Realizing Digital Innovation from Artificial Intelligence

Completed Research Paper

Anthony May
University of St.Gallen (HSG)
St. Gallen, Switzerland
anthony.may@student.unisg.ch

André Sagodi
University of St.Gallen (HSG)
St. Gallen, Switzerland
andre.sagodi@student.unisg.ch

Christian Dremel
University of Bamberg
Bamberg, Germany
University of St.Gallen (HSG)
St. Gallen, Switzerland
christian.dremel@uni-bamberg.de

Benjamin van Giffen
University of St.Gallen (HSG)
St. Gallen, Switzerland
benjamin.vangiffen@unisg.ch

Abstract

Artificial Intelligence (AI) promises to have a transformational impact on our economy and society. It offers the opportunity for digital innovation, as it can be embedded in products and services. However, although companies are adopting AI, success stories are limited. Similarly, research on how to realize digital innovation from AI is scarce. To analyze the role of AI for digital innovation and how it affects the venture creation process, we conduct an in-depth case study at a heavily-funded medical imaging AI company. Our case study reveals four AI-caused tensions, which a digital venture faces, and we discuss four ways in which it counters them: (1) Managing Over-Expectations of AI, (2) Designing Work Routines for AI, (3) Addressing Opposing User Perceptions of AI, and (4) Integrating Domain Expertise with AI. Ultimately, we hope to contribute to the understanding of digital innovation in the context of AI.

Keywords: Digital innovation, artificial intelligence, digital ventures, affordance theory

Introduction

Artificial Intelligence (AI) is a rapidly emerging phenomenon of economic and societal significance (Goasduff 2019; von Krogh 2018). Accordingly, it has become a fixed point on the agenda of many companies (Davenport 2018; Ransbotham et al. 2019). McKinsey & Company estimates that AI could deliver 13 trillion USD of economic value by 2030 (Bughin et al. 2018). In recent years, AI's capabilities have grown stronger, driven by the increasing availability of data, improved computing power, and more advanced algorithms (von Krogh 2018). AI can broadly be described as a collection of computer-assisted systems able to perform non-trivial tasks traditionally confined to humans (von Krogh 2018). Since the term AI remains fuzzy (Rzepka and Berger 2018; Kaplan and Haenlein 2019), we focus on Narrow AI, which is the most common form of AI today. Narrow AI handles a singular task in a narrow context (Stone et al. 2016). Embedding AI into products may enable the augmentation of today's human work routines (Davenport and Kirby 2015), and can enhance our cognitive performance (Goasduff 2019). However, in practice, many AI initiatives still fail (Ransbotham et al. 2019). In our research, we understand the process of embedding AI into products and services as a form of digital innovation. This understanding is based on Yoo et al. (2017), who define digital innovation as "the carrying out of new combinations of digital and physical components to produce novel products" (p. 725). We consider the process of realizing digital innovation from AI to be a socio-technical phenomenon based on the interplay between (1) a digital venture, (2) a digital artifact, (3) AI, and (4) a user. First, digital ventures are ventures that have a digital artifact at their core (von Briel et al., 2018). Hence, they provide a suitable context to observe the digital innovation process, as their "meaning-making process is interwoven with their core technology" (Huang et al. 2017, p. 312), which allows for perpetual alignment of user- and technology-related activities. Second, the digital venture recursively shapes the digital artifact, that is, "a digital component, application, or media content that is part of a new product and offers a specific functionality or value to the end-user" (Nambisan 2017, p. 1031). Third, the digital venture embeds AI in its digital artifact. Fourth, as a result, it supports the user at completing a task and achieving a goal. Thus, digital artifacts are the building blocks for digital ventures, which construct their market supply around them (von Briel, Recker, et al. 2018). Following Rzepka and Berger (2018), we refer to digital artifacts that contain AI as AI-enabled systems.

Anecdotal evidence suggests that digital innovation in the context of Narrow AI differs from how we currently understand digital innovation in several ways. First, in contrast to traditional information systems (IS), AI-enabled systems are capable of learning and improving over time (Davenport 2018). Second, they rely on vast amounts of labeled data to function properly (Litjens et al. 2017). Third, users might resist them due to the implications AI may have for the workforce (Fountaine et al. 2019). Thus, research is needed on how AI changes digital innovation (Berente et al. 2019). Specifically, while the role of digital artifacts for digital innovation and in the digital venture creation process has been studied before (e.g., von Briel et al. 2018), little is known about the intricacies that AI brings to digital innovation (Benbya et al. 2019; Berente et al. 2019; von Krogh 2018). Further, scholars suggest studying the relations between digital technology and venture creation (von Briel, Davidsson, et al. 2018; Nambisan 2017). To bridge this gap, we raise the following research question: *How do digital ventures realize digital innovation from AI by embedding AI into products?* To answer this question, we have conducted an in-depth case study of a heavily-funded medical imaging AI company, which we refer to as 'AICO'. In doing so, we have produced an empirical perspective on how a digital venture realizes digital innovation from AI. We have found that AI causes four tensions that AICO needed to counteract. Our findings contribute to understanding how AI affects digital innovation, and how it shapes the venture creation process. Ultimately, we hope to contribute to a more "informed, prudent, and realistic" approach to AI in practice (von Krogh 2018, p. 408).

The remainder of this paper is structured as follows. In the next section, we construct our theoretical model by reviewing existing literature on AI, digital innovation, and digital ventures, and affordance theory. Subsequently, we present our research design. After that, we discuss our findings, before we present our theoretical and practical implications. Finally, in the last section, we conclude our paper.

Theoretical Foundation

In this chapter, we build the basis for our theoretical model (cf. Figure 1) in three steps. First, we conceptualize our understanding of AI and relate it to big data analytics. Second, we outline related literature on digital innovation and digital ventures. Third, we introduce affordance theory, allowing us to take a socio-material view of the changing roles of AI arising from its material properties within an artifact.

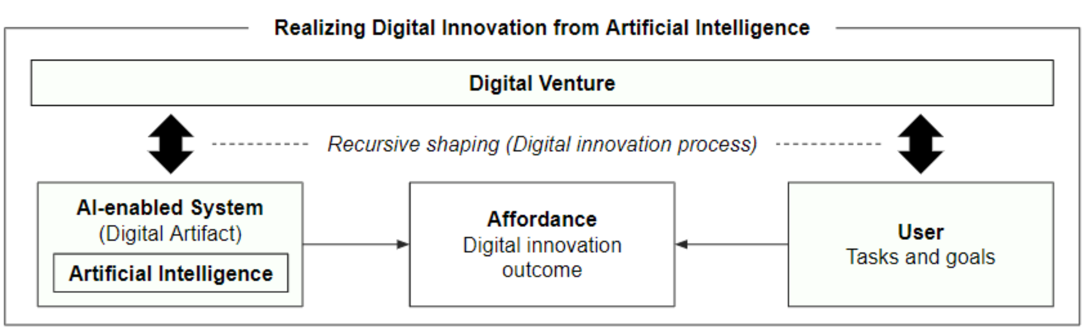

Figure 1. Theoretical model: Socio-material view on realizing digital innovation from AI

Artificial Intelligence

AI is not a new phenomenon. The term reaches back to the 1950s where research explored the nature of intelligence and its implementation in computer systems with famous contributors such as Alan Turing (Stone et al. 2016). As there is no commonly accepted definition of AI, one can describe it as a collection of computer-assisted systems able to perform non-trivial tasks traditionally confined to human-level intelligence (von Krogh 2018). AI models entail three components: (1) Task processes (algorithms), (2) task input (data), and (3) task output (decisions or solutions). First, to reach decisions, most popular AI models use machine learning algorithms such as computer vision or natural language processing to detect patterns from data. Today, supervised learning techniques are widespread (Litjens et al. 2017). In medical image analysis, the most popular architectures are convolutional neural networks (CNN). Second, in contrast to unsupervised machine learning models, supervised learning relies on labeled data, i.e., the marking of objects in images, in our case anomalies on medical image material. Thus, AI learns and improves from experience, i.e., from data that it relies on during training steps. Such models are probabilistic so that their performance is not based on rules but rather relies on modeling and analysis. Third, algorithms make predictions, which subsequently may be made accessible to the user through AI-enabled systems. Despite the ability of AI to perform tasks traditionally confined to humans (Davenport and Kirby 2015), automation happens on the level of tasks within a job instead of replacing the entire job (Manyika et al. 2017). Healthcare was one of the first industries to adopt AI (Davenport 2018). For instance, the first AI applications date back to the 1990s, where they started supporting radiologists in detecting cancer from medical images (Litjens et al. 2017). In those cases, AI-enabled systems contain computer vision algorithms (task process) that draw on large amounts of data (task input) to make predictions (task output) that support radiologists in their diagnostic decisions and can lead to higher accuracy of those decisions. Furthermore, IS research has focused on Big Data Analytics (BDA) as an adjacent research stream (Günther et al. 2017; Wiener et al. 2020). Such research tries to show how BDA leads to the realization of value for organizations (Dremel et al. 2020; Wiener et al. 2020). Understanding the relationship between BDA and AI is highly important due to their tied connection (Kallinikos and Constantiou 2015). On AI‘s foundation, BDA may lead to the automation of decision-making processes (Baesens et al. 2016), allowing for deeper integration in value-creating decision-making processes (Loebbecke and Picot 2015; Saboo et al. 2016; Sharma et al. 2014). Thus, AI enables automating and improving the data-to-insight process (Sharma et al. 2014), which is the ultimate goal of our case company.

Digital Innovation and Digital Venture Creation

Digital technologies have caused remarkable changes around us (Yoo et al. 2010). They are undeniable forces that cause major transformation in both our economy and society (Ciriello et al. 2018). This transition process is characterized by three properties of digital technologies: the storage and spread of digitized information, their re-programmability even after deployment, and their self-referencing capability (Ciriello et al. 2018; Kallinikos et al. 2013; Reuver et al. 2018; Yoo et al. 2010). Digital technology is self-referential, as it is both created by and creator of such technology (Ciriello et al. 2018; Reuver et al. 2018; Yoo et al. 2010). This so-called virtuous cycle leads to decreasing entry barriers and reduced learning costs, hence accelerates technology diffusion, which then leads to further digital innovation (Ciriello et al. 2018; Yoo et al. 2010). Digital technologies can be categorized according to two dimensions: specificity and relationality (von Briel, Davidsson, et al. 2018). Specificity describes the degree of optimization towards a specific task hence impedes to transfer an artifact to further tasks or context (von Briel, Davidsson, et al. 2018). Increased specificity is related to an increased potential of automating the intended tasks, hence to gain efficiencies and to free up resources from the substituted subject (Leonardi 2011). Thus, Narrow AI is highly specific. Relationality refers to the ability of artifacts to make value-deriving, functional connections with other actors (von Briel, Davidsson, et al. 2018; Kallinikos et al. 2013). Further, Narrow AI is highly relational, as AI-enabled systems can be used by multiple actors at the same time.

Triggered by digital technologies, the emergence of digital innovation affects products and services alike (Wiesböck and Hess 2020). Digital innovation is a multi-faceted phenomenon that includes constant exploration, creation, and a combination of functions that are enabled by digital technologies (Ciriello et al. 2018; Nambisan 2017). Focusing on product innovation, Yoo et al. (2010) refer to transaction-cost theory (Schumpeter 1934) and define digital innovation as the creation of new products by including combinations of both digital and physical parts. Convergence and generativity are two dimensions to organize the omnipresent digital innovations: convergence allows for the combination of artifacts to create or combine user experiences, e.g., by the combination of phone, mobile (internet), and media content; generativity emphasizes the transformational role, facilitated by reprogrammability and feature-variation (Yoo et al. 2012). Moreover, today's products and services are widely built on a combination of devices, networks, services, and digital content. They are consequently organized in a layered modular product architecture (Beverungen et al. 2019; Yoo et al. 2010). The manifold outcomes of digital innovation include gains in productivity and profitability and also impact fields like risk mitigation and customer loyalty (Kohli and Melville 2019). With the possibility to physically separate information from the place of execution, digital artifacts are increasingly included in products and services (Beverungen et al. 2019; Lusch and Nambisan 2015). Nambisan (2017) describes a digital artifact as "a digital component, application, or media content that is part of a new product (or service) and offers a specific functionality or value to the end-user" (p. 1031). Following this logic, a digital artifact may make use of AI as a digital component or feature, resulting in an AI-enabled system. Digital artifacts may be both means and end to digital innovation (Nambisan 2017) and can be facilitators and outcomes of digital innovation (Ciriello et al. 2018).

Digital artifacts are the fundamental building block for digital ventures that construct their market supply around them (von Briel, Recker, et al. 2018). These newly emerging ventures broadly operate in the early phases of development and growth (Klotz et al. 2014). In this context, digital technologies such as AI form a transformative "new era in entrepreneurship" (p. 1047), as they are becoming an integral part of entrepreneurial opportunities (Nambisan 2017), potentially triggering the creation of a digital venture. The formation of digital innovation can be rooted in both emerging technological opportunities as well as in domain-driven needs (Wiesböck and Hess 2020). Opportunities are the aggregation of temporary circumstances like technological breakthroughs (e.g., AI) and may cause different actors to create new ventures (Davidsson 2015).

Davidsson (2015) indicates that new venture ideas are initially "incomplete and malleable" (p. 687) and that their characteristics are likely to change along the venture creation process. Respective digital products and artifacts are likely to evolve steadily even after product launch, which impacts their scope, features, and value (von Briel et al. 2018; Nambisan et al. 2017). As of today, research on digital entrepreneurship is a nascent field that receives growing awareness (von Briel et al. 2018; Huang et al. 2017). To further understand enablers and constraints that have an impact on entrepreneurial activities it is fruitful to show causal relations between characteristics of digital technology and respective artifacts and facets of venture creation (von Briel et al. 2018; Nambisan et al. 2017), which is the approach we adopt in our case study.

An Affordance-Theoretic Perspective on Digital Innovation and Digital Venturing

The value of digital technologies can be phrased by its potential of changing the nature of the work and respectively enabling new actions (von Briel, Davidsson, et al. 2018). However, the mere presence of a new digital artifact (in our case an AI-enabled system) does not obligatorily result in a changing work routine of an individual (Leonardi 2011). Quite the opposite, if the new technology is perceived as a constraint to the previous workflow, even detrimental effects such as workarounds or rejection are possible (Leonardi 2011). Consequently, the value of an artifact is not inherent but rather constituted by the relation of the artifact-actor system. The promising lens of affordances allows us to illuminate AI as constructed material property (i.e., feature) of a digital artifact (i.e., AI-enabled system), which is shaped by a digital venture to allow for work routine improvement for the user. Together with its related philosophical stance on sociomateriality, it sees increasing interest in IS research (e.g., Autio et al. 2018; Dremel et al. 2020; Lehrer et al. 2018; Leonardi 2011; Seidel et al. 2013).

While affordance theory is originally used for studying individual-level interactions, it is also used for organizational-level studies like in the case at hand (cf. Markus and Silver 2008; Zammuto et al. 2007; Volkoff and Strong 2013; Strong et al. 2014; Dremel et al. 2020). In general, affordance theory fits well for building new theories in IS research on emerging technologies (Nambisan et al. 2017) - in our case AI. Moreover, this theory allows us to go beyond a mere technological view and rather to elaborate on the relationship and interaction between technology and individuals. Consequently, this research approach provides answers to the questions of how and why technology can lead to different socio-technical relationships and interactions, depending on context and actors (Nambisan et al. 2017). In relating to affordance theory, we acknowledge that socio-technical systems consisting, for instance, of technical artifacts, knowledge, or cultural meaning "do not function autonomously, but are the outcome of the activities of human actors [...] embedded in social groups" (Geels 2004, p. 902). In organizational studies, these socio-technical systems were understood to be "made up of social systems (hierarchies, communication networks, etc.) and technical systems, which are usually defined as technological artifacts" (Leonardi 2012, p. 38). The interactions between the social and the material (Leonardi 2013) might be seen as inherently recursive, that is "users shape the technology structure that shapes their use" (Orlikowski 2000, p. 407). We follow Leonardi (2012) in considering in our research the "recursive (not simultaneous) shaping of abstract social constructs and technical infrastructure that includes technology's materiality and people's localized responses to it" (p. 22). In this regard, affordance describes the "possibilities for goal-oriented action afforded to specified user groups by technical objects" (Leonardi, 2012, p. 622). Contrary to digital artifacts, affordance emerges and is perceived due to the relationship of the user as well as its goals and capabilities and the material properties of the digital artifact (i.e., features) (Strong et al. 2014). Even though the artifact's material properties persist over time, affordances may change depending on the context in which the user and artifact are located (Hutchby 2001; Leonardi 2012). Thus, as illustrated in Figure 1, the lens of affordance is at the center of our view of digital innovation used to analyze the case.

Research Design and Method

Currently, the successful implementation of AI as a contemporary digital technology is limited (Ransbotham et al. 2019), and as already illustrated in our theoretical foundation, further research is needed that investigates the connection between digital technology characteristics - embedded in an artifact - and characteristics of venture creation (von Briel et al. 2018; Nambisan et al. 2017). Therefore, to investigate the changing role of AI (i.e., digital technology) for digital innovation and venturing, we chose an inductive qualitative research design due to: (1) the novelty of the topic and (2) the lack of prior research on AI and its effects on digital innovation and venturing (Eisenhardt 1989; Myers 1997; Yin 2003). As little is known about this topic, an inductive exploratory case study research represents a suitable way to discover this nascent field by deriving insights from real-life situations. In particular, we draw on a single case study of a well-funded medical imaging AI company (AICO). We show the mechanisms of AI as a digital technology and its changing role for digital innovation as well as venture creation. As this study aims at discovering new phenomena and correlations from contemporary real-life context, a single case study sets a suitable foundation (Recker 2012; Yin 2003). Especially the AI business creation in the highly regulated health sector manifests the necessity to draw first insights in a revelatory manner. We intend to derive answers to 'how' questions in line with Yin (2003).

Case Context

AICO is an AI company in the healthcare industry. The company is a start-up established in 2017 and incorporated in 2018. It is a spin-off of an AI venture studio. Today, it employs 25 people. The venture studio conceptualizes, builds, and grows AI ventures. The venture studio is heavily-funded (it has raised two funds which accumulate to the tens of millions of EUR). AICO is funded by the venture studio as well as venture capitalists. AICO develops and distributes a cloud-based AI-enabled product, which we henceforth refer to simply as 'product', that is certified as a medical device under the CE mark. It is used in a mammography screening setting by radiologists, who analyze mammograms and decide whether a woman needs follow-up examinations or is healthy. For the radiologists, who use the product, it frees up time and allows them to focus on more complex cases. For radiology centers, it allows for productivity gains, as more women can be screened. Further, it frees up resources, allowing radiologists to perform other tasks that are potentially more vital for patients and/or valuable for providers.

Data Collection

Throughout the research project, one of the authors of this paper was deeply involved with the practices at the research site. Due to the long-time relationship of one of the authors we could assess AICO with a unique source of insight (Patton 1990). Our primary data in the form of interviews were collected between December 2019 and March 2020 with representatives across all functions to gain a holistic view of AICO. We ensured that key functions who had taken part during the venture creation process were interviewed. We selected our interviews following snowball sampling to obtain an adequate set of interviewees (Myers and Newman 2007). Triangulating our data with multiple data sources including interviews, observations made during site visits, meeting observations, and secondary data (e.g., internal presentations and public statements) helped us follow the interpretive research principles of researcher-subject interaction, suspicion, and multiple interpretations (Klein and Myers 1999). Table 1 summarizes our collected data:

Primary Data (Interviews: n=14)				
Role		Years in venture	Number of interviews	Duration (hours)
1	Chief Technology Officer (CTO)	3.2	1	1:05
2	Chief Medical Officer (CMO)	2.0	2	0:58
3	Chief Research Officer	2.4	1	0:45
4	Head of Product	2.7	2	2:08
5	Head of Operations	2.2	2	1:57
6	Product Design Lead	1.0	2	0:54
7	Business Development Manager	0.9	1	1:56
8	Software Engineering Lead	2.2	1	0:45
9	Machine Intelligence Engineer	1.5	1	0:49
10	Regulatory Affairs Manager	1.4	1	1:10
40% of the employees interviewed		*(μ=2.0)*	*Σ=14*	*Σ=11:22 (μ=0:52)*
Secondary Data				
Site visits: n=91		91 site visits between August 2019 and April 2020		
Meeting observations: n=3		UX meeting (1); Data and AI meeting (1); Product demo (1)		
Archival documents: n=18		Presentations (5); Write-ups (10); Public statements (3)		

Table 1. Collected data

Data Analysis

To analyze the data, we followed the well-established recommendations of Corbin and Strauss (1990). Specifically, we pursued step-wise coding, which consisted of open, axial, and selective coding to elaborate on the actualization of affordances and their organizational actions and actualized outcomes. In the open-coding stage, codes emerged through case write-ups and summaries which were used to condense the transcripts hence to obtain an initial overview of all case data (Yin 2003). Codes were initially developed inductively due to the novelty of the topic. In the axial coding stage, we condensed the data based on the dimensions of the affordance theory. Along with the three generic phases of prospecting, developing, and exploiting (Bakker and Shepherd 2017; von Briel, Recker, et al. 2018), we identified relevant aspects of the venture creation process. In doing so, we detailed the AI and non-AI material properties of the digital artifact along the venturing process of AICO. We aggregated emerging codes to identify recurring themes. Selective coding allowed us to finally sharpen our focus on the relations between the identified concepts. To analyze the data and systematically manage the collected data, we used ATLAS.ti as our computer-assisted qualitative data analysis software. During coding, we continuously corroborated the detailed insights derived from analyzing the interviews by constantly comparing and triangulating these insights with the results obtained from analyzing the internal (e.g., internal presentations) and external case material (e.g., public statements). We deemed this step as crucial as one of the authors was deeply engaged at the practices at the site to avoid any potential bias during data analysis. To validate our results, we draw on iterative discussions of all researchers according to Forman and Darmschroder (2007) after each coding iteration, and we seized our primary empirical data as well as the available secondary data (see Table 1). Further, to ensure validity and reliability, we were constantly aware that interview statements could be subject to personal bias and related to the roles of the interviewees.

Results

Our data analysis is categorized along the three phases prospecting, developing, exploiting (Bakker and Shepherd 2017; von Briel, Recker, et al. 2018) AICO underwent to achieve digital innovation from AI. We labeled these phases as Prospecting AI, Developing AI, and Exploiting AI. In each phase, we show how AICO came closer to a marketable AI-enabled digital product, and the challenges it experienced in the process.

Phase 1: Prospecting AI (April 2017 - April 2018)

In the first phase, *Prospecting AI*, AICO searched for the ideal use case to be solved with AI. The venture studio out of which AICO would later be spun off aims to build the next generation of 'category leaders' across different industries by leveraging AI. As the CEO of the venture studio said: *"AI is a general-purpose technology capable of creating at least as much value and disruption as the Internet has so far."* In April 2017, the venture studio reviewed more than 400 AI use cases across many industries. It identified healthcare as a target industry in which to create a digital venture. Building on these findings, an entrepreneur and a machine intelligence engineer examined AI use cases for healthcare.

Anomaly Detection for Chest CT

After generating many ideas for use cases, building on the analyses of the venture studio, AICO identified the chest computed tomography (CT) use case, by which it would help radiologists find anomalies in chest CT scans. It was met by the enthusiasm of radiologists in the field and decided to focus on developing an AI system for it. The system was supposed to use image recognition to identify anomalies. However, after promising a performant model to potential users, the team failed to develop one that matched the expectations of radiologists. Radiologists expected a more accurate model than the one presented by AICO. Thus, the initial promise to deliver such a safe model in only a few months was not held. The Chief Medical Officer later commented on the events: *"At the time, the team overestimated the difficulty of using machine learning for Thorax CT, and even more so the time it would take to implement it."*

Computer-Aided Detection (CAD) for Diagnostic Mammography

In September 2017, today's CEO, CTO, and Head of Product were hired. As of today, they are all still part of AICO, hence we call them AICO from hereon. Again, AICO started prospecting a broader set of around 100 potential radiology AI use cases. It initially performed desk research, and then tested a set of use cases through interviews with radiologists and by checking the feasibility of potential AI models. The analysis resulted in around 10 potential use cases, including the analysis of prostate x-rays, lung CT scans, the detection of age-related macular degeneration, and other eye diseases from ocular CT and retina scans, as well as diagnostic mammography. The use cases were evaluated based on criteria in three categories: (1) addressing a user need, (2) allowing for a financial business case that meets the expectations of venture capitalists, and (3) being feasible. After narrowing down the set of use cases with desk research, the team increasingly involved radiologists in the prospecting process. As the Chief Medical Officer said: *"The team started to enter into a close dialogue with radiologists and build partnerships with radiology centers, who provided us with data to start testing models for their use cases in return for potential future value from our machine learning models."*

In November 2017, AICO began to build an initial user interface (UI) for two purposes: Firstly, to understand radiologists, how they work, and what their needs are, and secondly, to start annotating and labeling data by letting radiologists work with the UI. Importantly, the UI mimicked the tools radiologists were familiar with, and thus imitated their known workflow. The Head of Product later pointed out: *"We started realizing that to be a leading AI company, we need more than just an algorithm. We began to build our annotation tool. Though we used it to annotate our data, our goal was actually to understand how radiologists work. We visited radiologists and asked questions to understand our user."*

Whilst prospecting different use cases, AICO increasingly focused on diagnostic mammography. In that domain, it tested whether it could build an AI model that would help radiologists find cancer in mammograms, so-called computer-aided detection (CAD). CAD generates boxes around anomalies in mammograms. This was not new in principle, though AICO hoped to use the latest technologies to outperform established solutions. After more closely examining the CAD use case for diagnostic mammography, AICO realized four shortcomings. First and foremost, it was questionable whether CAD provided an adequate business case for a high-growth startup seeking venture capital funding. Although some companies have already proven that CAD is monetizable, simply reducing the number of missed cancers did not add enough financial value for radiology centers. Second, some radiologists were skeptical of the efficacy of CAD. This was because, historically, CAD had not been accurate enough, and radiologists were aware of studies showing that CAD can slow them down and also increase false positives. Third, diagnostic mammography contains a lot of edge cases, which made it difficult for AICO to create an algorithm that performs well. The Chief Medical Officer explains: *"Diagnostic mammography is a difficult task for machine learning, as it contains many edge cases, that is cases that contain "special" and "rare" cancers - complex pathologies, cancers, and so on. That makes it difficult to train an algorithm, as it is not trained on all cases it could later encounter."* The fourth shortcoming was related to the publicly available data set for diagnostic mammography AICO was using. This data set had quality issues. For example, it contained film mammograms, which have lower technical quality and make it more difficult to train the model. For these reasons, AICO discarded CAD for diagnostic mammography and had yet to find a suitable use case. Consequently, a re-evaluation of the AI use cases began.

Eliminating Normal Cases in Screening Mammography

In February 2017, AICO started the re-evaluation of the AI use cases it had explored so far. The Chief Medical Officer summarized the challenge the venture faced at the time: *"The key requirement was always that we needed a pain point, and based on that a market size. If we didn't find a pain point, we couldn't start [developing a product and scaling the venture]."* The re-evaluation considered the learnings AICO had made. Accordingly, the Head of Operations recalled: *"We built detailed spreadsheets, examined value chains, and evaluated use cases with a scoring model. This resulted in the hypothesis that mammography screening provides the most value."*

In mammography screening, women are screened asymptomatically, i.e., without showing any symptoms. Usually, breast cancer screening is performed on an entire population of women within a certain age range, e.g., 45-70 years in a regular time interval, usually two years. There is a global shortage of breast cancer screening radiologists. This leads to a high workload, which puts a burden on screening radiologists. In combination with the low cancer incidence in a screening setting (less than 1% because it is asymptomatic, compared to 40% or more in diagnostic mammography), their work is highly repetitive. As a consequence, the job is tiring. It is also error-prone, as radiologists are biased towards not finding cancer, which causes false negatives, i.e., a lower sensitivity. Thus, the key difference of screening compared to diagnostic mammography is that it offers AICO an opportunity to create synergies between radiologists and AI by automating the repetitive and error-prone detection of normal exams and allowing radiologists focus their skills on complex cases. Importantly, this value translates into a more attractive business case for the venture, as the Head of Operations points out: *"What is the value of not missing cancer [the value that CAD offers]? You might be able to save court costs. But you don't have a direct added value. However, if you decrease the time a radiologist needs to read and report cases by 20%, then you are generating value."* For these and further reasons such as, e.g., greater data availability, AICO decided to develop an AI solution in screening mammography in April 2018.

Phase 2: Developing AI (April 2018 - September 2019)

Building a Certified Medical AI Product

The pivot to mammography screening in April 2018 was the beginning of the second phase, *Developing AI*. This phase centered around developing and certifying the product. AICO needed to make the algorithm appear value-promising to the user, build a business model around that is satisfiable for investors, and stay within the legal boundaries, (Note that doctors in Germany still need to make the final diagnostic decision themselves due to the so-called "Arztvorbehalt", or "medical reservation".) Competitors simply added AI to already existing workflow solutions as plug-ins. However, AICO realized that this was not a viable option to gain a competitive advantage. The Head of Product said: *"In April 2018, we hired our first designer. That was when we noticed how the existing software was not optimized for human-machine collaboration."* Besides design issues, a simple plug-in did not allow AICO to collect data with its product, although this is considered to be a crucial part of the aspired AI business model. Being in control of the workflow and thereby collecting data are prerequisites for AICO to achieve their vision to extend along the entire patient journey in the future. Such a vision was important to raise capital, the Product Design Lead explained: *"AI is just a tool. If you want to be successful [in the market], you need to build a product around AI."* Based on this assumption, AICO rebuilt the entire radiology workflow to optimize it for AI. In doing so, it combined both AI-enabled and non-AI-enabled features. The two AI-enabled features are a worklist that can be sorted by normal vs. potentially suspicious cases, and pre-filled reports for normal cases that contain the decision of the algorithm and can be submitted with one click. The non-AI feature is a radiology viewer that radiologists can use to mark findings. Subsequently, the system can generate reports automatically. During the development of the product, AICO was able to achieve synergies between its annotation tool and the final product. Importantly, it had already certified its annotation tool as a CE-marked medical device and could use parts of its quality management system documentation for the certification of its final product, which it successfully certified in September 2019.

By the end of the development in September 2019, the product was able to rule out 50% of all normal cases at a sensitivity of 99%. In other words, out of 100 cancers, the product only misses one. With a cancer incidence of 0.6% in a mammography screening setting, this implies that the algorithm makes a mistake (i.e., tags a cancer case as normal) every 160'000 cases. This is more accurate than manual screening by radiologists, whose sensitivity is around 60-90%. The model performance is due to AICOs efforts in data acquisition and annotation as well as due to comprehensive development, training, and evaluation of its model. We elaborate on these points in the following.

Building the Machine Learning Model: Improving the Data Set and the Algorithm

Before AICO decided to pivot to mammography screening in April 2018, it had taken a pragmatic approach to developing the AI system. It tested the general feasibility of AI for the different use cases with 'minimum viable models'. However, its model did not have the performance needed to provide value to radiologists. The CTO explains: *"If calibrated at a radiologist-level sensitivity of 80%, our model would not have been able to identify any cases as normal, i.e., it had an elimination rate of 0%."* Though the machine learning algorithm itself had its limitations, the main reason for the performance gap was the low quality of the dataset. This was caused by deficiencies in both the data acquisition and the data annotation process, which we detail in the following. In terms of data acquisition, AICO used public data sources. It had also built first partnerships with teleradiology groups who provided their data in exchange for potential future business value through AI. However, these data sets were small and did not contain enough "edge" cases. In terms of data annotation, there were two problems. The first problem of the data annotation process was that it was unprofessional, as the Head of Operations recalls: *"For our first annotations we were using 'JotForm', which is like SurveyMonkey. The annotations were not clinically accurate, and the process was not scalable. But the even greater problem was that there were neither guidelines nor did we train radiologists. Nor were there any control mechanisms."* The second problem of the data annotation process was that it lacked domain knowledge, as it was working with general radiologists rather than radiologists specialized in mammography screening. To resolve these problems, AICO initiated a series of meetings, as the CTO recalled: *"We carried out a 'specathon', a series of meetings in which we specified the requirements for the machine learning model and data."*

The specathon helped AICO formulate requirements for its data set. This led to several initiatives to acquire data. First, AICO started by creating a dedicated Head of Data Operations role (taken on at that time by the current Head of Operations), who was responsible for managing data collection efforts. Second, this, in turn, led to partnerships signed with 10 providers across Europe. As in most cases, the data was stored on local hard disks, thus the team needed to travel to the centers to collect the data and to upload it to the AICO cloud. Besides the initiatives taken to acquire data, AICO took various measures to improve annotation. The Head of Operations built a network of 15 freelance radiologists working remotely to annotate data. He said: *"At peak times, our 15 freelance radiologists produced between 4'000 and 5'000 annotations per month."* To manage the freelance radiologists, AICO defined a process, developed corresponding guidelines, and trained radiologists. Moreover, it advanced its proprietary annotation tool and tailored it to mammography screening. This allowed AICO to perform analytics within their annotation process. For instance, it became visible which data was still needed, how productive the annotation workforce was, and it allowed AICO to assign tasks to radiologists. Additionally, the annotations were uploaded to the cloud.

By December 2018, AICO compiled Europe's largest mammography screening data set. The set contained 2 million mammograms. This included 8'000 cancer cases, which had a ground truth from biopsies. This is highly important because the algorithm needs to be trained on actual rather than on assumed cases of cancer. Since then, the data set grew and further initiatives led to the improvement of the model's performance, as summarized by the CTO: *"Largely due to the efforts related to our data set, our performance improved. At the beginning of 2019, we were able to classify 25% of all cases as normal at the sensitivity of a radiologist."* Besides providing the initial system performance it is necessary to continuously evaluate the model performance and to check the quality of data sets from a medical perspective. A machine intelligence engineer explained: *"From time to time, we do what we call 'fishing', where our medical and machine learning team come together and systematically look for mistakes the algorithm makes. We then examine the underlying data, and find improvements we need to make to the overall data set to increase the medical accuracy."* To further improve the model, AICO advanced the algorithm by constantly "tweaking" it, and by developing entirely new models. For example, AICO started to develop a proprietary algorithm in Spring 2019. Cumulatively, these efforts resulted in a rule-out of 50% at 99% sensitivity by September 2019.

Phase 3: Exploiting AI (September 2019 - May 2020)

Currently, AICO is in the *Exploiting AI* phase. It is releasing its product in a so-called closed commercial release. Currently, the product is being deployed and used at around ten radiology centers.

Distributing the Product and Extending It with a Safety Net

As the distribution and deployment of the product began in September 2019, AICO faced the challenge of how to communicate its value proposition to users. Because of the relatively long history of AI in breast cancer screening, users have a preconception of the AI functionalities. CAD has seemed to develop into a synonym for AI in the field, the Head of Operations reported: *"Radiologists know AI in the form of CAD. Our approach is something new that changes the workflow of radiologists. Because of this, it is challenging to explain to radiologists."* Additionally, it found that radiologists have two 'personas', a Business Development Manager said: *There are two types of radiologists: The confident and the insecure. The insecure use of CAD to avoid missing cancers. These radiologists missed the CAD feature in our solution. The others, however, do not want CAD. Therefore, we needed to find a way to suit both types of users.* To make the product valuable for both personas, AICO is currently developing a Safety Net feature. It is a way of providing decision-support for cancer detection while at the same time avoiding a large number of false positives. The feature only appears if a radiologist assesses a case as inconspicuous, although it is likely to be suspicious from a technical viewpoint. In this case, the feature indicates a notification to the user. By doing so, it is supposed to avoid both a large number of false positives as well as slowing down the user. For this reason, it is different from existing CAD solutions. It can be switched on optionally.

Discussion and Implications

Countering AI-caused Tensions in Digital Venturing

To address the research question "*How do digital ventures realize digital innovation from AI by embedding AI into products and services?*", we conducted an in-depth case study that illustrates how a digital venture recursively shapes a digital artifact to create affordances for its potential users, thereby attempting to improve the problem-solution design pair of the digital artifact and the user's needs (cf. Nambisan et al., 2017). Our case study reveals four AI-caused tensions that AICO encountered in the venture creation process. Countering these tensions has been crucial for AICO to embed AI in its digital product and therefore to realize digital innovation. Table 2 below shows the tensions and counteractions.

Managing Over-Expectations of AI (Countering Tension #1)

The first tension is a dyad between the presumed affordances of AI and its implementation speed versus the actual effort to leverage Narrow AI capabilities. More specifically, AI was initially seen as a valuable opportunity to create a venture, triggering the venture creation process. While AICO first believed it could free radiologists from the task of finding and reporting cancers in medical images, it realized over time that it was neither legally nor technically possible to do so, which somewhat sobered the views AICO had of AI. It forced AICO to focus on incremental affordances and to start combining AI with other digital technologies. Put differently, AICO needed to manage its initial over-expectations of AI and shift from a pure technology push to more of a product-oriented mindset. Thus, throughout the venturing process at AICO, the perception and role of AI changed dramatically. AICO encountered numerous challenges (Chest CT did not work; public data sets did not create a performant model fast; simply automating AI does not work because of legal and performance constraints; etc.), and the corresponding perpetual business case and user affordance reassessment made clear that the value AI promises might not be as easily achievable and could not be achieved with AI alone. For example, merely automating the recognition-task does not result in a market-ready product, much less a business model. Thus, it became clear over time that what had to be built was not AI as such, but an AI-enabled system that both performs reliably and facilitates human-machine collaboration. Hence, the venture-focus shifted from 'what to build' towards 'how to achieve value' for radiologists.

Designing Work Routines for AI (Countering Tension #2)

The second tension is the dyadic relationship between adding AI to a current workflow versus redesigning the workflow based on AI capabilities. Simply focusing on the task that Narrow AI can solve within the current user workflow stands in contrast to rethinking the entire workflow, within which AI takes a relatively narrow function. Our study suggests that to create such a collaborative system a digital venture needs to design an artifact in a way that creates affordance that improves the working routines and patterns of the user. This is in line with Davenport and Kirby (2015), who see a collaborative approach between machines and employees as promising for the future with the potential to result in a competitive advantage. Thus, for AICO, it was not enough to simply incorporate AI into an existing workflow, as existing workflows did not allow the value of AI to realize. AI-enabled systems need to be designed to translate the capabilities of AI (e.g., automation, or detection) to affordance for the user - always considering the socio-technical context and in particular the existing work routines. For example, as in our case, if a user needs to save time, simply making a recommendation is not enough, as his job is both to read (AI can help to detect) and report (IS can translate the decision and other data to an automatically generated report).

Addressing Opposing User Perceptions of AI (Countering Tension #3)

The third tension arises from dyadic user perceptions between AI as an opportunity versus AI as a threat. Our case revealed that radiologists have different associations towards the emotive word 'AI'. While the same AI feature (CAD) created value opportunities for some (e.g., finding cancer, not missing cancer), it created negative value for others (e.g., biased towards cancer, slowed down). Thus, AI can have a double-sided role and needs to be included as an artifact under careful consideration thereof. Similarly, AICO needed to carefully think of how it creates AI value not simply by considering the value resulting directly from the AI feature itself (tagging of normal cases), but also by how the decision is aesthetically conveyed to the user (streamlined list of normal cases, simple interface conveying the AI output), and to what degree the user is made aware of the presence of AI at all (value communication during the Exploiting AI phase).

Integrating Domain Expertise with AI (Countering Tension #4)

The fourth tension is a dyad between uncontextualized Narrow AI on one side, which is generative and has a low specificity, and contextualized Narrow AI on the other, which has high specificity. Our case reveals that over time AI increasingly requires the representation of domain expertise in the data so that the algorithm reaches sufficient performance, i.e., accuracy. Moreover, the interface needs to be aligned with the medical-professional context to allow for affordance actualization for radiologists. AICO realized it needed to understand the breast cancer screening process as well as the tasks of screening radiologists. It needed to incorporate specific medical knowledge into the process of specification, data acquisition, pre-processing, development and training, evaluation, and deployment of its machine learning model. The need to integrate domain expertise into the AI development process meant AICO shifted from exploring different AI models and technologies through the provision of open-source AI resources and services (e.g., public data sets, models, or cloud services) to proprietarily acquiring and annotating data, and developing models. AICO managed this by leveraging its proprietary annotation tool, receiving data from partners in exchange for potential future value, and by involving third-parties (i.e., freelance radiologists) in the development process. This shows how digital technologies and artifacts as well as new forms of organizing for innovation are beneficial along the digital innovation process.

Managing Over-Expectations of AI (Countering Tension #1)		
Pole 1 Particularities of AI	**Pole 2** Particularities of AI	**Countering of AICO**
Expected high affordance of AI • Fuzziness of the term AI • Ability to solve human-level cognitive tasks • Learning capabilities	**Realizable limited affordance of AI** • Narrow AI: Single task with narrow scope • Higher realization effort • Legal constraints	• Shift of focus from technology to product • Recognition that "AI is just a tool" • Recursive shaping of user base (in search of a user-feature fit)
Designing Work Routines for AI (Countering Tension #2)		
Affordance of current workflows with AI • AI can be integrated in existing workflow • Narrow AI leads to task rather than workflow focus	**Affordance potential of new workflows enabled by AI** • AI enables new productivity-focused workflow • Human-machine collaboration enabled through AI	• Developing a product that includes aspects of the traditional workflow and leverages AI in an improved workflow
Addressing Opposing User Needs (Countering Tension #3)		
Users perceive AI as affordance • Cognitive augmentation • Improved productivity	**Users perceive AI as constraint** • Cognitive bias • Perceived threat	• Balancing opposing user needs by developing a set of in some cases optional AI-enabled features
Integrating Domain Expertise with AI (Countering Tension #4)		
Generic use of Narrow AI • High accessibility of generic models and data • Low performance without contextualization • Easy to implement	**Specific use of Narrow AI** • Complex modeling and data requirements • High performance with contextualization • Complex to implement	• Initial broad exploration • Gathering of ground-truth data via a network of radiologists • 'Fishing': Medical and machine learning team improving data

Table 2. Tensions: Poles, AI particularities leading to tension, and mitigation of AICO

Implications

Theoretical Implications

Our contribution to theory is threefold. First, we contribute to the body of knowledge on digital innovation. We show that AI as a low-specificity, general-purpose digital technology triggers diverse new venture ideas and innovation (technology push) (Ciriello et al. 2018; Wiesböck and Hess 2020). The need for specificity increases as the venture creation process matures and developing activities prevail. This may be owed to the nature of Narrow AI, which focuses on specific tasks in bounded contexts (Stone et al. 2016). We also see that AI is loosely coupled with the other parts of the AI-enabled system and rather perpetual, which supports propositions that such characteristics may require a diverse set of input factors, causing tensions in the venture creation process (von Briel, Recker, et al. 2018). Convergence enables the combination of user experiences (Yoo et al. 2012). From this perspective, AI is just a feature and plays a subordinate role. However, the technology push of AI causes superordinate artifact creation. From a broader perspective, we may also contribute to ongoing discussions on the role of digital technologies as a means and end to digital innovation (Ciriello et al. 2018). AI can make use of digital technologies both in its development (as a means) and to make it accessible to the user. Second, our research uses affordance theory as an individual-level perspective to analyze digital venture creation. Digital ventures are means to an end for digital innovation and digital innovation is triggered by digital technology. In our case, the (technically necessary) task-relatedness of Narrow AI requires user-centric venturing to create a valuable digital artifact. This perspective may contribute to broadening the application range of affordance theory, especially within the scope of Narrow AI. Third, we contribute to research on human-machine collaboration from a socio-technical perspective by offering a view of the intricacies that AI brings. We complement literature that has mainly focused on the creation of affordance and neglects the necessity to reduce constraints as well (Volkoff and Strong 2013). Further, our case underlines the view of Pentland and Feldman (2008) that "[a]rtifact-centered assumptions about design not only reinforce a widespread misunderstanding of routines as things, they implicitly embody a rather strong form of technological determinism" (p. 235). Moreover, we show that AI-enabled systems may have multiple affordance dimensions that are key to affordance-creation in artifacts (Rafaeli and Vilnai-Yavetz 2004): instrumentality, aesthetics, and symbolism. In this regard, our findings are in line with the extant body of knowledge on AI and analytics (cf. Davenport 2014; Dremel et al. 2020; Kunene and Weistroffer 2005).

Practical Implications

Derived from the four identified tensions and counteractions, we provide four implications for practitioners. First, we suggest having a more realistic view of the value that AI can bring. While it is undeniable that AI is an opportunity and an inspiration for new venture ideas, digital ventures should acknowledge that to realize digital innovation from AI it is not enough to develop an AI system. Rather, they need to take a product view on AI and think about ways in which AI can add value to the user and the workflow, and how it is integrated into an overall AI-enabled system. Second, to unlock the full potential of AI, when developing AI-enabled systems, we recommend practitioners to consider how AI can change work routines and patterns. In contrast to simply integrating AI in existing workflows, AI likely requires the careful design of patterns and routines that allow companies to leverage AI's full potential. Third, practitioners should beware that AI might be perceived differently by different users, creating value for some, and limitations for others. For addressing this relational ontology of agent(s) and an artifact, the socio-material perspective may help improve our knowledge for AI-specific intricacies. This may guide a more flexible view of how AI may be included in a product. Fourth, we highlight the importance of the balancing act between recognizing the general-purpose technology AI is and contextualizing it in a domain. Realizing digital innovation from AI means closely considering the domain it is intended to create value in, at least in current times of Narrow AI.

Conclusion

In this paper, we shed light on the role of AI in digital innovation and how it affects the venture creation process. To achieve this, we constructed our theoretical model based on AI, digital innovation and digital ventures, and affordance theory. We analyzed and discussed an in-depth case study covering three years of venturing at a medical imaging AI company. We found that AI causes four tensions to arise in the venture creation process, which AICO countered in four ways: (1) Managing Over-Expectations of AI, (2) Designing Work Routines for AI, (3) Addressing Opposing User Needs of AI, and (4) Integrating Domain Expertise with AI. Consciously countering the tensions may be beneficial for digital ventures to create digital innovation from AI. Our work contributes to understanding the role of AI as an artifact and how its particularities influence digital venture mechanisms. We hope that we can contribute in a meaningful way to understanding and realizing digital innovation from AI in practice.

Finally, future studies could build on four limitations of our work. First, we draw on a single case study in the context of a digital venture. We acknowledge the fact that, so far, there is no evidence to claim uniqueness or generalizability of the identified tensions, neither in digital venturing nor in other contexts (e.g., well-established incumbents). However, we think that future research could validate our tensions in AI-related digital innovation processes either in other venturing contexts or in intra-entrepreneurship activities in well-established incumbents. Second, AICO's final realization of digital innovation is naturally not proven, being a fairly young venture. Future research could build on our identified tensions with more mature companies on a larger scale and productive use. Third, we study the user and affordances from the viewpoint of AICO. Future research could benefit from studying the user first hand. Fourth, from the outset, AICO focused on supervised learning for an image recognition task. Future research could include other AI algorithms and tasks to derive more generalizable results.

References

Autio, E., Nambisan, S., Thomas, L. D. W., and Wright, M. 2018. "Digital Affordances, Spatial Affordances, and the Genesis of Entrepreneurial Ecosystems," *Strategic Entrepreneurship Journal* (12:1), Wiley Online Library, pp. 72–95. (https://onlinelibrary.wiley.com/doi/abs/10.1002/sej.1266).

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., and Zhao, J. L. 2016. "Transformational Issues of Big Data and Analytics in Networked Business," *MIS Quarterly* (40:4). (https://pdfs.semanticscholar.org/0fc1/5b775475b97c5e29d1422af5df6afef8e446.pdf).

Bakker, R. M., and Shepherd, D. A. 2017. "Pull the Plug or Take the Plunge: Multiple Opportunities and the Speed of Venturing Decisions in the Australian Mining Industry," *Academy of Management Journal* (60:1), Academy of Management, pp. 130–155. (https://doi.org/10.5465/amj.2013.1165).

Benbya, H., Pachidi, S., Davenport, T., and Jarvenpaa, S. 2019. *Call for Papers Journal of the Association for Information Systems (JAIS) -MISQ Executive (MISQE) Joint Special Issue on Artificial Intelligence in Organizations: Opportunities for Management and Implications for IS Research*.

Berente, N., Gu, B., Recker, J., and Santhanam, R. 2019. "Call for Papers MISQ Special Issue on Managing AI," *MIS Quarterly*.

Beverungen, D., Müller, O., Matzner, M., Mendling, J., and vom Brocke, J. 2019. "Conceptualizing Smart Service Systems," *Electronic Markets* (29:1), pp. 7–18. (https://doi.org/10.1007/s12525-017-0270-5).

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., and Venkatraman, N. 2013. "Digital Business Strategy: Toward a Next Generation of Insights," *MIS Quarterly* (37:2), Management Information Systems Research Center, University of Minnesota, pp. 471–482. (http://www.jstor.org/stable/43825919).

Boland, R. J., Lyytinen, K., and Yoo, Y. 2007. "Wakes of Innovation in Project Networks: The Case of Digital 3-D Representations in Architecture, Engineering, and Construction," *Organization Science* (18:4), INFORMS, pp. 631–647. (https://doi.org/10.1287/orsc.1070.0304).

von Briel, F., Davidsson, P., and Recker, J. 2018. "Digital Technologies as External Enablers of New Venture Creation in the IT Hardware Sector," *Entrepreneurship Theory and Practice* (42:1), pp. 47–69. (https://doi.org/10.1177/1042258717732779).

von Briel, F., Recker, J., and Davidsson, P. 2018. "Not All Digital Venture Ideas Are Created Equal: Implications for Venture Creation Processes," *The Journal of Strategic Information Systems* (27:4), pp. 278–295. (https://doi.org/10.1016/j.jsis.2018.06.002).

Bughin, J., Seong, J., Manyika, J., Chui, M., and Joshi, R. 2018. "Notes from the AI Frontier: Modeling the Impact of AI on the World Economy," *McKinsey Global Institute*, caii.ckgsb.com. (http://caii.ckgsb.com/uploads/life/201904/23/1555983100203053.pdf).

Chui, M. 2017. "Artificial Intelligence the Next Digital Frontier?," *McKinsey and Company Global Institute* (47), calpers.ca.gov, pp. 3–6. (https://www.calpers.ca.gov/docs/board-agendas/201801/full/day1/06-technology-background.pdf).

Ciriello, R. F., Richter, A., and Schwabe, G. 2018. "Digital Innovation," *Business & Information Systems Engineering* (60:6), pp. 563–569. (https://doi.org/10.1007/s12599-018-0559-8).

Corbin, J. M., and Strauss, A. 1990. "Grounded Theory Research: Procedures, Canons, and Evaluative Criteria," *Qualitative Sociology* (13:1), Springer, pp. 3–21. (https://idp.springer.com/authorize/casa?redirect_uri=https://link.springer.com/article/10.1007/BF00988593&casa_token=6WEL8RAFdMkAAAAA:lkRXkL7sJJigEEgeavs70w4i2e3M-bEVIK0Wk_SHqQddD1M9loywfvG2040gpkO7M6Glls4bAhxTJCM).

Davenport, T. 2014. *Big Data at Work: Dispelling the Myths, Uncovering the Opportunities*, Harvard Business Review Press. (https://play.google.com/store/books/details?id=apjBAgAAQBAJ).

Davenport, T. H. 2018. "From Analytics to Artificial Intelligence," *Journal of Business Analytics* (1:2), Taylor & Francis, pp. 73–80. (https://doi.org/10.1080/2573234X.2018.1543535).

Davenport, T. H., and Kirby, J. 2015. "Beyond Automation," *Harvard Business Review* (93:6), pp. 58–65.

Davidsson, P. 2015. "Entrepreneurial Opportunities and the Entrepreneurship Nexus: A Re-Conceptualization," *Journal of Business Venturing* (30:5), pp. 674–695. (https://doi.org/10.1016/j.jbusvent.2015.01.002).

Dremel, C., Herterich, M. M., Wulf, J., and vom Brocke, J. 2020. "Actualizing Big Data Analytics Affordances: A Revelatory Case Study," *Information & Management* (57:1), p. 103121. (https://doi.org/10.1016/j.im.2018.10.007).

Eisenhardt, K. M. 1989. "Building Theories from Case Study Research," *Academy of Management Review. Academy of Management* (14:4), Academy of Management, pp. 532–550. (https://doi.org/10.2307/258557).

Forman, J., and Damschroder, L. 2007. "Qualitative Content Analysis," in *Empirical Methods for Bioethics: A Primer* (Vol. 11), Advances in Bioethics, L. Jacoby and L. A. Siminoff (eds.), Emerald Group Publishing Limited, pp. 39–62. (https://doi.org/10.1016/S1479-3709(07)11003-7).

Geels, F. W. 2004. "From Sectoral Systems of Innovation to Socio-Technical Systems: Insights about Dynamics and Change from Sociology and Institutional Theory," *Research Policy* (33:6), pp. 897–920. (https://doi.org/10.1016/j.respol.2004.01.015).

Goasduff, L. 2019. "Top Trends on the Gartner Hype Cycle for Artificial Intelligence, 2019," *Gartner*, September 12. (https://www.gartner.com/smarterwithgartner/top-trends-on-the-gartner-hype-cycle-, accessed April 17, 2020).

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., and Feldberg, F. 2017. "Debating Big Data: A Literature Review on Realizing Value from Big Data," *The Journal of Strategic Information Systems* (26:3), pp. 191–209. (https://doi.org/10.1016/j.jsis.2017.07.003).

Henfridsson, O., and Bygstad, B. 2013. "The Generative Mechanisms of Digital Infrastructure Evolution," *MIS Quarterly* (37:3), Management Information Systems Research Center, University of Minnesota, pp. 907–931. (http://www.jstor.org/stable/43826006).

Huang, J., Henfridsson, O., Liu, M. J., and Newell, S. 2017. "Growing on Steroids: Rapidly Scaling the User Base of Digital Ventures through Digital Innovation," *MIS Quarterly* (41:1). (http://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=02767783&AN=121204234&h=fchKOFcqxB50ASiNRVLzkK2s29FLnI%2BEspLZcCpLcdnIQ3I4%2B8SfgWYAGv5Yrcgq%2FJUj5l3GKpjWzFLSuEvfTQ%3D%3D&crl=c).

Hutchby, I. 2001. "Technologies, Texts, and Affordances," *Sociology* (35:2), Cambridge University Press, pp. 441–456. (https://doi.org/10.1017/S0038038501000219).

Kallinikos, J., Aaltonen, A., and Marton, A. 2013. "The Ambivalent Ontology of Digital Artifacts," *MIS Quarterly* (37:2), Management Information Systems Research Center, University of Minnesota, pp. 357–370. (http://www.jstor.org/stable/43825913).

Kallinikos, J., and Constantiou, I. D. 2015. "Big Data Revisited: A Rejoinder," *Journal of Information Technology*, pp. 70–74. (https://doi.org/10.1057/jit.2014.36).

Kaplan, A., and Haenlein, M. 2019. "Siri, Siri, in My Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence," *Business Horizons* (62:1), Elsevier, pp. 15–25.

Keller, R., Stohr, A., Fridgen, G., Lockl, J., and Rieger, A. 2019. "Affordance-Experimentation-Actualization Theory in Artificial Intelligence Research – A Predictive Maintenance Story," in *ICIS 2019 Proceedings*. (https://aisel.aisnet.org/icis2019/is_development/is_development/1/).

Kimble, C., and Milolidakis, G. 2015. "Big Data and Business Intelligence: Debunking the Myths," *Global Business and Organizational Excellence* (35:1), pp. 23–34. (https://doi.org/10.1002/joe.21642).

Klein, H. K., and Myers, M. D. 1999. "A Set of Principles for Conducting and Evaluating Interpretive Field Studies in Information Systems," *MIS Quarterly* (23:1), Management Information Systems Research Center, University of Minnesota, pp. 67–93. (https://doi.org/10.2307/249410).

Klotz, A. C., Hmieleski, K. M., Bradley, B. H., and Busenitz, L. W. 2014. "New Venture Teams: A Review of the Literature and Roadmap for Future Research," *Journal of Management* (40:1), SAGE Publications Inc, pp. 226–255. (https://doi.org/10.1177/0149206313493325).

Kohli, R., and Melville, N. P. 2019. "Digital Innovation: A Review and Synthesis," *Information Systems Journal* (29:1), pp. 200–223. (https://doi.org/10.1111/isj.12193).

von Krogh, G. 2018. "Artificial Intelligence in Organizations: New Opportunities for Phenomenon-Based Theorizing," *Academy of Management Discoveries* (4:4), Academy of Management, pp. 404–409. (https://doi.org/10.5465/amd.2018.0084).

Kunene, N., and Weistroffer, H. R. 2005. "Expanding the Knowledge Base for More Effective Data Mining," *ECIS 2005 Proceedings*, p. 58. (https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1069&context=ecis2005).

Lehrer, C., Wieneke, A., vom Brocke, J., Jung, R., and Seidel, S. 2018. "How Big Data Analytics Enables Service Innovation: Materiality, Affordance, and the Individualization of Service," *Journal of Management Information Systems* (35:2), Routledge, pp. 424–460. (https://doi.org/10.1080/07421222.2018.1451953).

Leonardi, P. M. 2011. "When Flexible Routines Meet Flexible Technologies: Affordance, Constraint, and the Imbrication of Human and Material Agencies," *MIS Quarterly* (35:1).

Leonardi, P. M. 2012. "Materiality, Sociomateriality, and Socio-Technical Systems: What Do These Terms Mean? How Are They Different? Do We Need Them," *Materiality and Organizing: Social Interaction in a Technological World* (25), Oxford University Press Oxford. (https://books.google.com/books?hl=en&lr=&id=SEdoAgAAQBAJ&oi=fnd&pg=PA25&dq=leonardi+materiality+sociomateriality&ots=g10L6O4BmW&sig=ObMoRV3lmLHPB6x7m6ymENjH5hk).

Leonardi, P. M. 2013. "Theoretical Foundations for the Study of Sociomateriality," *Information and Organization* (23:2), pp. 59–76. (https://doi.org/10.1016/j.infoandorg.2013.02.002).

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., and Sánchez, C. I. 2017. "A Survey on Deep Learning in Medical Image Analysis," *Medical Image Analysis* (42), pp. 60–88. (https://doi.org/10.1016/j.media.2017.07.005).

Loebbecke, C., and Picot, A. 2015. "Reflections on Societal and Business Model Transformation Arising from Digitization and Big Data Analytics: A Research Agenda," *The Journal of Strategic Information Systems* (24:3), pp. 149–157. (https://doi.org/10.1016/j.jsis.2015.08.002).

Lusch, R. F., and Nambisan, S. 2015. "Service Innovation: A Service-Dominant Logic Perspective," *MIS Quarterly* (39:1). (https://doi.org/10.25300/MISQ/2015/39.1.07).

Lyytinen, K., Yoo, Y., and Boland, R. J., Jr. 2016. "Digital Product Innovation within Four Classes of Innovation Networks," *Information Systems Journal* (26:1), pp. 47–75. (https://doi.org/10.1111/isj.12093).

Manyika, J., Lund, S., Chui, M., and Bughin, J. 2017. "Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation," *McKinsey Global*, voced.edu.au. (https://www.voced.edu.au/content/ngv:78297).

Markus, M. L., and Silver, M. S. 2008. "A Foundation for the Study of IT Effects: A New Look at DeSanctis and Poole's Concepts of Structural Features and Spirit," *Journal of the Association for Information Systems* (9:10), p. 5. (https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1481&context=jais).

Matt, C., Hess, T., and Benlian, A. 2015. "Digital Transformation Strategies," *Business & Information Systems Engineering* (57:5), Springer, pp. 339–343. (https://idp.springer.com/authorize/casa?redirect_uri=https://link.springer.com/article/10.1007/s12599-015-0401-5&casa_token=iK62LW8OBeIAAAAA:JO_91Tq19Ng8Z__HbiDJqR4MGDSYGgtHGPD7Olj79Fb2DwwuqcE11wokKJrwMXsdGLniVM9Le7TNI3TwsQ).

Mikalef, P., Pappas, I. O., Krogstie, J., and Giannakos, M. 2018. "Big Data Analytics Capabilities: A Systematic Literature Review and Research Agenda," *Information Systems and E-Business Management* (16:3), Springer, pp. 547–578. (https://idp.springer.com/authorize/casa?redirect_uri=https://link.springer.com/article/10.1007/s10257-017-0362-y&casa_token=JWPbcw6VuMYAAAAA:u68K7i2ne8kX8f_MUeekvWwzCum1iNXQ3E3bNWbw1sxmcxBXwoyRwmHjvsR0QVKumW7eQK5ygZ2aCtA).

Myers, M. D. 1997. "Qualitative Research in Information Systems," *MIS Quarterly*, p. 241.

Myers, M. D., and Newman, M. 2007. "The Qualitative Interview in IS Research: Examining the Craft," *Information and Organization* (17:1), pp. 2–26. (https://doi.org/10.1016/j.infoandorg.2006.11.001).

Nambisan, S. 2013. "Information Technology and Product/Service Innovation: A Brief Assessment and Some Suggestions for Future Research," *Journal of the Association for Information Systems* (14:4), p. 1. (https://doi.org/10.17705/1jais.00327).

Nambisan, S. 2017. "Digital Entrepreneurship: Toward a Digital Technology Perspective of Entrepreneurship," *Entrepreneurship Theory and Practice* (41:6), SAGE Publications Inc, pp. 1029–1055. (https://doi.org/10.1111/etap.12254).

Nambisan, S., Lyytinen, K., Majchrzak, A., and Song, M. 2017. "Digital Innovation Management: Reinventing Innovation Management Research in a Digital World," *MIS Quarterly* (41:1). (https://www.misq.org/misq/downloads/issue/id/169/).

Orlikowski, W. J. 2000. "Using Technology and Constituting Structures: A Practice Lens for Studying Technology in Organizations," *Organization Science* (11:4), INFORMS, pp. 404–428. (https://doi.org/10.1287/orsc.11.4.404.14600).

Orlikowski, W. J., and Iacono, C. S. 2001. "Research Commentary: Desperately Seeking the 'IT' in IT Research—A Call to Theorizing the IT Artifact," *Information Systems Research* (12:2), INFORMS, pp. 121–134. (https://doi.org/10.1287/isre.12.2.121.9700).

Patton, M. Q. 1990. *Qualitative Evaluation and Research Methods*, SAGE Publications, inc. (https://psycnet.apa.org/record/1990-97369-000).

Pentland, B. T., and Feldman, M. S. 2008. "Designing Routines: On the Folly of Designing Artifacts, While Hoping for Patterns of Action," *Information and Organization* (18:4), pp. 235–250. (https://doi.org/10.1016/j.infoandorg.2008.08.001).

Pozzi, G., Pigni, F., and Vitari, C. 2014. *Affordance Theory in the IS Discipline: A Review and Synthesis of the Literature*. (https://halshs.archives-ouvertes.fr/halshs-01923663/document).

Rafaeli, A., and Vilnai-Yavetz, I. 2004. "Instrumentality, Aesthetics, and Symbolism of Physical Artifacts as Triggers of Emotion," *Theoretical Issues in Ergonomics Science* (5:1), Taylor & Francis, pp. 91–112.

Ransbotham, S., Khodabandeh, S., Fehling, R., La Fountain, B., and Kiron, D. 2019. *Winning With AI*. (https://image-src.bcg.com/Images/Final-Final-Report-Winning-With-AI-R_tcm9-231660.pdf).

Recker, J. 2012. *Scientific Research in Information Systems: A Beginner's Guide*, Springer Science & Business Media. (https://play.google.com/store/books/details?id=LzGbLKxjKHAC).

Reuver, M. de, de Reuver, M., Sørensen, C., and Basole, R. C. 2018. "The Digital Platform: A Research Agenda," *Journal of Information Technology*, pp. 124–135. (https://doi.org/10.1057/s41265-016-0033-3).

Rzepka, C., and Berger, B. 2018. *User Interaction with AI-Enabled Systems: A Systematic Review of IS Research*, presented at the ICIS 2018 Proceedings, December 14.

Saboo, A. R., Kumar, V., and Park, I. 2016. "Using Big Data to Model Time-Varying Effects for Marketing Resource (Re)Allocation," *MIS Quarterly* (40:4). (https://doi.org/10.25300/MISQ/2016/40.4.06).

Schumpeter, J. 1934. "The Theory of Economic Development Harvard University Press," *Cambridge, MA*.

Seidel, S., Recker, J., and vom Brocke, J. 2013. "Sensemaking and Sustainable Practicing: Functional Affordances of Information Systems in Green Transformations," *MIS Quarterly* (37:4), Management Information Systems Research Center, University of Minnesota, pp. 1275–1299. (http://www.jstor.org/stable/43825792).

Sharma, R., Mithas, S., and Kankanhalli, A. 2014. "Transforming Decision-Making Processes: A Research Agenda for Understanding the Impact of Business Analytics on Organisations," *European Journal of Information Systems* (23:4), Taylor & Francis, pp. 433–441. (https://doi.org/10.1057/ejis.2014.17).

Stone, P., Brooks, R., Brynjolfsson, E., and Others. 2016. *One Hundred Year Study on Artificial Intelligence (AI100)*. (https://ai100.stanford.edu/sites/g/files/sbiybj9861/f/ai100report10032016fnl_singles.pdf).

Strong, D. M., Volkoff, O., Johnson, S. A., Pelletier, L. R., Tulu, B., Bar-On, I., Trudel, J., and Garber, L. 2014. "A Theory of Organization-EHR Affordance Actualization," *Journal of the Association for Information Systems* (15:2), p. 2. (https://doi.org/10.17705/1jais.00353).

Traumer, F., Oeste-Reiß, S., and Leimeister, J. M. 2017. *Towards a Future Reallocation of Work between Humans and Machines – Taxonomy of Tasks and Interaction Types in the Context of Machine Learning*, December 10. (https://doi.org/10.2139/ssrn.3159131).

Volkoff, O., and Strong, D. M. 2013. "Critical Realism and Affordances: Theorizing It-Associated Organizational Change Processes," *MIS Quarterly* (37:3), Management Information Systems Research Center, University of Minnesota, pp. 819–834. (http://www.jstor.org/stable/43826002).

Wiener, M., Saunders, C., and Marabelli, M. 2020. "Big-Data Business Models: A Critical Literature Review and Multiperspective Research Framework," *Journal of Information Technology Impact* (35:1), SAGE Publications Ltd, pp. 66–91. (https://doi.org/10.1177/0268396219896811).

Wiesböck, F., and Hess, T. 2020. "Digital Innovations," *Electronic Markets* (30:1), pp. 75–86. (https://doi.org/10.1007/s12525-019-00364-9).

Yin, R. K. 2003. "Case Study Research Design and Methods Third Edition," *Applied Social Research Methods Series* (5), Sage Publications Inc.

Yoo, Y. 2015. "It Is Not about Size: A Further Thought on Big Data," *Journal of Information Technology Impact* (30:1), SAGE Publications Ltd, pp. 63–65. (https://doi.org/10.1057/jit.2014.30).

Yoo, Y., Boland, R. J., Lyytinen, K., and Majchrzak, A. 2012. "Organizing for Innovation in the Digitized World," *Organization Science*, pp. 1398–1408. (https://doi.org/10.1287/orsc.1120.0771).

Yoo, Y., Henfridsson, O., and Lyytinen, K. 2010. "Research Commentary—The New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research," *Information Systems Research*, pp. 724–735. (https://doi.org/10.1287/isre.1100.0322).

Zammuto, R. F., Griffith, T. L., Majchrzak, A., Dougherty, D. J., and Faraj, S. 2007. "Information Technology and the Changing Fabric of Organization," *Organization Science* (18:5), INFORMS, pp. 749–762.