not obvious to the traders. Here, we invite future studies to help analyze further aspects, such as motives or activities, that remained hidden to us by relying on different contexts, methods, or foci.

8.6 Acknowledgements

This study has been funded by the German Federal and Hessen State Ministry for Education and Research within their support of the National Research Center for Applied Cybersecurity ATHENE.

9 Contributions and Implications

Digital technologies offer organizations new opportunities for innovation (e.g., Nylén and Holmström 2015; Piccinini et al. 2015; Yoo et al. 2012). Their unique properties, which include high connectivity and embedding, as well as a multi-layered modular architecture, are changing the way innovation processes take place in companies (Nambisan et al. 2017). At the same time, digital technologies are transforming the core of many products, services, and business models (Yoo et al. 2010). Driven by these changes, digital innovation poses a challenge to existing innovation and IS theories and offers promising avenues for future research (Nambisan et al. 2017). This thesis aims to improve the understanding of the digital innovation process in organizations. Specifically, the following research objectives were in focus:

- Analysis of IT-supported idea crowdsourcing for innovation in organizations under the influence of organizational culture (chapter 3)
- Exploring the importance of digital technologies for digital innovation across different innovation collectives in times of crisis (chapter 4)
- Exploring the contextual factors in the innovation process of digital service innovation in plant and mechanical engineering (chapter 5)
- Demonstrate the use of cloud-based ML services to implement a visual inspection prototype in the manufacturing industry (chapter 6)
- Exploring the implementation of service innovation in manufacturing firms utilizing the work system theory (chapter 7)
- Unravel the complex bilateral human-machine relationship in organizational learning (chapter 8)

9.1 Theoretical Contributions

The first two research papers (i.e., Paper A and Paper B) contribute to digital innovation initiation, which is overall poorly explored in the existing literature. Paper A, for one, confirms that the organizational culture as a whole influences the status of idea platform implementation. It also shows that the organizational environment, of which culture is a part and in which digital innovation takes place, should be considered when using digital technologies in the innovation process (Kohli and Melville 2019). Furthermore, it explores how companies use idea crowdsourcing platforms to open up their innovation processes and diffuse them more widely

(Ili et al. 2010). Next, Paper B contributes as a case study to theorizing in the larger context of digital innovation (Eisenhardt 1989) while highlighting the increasing importance of partnerships and collaborative development, particularly in light of the digital revolution (Rindfleisch et al. 2017). Specifically, it shows that non-specialized innovation collectives can form in closed markets, effectively accumulate knowledge, and develop a highly complex product in a short period. Furthermore, the Paper B explores the different types of innovation collectives and their innovation outcomes. Although literature emphasizes the importance of open design (Baldwin and Von Hippel 2011), projects with commercial backgrounds were the most advanced in the study and, therefore, relatively more successful, i.e., having completed development and received regulatory approval. This fact raises the question of the extent to which communities are able to market the designs they develop. Moreover, the results show the initiatives' willingness to share their knowledge and innovations (inside-out process). However, the initiatives reported little absorption of knowledge and innovations (outside-in process). Both findings are consistent with the challenges that open designs face in dealing with legislation, financing, manufacturing, commercialization, and intellectual protection of new products (Hopp et al. 2018). Lastly, the study illustrates how digital technologies can facilitate the innovation process (Bstieler et al. 2018; Felin and Zenger 2014; Yoo et al. 2010) making collaborative innovation viable across a broader range of innovation activities than before (Baldwin and Von Hippel 2011).

The next two research papers (i.e., Paper C and Paper D) contribute to the research stream of digital innovation development. Paper C extends previous studies on servitization, i.e., the transition from product manufacturer to service provider, focusing on digital service innovations. It contributes to the adoption and diffusion research of digital innovations (Kohli and Melville 2019) by providing insights into the introduction, adoption, and routinization of digital service artifacts in the machinery and manufacturing industries. The results constitute an integrative model based on the technology-organization-environment (TOE) framework that considers various contextual factors as important components of the assimilation of digital service innovation. In particular, the paper also contributes to a better understanding of what inhibits assimilation, which is a field for further research in the area (Kohli and Melville 2019). Paper D, in turn, focuses on the design science research stream on digital innovation and on the question of what works in terms of designed technological artifacts. Following Gregor and Hevner (2013), the implemented novel artifact embodies design ideas and theories while contributing to the real-world application environment. The artifact shows how MLaaS can be used to implement a visual inspection solution in manufacturing. In doing so, two issues important for theorizing are addressed at a higher level of abstraction. First, the artifact shows to what extent the standardization of a cloud platform ML-service needs to be individualized for development within the industry and what role AI services play in this. Thereby, it contributes to the value of standardization and vendor-provided IS architecture concepts for digital innovation (Kohli and Melville 2019). Second, it shows how such innovations can facilitate further innovations in manufacturing, i.e., data generation and thus knowledge extraction for further process control and improvement.

The remaining two papers contribute to the research stream of implementation (Paper E) and exploitation (Paper F) of digital innovation. Paper E uses work systems theory as a theoretical basis to structure the results and analyze them through the lens of service systems. While this analysis helps identify the organizational changes resulting from the implementation of digital service innovations, the paper also provides a basis for further research with a systematic analysis and a new perspective. In the last research paper F, a case study from the trading industry with a real-world organizational context is used to show how bilateral learning between humans and machines can improve the overall performance in trading. The study contributes to theory in multiple ways. First, it emphasizes that the organizational learning perspective should not be neglected in addressing the emerging bilateral human-AI dynamic. Second, the study summarized the key characteristics of human learning and ML from the existing literature in order to identify the potential for change when human learning is replaced or augmented by ML. Third, it employs a novel methodology based on human-machine pattern recognition, showing how human-machine collaboration can also benefit research. Fourth, the study adds empirical evidence to the ongoing debate about automation and augmentation, which addresses whether humans should be "taken out of the loop" once ML systems can reliably replace them in their routines (e.g., Brynjolfsson and Mitchell 2017; Raisch and Krakowski 2021). Finally, the study further contributes to the emerging debate on whether ML enhances (e.g., Balasubramanian et al. 2021) or weakens (e.g., Sturm et al. 2021) organizations' learning myopia (i.e., the tendency to favor exploitation over exploration; Levinthal and March 1993).

9.2 Practical Implications

Besides theoretical contributions, the results are also relevant for practitioners. Overall, the thesis explores the potential that digital technologies, especially service innovations and ML, pose for companies within their digital innovation activities: initiation, development, implementation, and exploitation. Doing so illustrates several aspects of how innovation processes and results in companies are changing as a result of increasing digitization and the pervasive use of digital technologies. When initiating innovations, companies will adapt to increasingly distributed and open innovation processes. This confronts companies with more than just technological challenges. To effectively use these new sources of knowledge, companies must consider their organizational environment, including an appropriate corporate culture. Distributed innovation collectives are relevant to companies of all sizes and present both opportunities and threats, as digitization is known to lower market barriers and bring new competitors that may compete even with complex products and services offered by incumbents.

When developing and implementing digital services and business models, the thesis shows that digital technologies require companies to adopt new processes and perspectives. For one, it illustrates several challenges within the industrial organization in its transition to a service provider. Thereby, it helps companies conduct a structured analysis of their status quo and identify opportunities for improvement in the adoption of digital service innovations and guides managerial decision-making. For another, implementing digital innovations, e.g., new digital services, also requires comprehensive organizational change within the company. Here, the findings support practitioners in assessing and managing the preconditions and effects of digital innovation implementation. From a service systems perspective, it helps companies identify and visualize the operational significance of service transformation based on digital technologies and the associated challenges.

Finally, the work focuses on ML as digital technology. It explores the technological and organizational implications of developing and exploiting such digital innovations beyond ML-based automation of routine processes. Instead, the full potential of ML lies in exploiting the data generated by ML and in the possible forms of collaboration between humans and ML systems. Practitioners should already take both into account when developing such systems. In this context, organizations must consciously consider the idiosyncrasies of both humans and ML systems in order to effectively coordinate their emerging dynamics. This is not just a matter of organizational design but reflects a new management problem in exploiting innovation based on ML systems.

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