Discovery and Diffusion of Digital Innovations

An Analysis of Enterprise Social Networks and Data-Driven Business Models

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Adrian Engelbrecht

Darmstadt, 16.08.2018

Abstract

Digital technologies radically transform today's organizations as they permeate both innovation processes and outcomes. While the potential of digital innovations is tremendous, many companies hardly realize the extensive benefits of digital technologies so far. Furthermore, the theoretical understanding of digital innovations is limited since scholars started to challenge the assumptions made in traditional innovation research due to digital technologies' affordances. Therefore, this thesis seeks to improve the knowledge about digital innovations by analyzing their discovery and diffusion.

The discovery of innovations relates to the development of ideas, which can result in new products, processes, or business models. It is essential to investigate companies' innovation discovery as they often struggle to create innovative ideas and existing theory rarely incorporates the increasing diversity of employees involved in these processes. Papers A and B of this thesis address these issues by examining how Enterprise Social Networks (ESNs) facilitate employees' innovation discovery. According to Communication Visibility Theory (CVT), the consideration of ESNs is crucial in this regard as they make employees' everyday communication permanently visible, which provides a basis for acquiring new knowledge.

Paper A validates and extends the newly developed CVT. By incorporating individuals employed in diverse contexts, it empirically supports the theory's external validity. Therefore, different companies can draw on ESNs to foster their innovation discovery, which is made possible through improvements in employees' meta-knowledge. Besides, the paper reveals that meta-knowledge is not merely formed in the long-run, as indicated by previous research, but in the short-run as well. Interestingly, it also shows that managers can gain more meta-knowledge using ESNs compared to non-managers, which is in contrast with prior literature's findings.

Paper B investigates when employees disclose information in ESNs, which is essential to attain high communication visibility and, in this way, to facilitate the discovery of innovations. To that end, the paper transfers theory on Online Social Networks (OSNs) to the ESN context. It finds that employees' trusting and risk beliefs are associated with their information disclo-

sure. Additionally, the paper reveals that a company's group and development culture influence these beliefs, with error aversion culture transmitting the effect of development culture.

Innovation diffusion relates to the distribution of a novel product, process, or business model across a group of target users. It is important to better understand the diffusion of digital innovations as companies often lack knowledge about why new offerings are rejected, which limits their chances of counteracting the underlying issues. Furthermore, digital technologies impact the innovation diffusion by blurring industry boundaries and facilitating competition. Papers C and D of this thesis investigate the diffusion of digital innovations in the context of data-driven business models. This context is especially affected by new competition arising across previous boundaries and, thus, necessary to analyze as diverse organizations have high incentives to utilize their data in new ways.

Paper C analyzes which dimensions substantially differentiate between distinct data-driven business models. For this purpose, it leverages practitioners' perceptions of business models obtained from a start-up database. Based on three identified dimensions, the paper creates a taxonomy that classifies the business models into eight ideal-typical categories. The number of business models present in each category provides insights into their diffusion. By offering basic knowledge about the nature of data-driven business models, the paper can be used as a foundation for future research that seeks to dig deeper into this new field and for companies that aim at developing data-driven business models.

Paper D investigates how individuals evaluate data-driven services that are offered by highly diverse companies. Based on a qualitative study, the paper shows that individuals' perception of fit between a service and its provider is crucial for their evaluations. It also reveals the dimensions that influence this perception. Additionally, it explores the consequences that come with a perception of fit. Using these results, the paper offers a new perspective on individuals' service evaluations, which is vital to the diffusion of the services as well as the associated business models and helps organizations in developing and promoting data-driven services.

Abstract (Deutsche Übersetzung)

Digitale Technologien beeinflussen Unternehmen grundlegend, indem sie die Entwicklung von Innovationen unterstützen und Bestandteile der entstehenden Angebote werden. Während das Potenzial digitaler Innovationen unübersehbar ist, haben viele Unternehmen Schwierigkeiten, die Mehrwerte digitaler Technologien umfänglich zu nutzen. Zudem ist das theoretische Verständnis digitaler Innovationen begrenzt, da Forscher begonnen haben, traditionelle Annahmen der Innovationsforschung im Kontext neuer Technologien zu hinterfragen. Das Ziel dieser Dissertation besteht daher darin, das bestehende Wissen über digitale Innovationen durch eine Analyse der Innovationsentdeckung und -diffusion zu verbessern.

Die Entdeckung von Innovationen bezieht sich auf die Generierung von Ideen zur Entwicklung neuer Produkte, Prozesse oder Geschäftsmodelle. Die Untersuchung der Innovationsentdeckung ist wichtig, da es Unternehmen oft schwerfällt, innovative Ideen hervorzubringen. Zudem geht die bestehende Theorie kaum auf die zunehmende Diversität der Beschäftigten ein, die heute Teil vieler Innovationsprozesse ist. Die ersten beiden Artikel dieser Arbeit adressieren diese Aspekte. Sie betrachten im Speziellen, wie Enterprise Social Networks (ESNs) die Entdeckung von Innovationen fördern. ESNs sind für die Entstehung von innovativen Ideen gemäß der Communication Visibility Theory (CVT) relevant, da sie bisher unsichtbare Kommunikation dauerhaft sichtbar machen und so den Aufbau neuen Wissens ermöglichen.

Artikel A validiert und erweitert die neu entwickelte CVT. Durch die Berücksichtigung von Beschäftigten verschiedener Kontexte bestätigt die Studie die externe Validität der Theorie. Demnach können unterschiedliche Unternehmen ESNs verwenden, um die Entdeckung von Innovationen zu unterstützen. Dies wird durch ein verbessertes Metawissen der Beschäftigten möglich. Der Artikel zeigt zudem, dass Metawissen in ESNs nicht nur lang- sondern auch kurzfristig entstehen kann, wodurch die vorangegangene Forschung ergänzt wird. Außerdem wird deutlich, dass Führungskräfte mehr Metawissen in ESNs entwickeln können als andere Angestellte. Dieses Ergebnis steht im Gegensatz zu den Erkenntnissen bisheriger Studien.

Artikel B untersucht, wann Beschäftigte bereit sind, Informationen in ESNs preiszugeben. Die Informationspreisgabe ist wichtig, um eine hohe Sichtbarkeit alltäglicher Kommunikation zu

erreichen, welche die Innovationsentdeckung gemäß der CVT fördert. Im Rahmen des Artikels wird Theorie zu Online Social Networks (OSNs) in den Kontext von ESNs übertragen. Auf dieser Grundlage zeigt sich, dass die Vertrauens- und Risikowahrnehmungen der Beschäftigten ihre Informationspreisgabe beeinflussen. Zudem wirkt sich die Unternehmenskultur in Form der Group und Development Culture auf diese Wahrnehmungen aus, wobei Error Aversion Culture den Effekt der Development Culture mediiert.

Die Diffusion von Innovationen bezieht sich auf deren Verteilung innerhalb einer Zielgruppe. Für Unternehmen ist ein verbessertes Diffusionsverständnis wichtig, um das Verhalten potenzieller Kunden besser zu verstehen und dadurch eine hohe Akzeptanz neuer Angebote sicherzustellen. Darüber hinaus verändern digitale Technologien die Diffusion von Innovationen, indem sie zur Auflösung traditioneller Branchengrenzen beitragen und die Intensität des Wettbewerbs erhöhen. Vor diesem Hintergrund untersucht der zweite Teil dieser Arbeit die Diffusion von datenbasierten Geschäftsmodellen. Diese sind besonders von der branchenübergreifenden Intensivierung des Wettbewerbs betroffen, da verschiedenste Unternehmen starke Anreize besitzen, ihre Daten auf neue Arten zu nutzen.

Artikel C analysiert, welche Dimensionen zur Unterscheidung datenbasierter Geschäftsmodelle geeignet sind. Zu diesem Zweck wird die Wahrnehmung von Experten hinsichtlich der Geschäftsmodelle verschiedener Start-ups untersucht. Darauf aufbauend werden drei Dimensionen zur Entwicklung einer Taxonomie genutzt, mit deren Hilfe die Geschäftsmodelle in acht idealtypische Kategorien unterteilt werden. Die Anzahl der Geschäftsmodelle pro Kategorie weist dabei auf deren Diffusion hin. Dank dieser grundlegenden Erkenntnisse bildet der Artikel eine Basis für zukünftige Forschungen und für Unternehmen, die sich die Entwicklung datenbasierter Geschäftsmodelle zum Ziel setzen.

Artikel D untersucht, wie potenzielle Nutzer datenbasierte Dienstleistungen bewerten, wenn diese von verschiedensten Unternehmen angeboten werden. Eine qualitative Studie zeigt, dass die Wahrnehmung eines „Fits“ zwischen der Dienstleistung und dem Anbieter für die Bewertung der Nutzer entscheidend ist. Der Artikel identifiziert zudem die Dimensionen, die dieser Wahrnehmung zugrunde liegen. Außerdem werden mögliche Konsequenzen eines Fits betrachtet. Auf der Basis dieser Ergebnisse bietet der Artikel eine neue Perspektive hinsichtlich der Bewertung datenbasierter Dienstleistungen, die Unternehmen bei der Entwicklung und Vermarktung dieser unterstützen kann und für die Diffusion der Dienstleistungen und der zugehörigen Geschäftsmodelle wichtig ist.

Content Overview

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List of Abbreviations

AVE	Average Variance Extracted
CA	Cronbach's Alpha
CEO	Chief Executive Officer
CMB	Common Method Bias
CR	Composite Reliability
CV	Control Variable
CVF	Competing Values Framework
CVT	Communication Visibility Theory
ECIS	European Conference on Information Systems
ESM	Enterprise Social Media
ESN(s)	Enterprise Social Network(s)
H	Hypothesis
HTMT	Heterotrait-Monotrait-Ratio
ICIS	International Conference on Information Systems
IS	Information System(s)
IT	Information Technology
M	Mean
MDS	Multidimensional Scaling
OSN(s)	Online Social Network(s)
PLS-SEM	Partial Least Squares Structural Equation Modeling
ProFit	Property Fitting
SD	Standard Deviation
SEM	Structural Equation Modeling
TMS	Transactive Memory System(s)
VHB	Verband der Hochschullehrer für Betriebswirtschaft e.V.
VIFs	Variance Inflation Factors

1 Introduction

"Innovation distinguishes between a leader and a follower."

Steve Jobs, co-founder and former CEO of Apple (Forbes 2013)

1.1 Motivation

Nowadays, organizations can easily access a wide range of digital technologies that have the potential to change previous products and services fundamentally (Yoo et al. 2012). According to Fichman et al. (2014, p. 330), the technological progress has led us into a "golden age of digital innovation." The term "digital innovation" refers to both the use of digital technologies during the innovation process and the outcomes that originate from this process (Huang et al. 2017; Nambisan et al. 2017). A digital innovation outcome has been defined as "a product, process, or business model that is perceived as new, requires some significant changes on the part of adopters, and is embodied in or enabled by IT" (Fichman et al. 2014, p. 330). It is important to note that these innovation outcomes do not necessarily have to be digital to be classified as digital innovations as long as they "are made possible through the use of digital technologies and digitized processes" (Nambisan et al. 2017, p. 224).

Digital innovations are a central driver of economic value and competitive advantage (e.g., Fichman et al. 2014; Pisano 2015). Therefore, numerous organizations strive for the development of digital innovations. However, while the promises associated with the use of digital technologies are tremendous, many organizations are faced with challenges putting their potential to practice (Pisano 2015). The underlying issues can be manifold. This thesis concentrates on issues related to two stages of the digital innovation process.

First, this thesis discusses the *discovery* of innovations, which refers to how organizations can develop ideas that translate into process, product or business model innovations (Fichman et al. 2014). This work focuses on the role of digital technologies in facilitating this process. Improving the understanding of organizations' innovation discovery is necessary since the literature has emphasized that "the search for new business ideas […] is hit-or-miss in most corporations" (Parmar et al. 2014, p. 88). Along these lines, managers who are used to follow

well-defined strategies have been said to have a hard time thinking out-of-the-box (Parmar et al. 2014), which might apply to most non-managers as well. As a consequence, companies' ability to create innovative ideas is often limited. However, as pointed out by van den Ende et al. (2015, p. 482), "ideas constitute the lifeblood for firms in generating new products or services, new business models, new processes, and bringing about general organizational or strategic change." Therefore, organizations could profit from increased knowledge about how to use digital technologies to develop new ideas.

Besides its practical relevance, improving the understanding of companies' innovation discovery is required from a theoretical perspective. So far, prior research mainly relied on the assumption that organizations develop innovations in centralized structures, which means that participating individuals are expected to purposefully organize their efforts (Nambisan et al. 2017). However, this assumption is challenged as innovation processes are increasingly distributed and become more open (e.g., Bogers and West 2012). This results primarily from digital technologies' affordances (Yoo et al. 2012), which enable new forms of collaboration. While most more recent approaches explicitly consider actors outside the organization (e.g., open innovation described by Chesbrough (2003)), the creation of innovations also opens up within organizations, hence involving a variety of employees (Edmondson and Harvey 2017; Rizy et al. 2011). Therefore, additional research overcoming previous assumptions is needed to better understand how digital technologies enable an organization's employees to jointly develop innovative ideas across different teams, departments, and locations.

Within the scope of organizations' innovation discovery, this thesis focuses on examining the role of *Enterprise Social Networks* (ESNs). To illustrate the relevance of ESNs in this regard, it is important to highlight that workplace transformations can be crucial for organizations to foster innovation (Dery et al. 2017). Regularly, these transformations include the provision of new technologies that shape the ways how employees carry out work (Colbert et al. 2016). In this context, Enterprise Social Media (ESM) provide particular potential as they "represent one of the most transformative impacts of information technology on business" (Aral et al. 2013, p. 3). ESM refer to the use of digital tools such as blogs, wikis, and ESNs to facilitate a company's internal communication and collaboration (Leonardi et al. 2013). In contrast to blogs and wikis, ESNs offer a unique value as they make regular conversations visible, which have been invisible within the organization before (Kane et al. 2014; Majchrzak et al. 2013a; Treem and Leonardi 2012). This is possible since these systems are usually configured to provide everyone access to the content posted on others' profile pages (e.g., Leonardi 2014).

The communication visibility of ESNs is important since it fosters the discovery of innovations by improving employees' knowledge about each other (i.e., meta-knowledge), as shown by the recently developed communication visibility theory (CVT) (Leonardi 2014). More precisely, employees develop innovative ideas more frequently as their meta-knowledge enables them to increasingly recombine existing ideas to address unsolved problems (Leonardi 2014). However, given CVT's novelty, Leonardi (2014, p. 814) has highlighted that "a good deal of work is needed to refine this theory, introduce scope, and test its predictions in varied organizational contexts." In response to this call for research, two papers within this thesis aim at improving the knowledge of how ESNs facilitate the discovery of innovations.

Second, this thesis discusses the *diffusion* of digital innovations, which refers to how an innovation "spreads across a population of potential users" (Fichman et al. 2014, p. 336). Enhancing organizations' knowledge of how innovations diffuse is essential since they regularly face the risk that potential customers might decline an innovation (Forbes 2018). In particular, this is the case as organizations often have difficulties in implementing a holistic customer focus (Ringel et al. 2018; Silverstone and McMillan 2016). Without a holistic customer focus, organizations barely understand their customers' needs. Therefore, they can hardly manage gaps between these needs and features of the innovations they develop. However, an increased knowledge of how innovations diffuse could help organizations to understand how potential customers evaluate their innovations and, thus, counteract this issue.

Intensifying the investigation of digital innovations' diffusion is also vital from a theoretical perspective since existing market conditions have fundamentally changed during the last years. Specifically, the emergence of digital technologies has caused a convergence in organizations' activities, which means that established industry boundaries blur and new competition arises (Seo 2017; Yoo et al. 2012; Yoo et al. 2010). For instance, incumbent organizations (i.e., inherently non-digital enterprises such as transportation or automotive companies) now increasingly compete with inherently digital organizations (such as Apple, Google, or digital start-ups). So far, theories describing the adoption and diffusion of innovations do not sufficiently account for these new dynamics. However, as a company's competitive situation can impact an innovation's diffusion (Robertson and Gatignon 1986), it is required to deliberately consider the present competition in this regard.

Within the scope of organizations' innovation diffusion, this thesis focuses on *data-driven business models*. Owing to the growing emergence of digital data (Goes 2014) and tools for its analysis (Parmar et al. 2014), scholars expect companies to create innovative business

models (e.g., Buhl et al. 2013; Loebbecke and Picot 2015). The diffusion of these data-driven business models is of increasing interest since the blurring of industry boundaries is exceptionally strong in this context. This is because new competition arises between incumbent and inherently digital companies as both have strong incentives to utilize their data in new ways. While incumbent companies can benefit from the vast amounts of data they gathered as by-products of past activities to create innovations (Yoo et al. 2012), digital start-ups can capitalize on their data to quickly scale their business (Huang et al. 2017). Due to this new competition, it is often unclear which companies' business models will diffuse successfully. Against this backdrop, two papers of this thesis seek to improve the knowledge of the diffusion of data-driven business models, which is closely linked to users' evaluations of the products and services that are part of these business models.

1.2 Structure of the Thesis

This thesis includes four papers that aim at enhancing the understanding of the discovery and diffusion of digital innovations. These papers are listed below.

Papers related to the discovery of digital innovations:

- **Paper A:** Engelbrecht, Adrian; Gerlach, Jin P.; Benlian, Alexander; Buxmann, Peter: "How Employees Gain Meta-Knowledge Using Enterprise Social Networks: A Validation and Extension of Communication Visibility Theory."[1]
- **Paper B:** Engelbrecht, Adrian; Gerlach, Jin P.; Benlian, Alexander; Buxmann, Peter (2017): "Analyzing Employees' Willingness to Disclose Information in Enterprise Social Networks: The Role of Organizational Culture." In: Twenty-Fifth European Conference on Information Systems (ECIS), Guimarães, Portugal.

Papers related to the diffusion of digital innovations:

- **Paper C:** Engelbrecht, Adrian; Gerlach, Jin P.; Widjaja, Thomas (2016): "Understanding the Anatomy of Data-Driven Business Models – Towards an Empirical Taxonomy." In: Twenty-Fourth European Conference on Information Systems (ECIS), Istanbul, Turkey.
- **Paper D:** Engelbrecht, Adrian; Gerlach, Jin P.; Widjaja, Thomas; Buxmann, Peter (2017): "The Nature of Enterprise-Service-Fit in the Context of Digital Services." In: Thirty-Eighth International Conference on Information Systems (ICIS), Seoul, South Korea.

[1] Please note: At the time of this thesis' submission, this paper was in the review process of a VHB-ranked IS journal.

The remainder of this section provides an overview of each paper's content and emphasizes how they relate to the discovery and diffusion of innovations.

Paper A is concerned with the recently developed CVT, which describes that employees' *discovery of innovations* can be enhanced if they have access to an ESN. Specifically, ESNs enable employees to improve their knowledge about their coworkers (i.e., meta-knowledge), which, in turn, helps them to recombine existing ideas to address new problems. However, due to the theory's novelty, validation across different contexts is needed. Based on a quantitative study of 206 individuals working in diverse departments, companies, and industries, the paper supports the broad validity of CVT. Thus, the results indicate that different organizations can profit from an increased innovation discovery through ESNs. Beyond that, the paper suggests two theory extensions. First, employees can gain meta-knowledge not only in the long-run, as implied by Leonardi (2014), but also in relatively short time. Second, managers differ from non-managers in the extent to which they gain meta-knowledge when using ESNs. The study's results provide evidence for both extensions suggested. The insights into managers' unique meta-knowledge gains are particularly interesting as they are in contrast with prior literature, which has indicated that managers often consider their benefits of ESNs as insufficient.

Paper B addresses the question of how an organization's culture influences employees' trusting and risk beliefs and, therefore, their willingness to disclose information in ESNs. Information disclosure is vital to the benefits of ESNs as employees can only profit from other's communication if their conversations are visible (i.e., publicly disclosed within an organization). According to CVT, learning through others' communication enhances employees' meta-knowledge, which facilitates *the discovery of innovations*. Consequently, an organization's culture could impact its innovation discovery through the information disclosure in an ESN. Based on a quantitative study among 282 individuals employed in diverse organizations, the paper shows that an organization's group culture is positively associated with trusting and negatively associated with risk beliefs. Furthermore, development culture has a negative impact on error aversion culture, which, in turn, exerts a negative effect on employees' trusting beliefs. While trusting beliefs are positively associated with employees' information disclosure, risk beliefs exert a negative effect in this regard. As a consequence, the paper highlights the importance of purposefully considering an organization's culture and employees' trusting and risk beliefs if a company tries to increase the discovery of innovations through ESNs.

Paper C is concerned with improving the understanding of data-driven business models by identifying the dimensions that meaningfully distinguish these models. To that end, business models from a start-up database were collected, and practitioners were asked to evaluate their similarity. A combination of multidimensional scaling and property fitting revealed that the utilized data source, the target audience, and the required technological efforts are the most important dimensions distinguishing data-driven business models. The paper used these dimensions to create a taxonomy of data-driven business models. As part of the taxonomy, the analyzed business models were assigned to eight ideal-typical categories. The taxonomy can be particularly useful in three ways. First, it offers a solid foundation for future research to dig deeper into this new field of research. Second, it can help organizations to develop data-driven business models by inspiring them on how their data could prospectively provide value. Third, owing to its focus on business models present in today's economy, it reflects the actual *diffusion of digital innovations* in the case of data-driven business models.

Paper D addresses the question of how potential users evaluate digital services offered by highly different companies such as incumbent and inherently digital organizations. Considering such scenarios is essential since existing industry boundaries increasingly blur and little is known about the *diffusion of digital innovations* in such contexts. In particular, the paper regards the example of a data-driven service. Data-driven services are regularly a part of data-driven business models. The paper's idea is that potential users evaluate a service more positively if they perceive a fit between the service and its provider, which is referred to as "enterprise-service-fit." This perspective presents a novel approach to users' evaluation of digital services since prior research has yet overlooked the possibility that users might consider the interactions of a company's and a service's characteristics in this regard. Based on a grounded theory approach, the paper conceptualizes the idea of an enterprise-service-fit. In particular, it shows that users consider enterprise-service-fit in five dimensions that refer to the necessary 1) customer data, 2) non-customer data, 3) service functionalities, 4) domain-specific expertise, and 5) technological expertise. By incorporating these dimensions, a definition for enterprise-service-fit is offered. Furthermore, the consequences of users' fit perceptions are analyzed. Based on the study's insights, organizations can better understand how users evaluate data-driven services, which is important for the diffusion of the associated business models.

2 Theoretical Background

This section consists of three subsections. The first subsection provides background on digital innovations. The second subsection offers an overview of ESNs, which can contribute to the discovery of innovations. The third subsection elaborates on data-driven business models, which are considered within the scope of the diffusion of digital innovations.

2.1 Digital Innovations

Research and practice have widely acknowledged the potential of digital technologies, which permeate innovation processes and outcomes (Nambisan et al. 2017). To outline how this potential can translate into actual innovations, this section presents the stages of the digital innovation process and elaborates on the characteristics of digital technologies, which enable companies to flexibly advance the offerings they are embedded in. In addition, common challenges associated with the creation of digital innovations are highlighted.

2.1.1 Stages of the Digital Innovation Process

Previous research has introduced a digital innovation process, which describes the stages involved in the creation of digital innovations. As stated by Fichman et al. (2014), the process comprises the discovery, development, diffusion, and impact of digital innovations. Discovery relates to the generation of new ideas, development deals with the conversion of these ideas into actual outcomes (e.g., new products), diffusion concerns the distribution of these outcomes across target users, and impact refers to the effects of these outcomes on organizations, individuals, and the society (Fichman et al. 2014). The papers included in this thesis focus on the discovery and diffusion of digital innovations.

While the digital innovation process is useful for scholars and practitioners to get an overview of how innovations emerge, it is important to note that its stages do not always unfold in the same way (Fichman et al. 2014). This is particularly the case when comparing the different innovation outcomes (i.e., product, process, and business model innovations), which are collectively covered by the process (Fichman et al. 2014). Furthermore, there is variation in how the stages occur as the literature has emphasized that “innovation is neither smooth nor linear,

nor often well-behaved. Rather it is complex, variegated, and hard to measure" (Kline and Rosenberg 1986, p. 285). Therefore, the process should primarily be seen as a rough guideline rather than a detailed schedule modeling the full complexity of organizations' innovation creation.

2.1.2 Key Characteristics of Digital Technologies

Within the digital innovation process, digital technologies play a decisive role. Digital technologies can be defined as "combinations of information, computing, communication, and connectivity technologies" (Bharadwaj et al. 2013, p. 471). While the use of digital technologies can foster the discovery of innovations (e.g., in the case of ESNs as outlined by Leonardi (2014)), they also become embedded in newly developed products and services (Bharadwaj et al. 2013).[2] Therefore, companies can benefit from the characteristics of digital technologies within these offerings. In particular, two characteristics enable organizations to continuously enhance the products and services that are infused with digital technologies.

First, digital technologies are reprogrammable, which means that the functional logic is separated from the physical device executing it and, thus, the same device can be used to perform a variety of tasks (Yoo et al. 2010). This is exemplified by the plurality of use cases that today's smartphones cover. For instance, the Google Play Store offered its users more than 3.5 million apps in 2018 (Statista 2018). Second, digital technologies take advantage of the homogenization of data, which refers to the possibility to store, transmit, process, and display any digital content on various digital devices (Yoo et al. 2010). Accordingly, as long as developers adhere to technological standards, digital content can travel across several devices that instantly handle it the right way (Huang et al. 2017). In contrast to the flexible programmability of digital technologies, the homogenization of data does not refer to the functional logic of an application, but rather to the content (i.e., text, image, audio or video data) that is embedded within an application.

Based on these characteristics, organizations can refine and extend their offerings even after they have been released (Nambisan et al. 2017), for instance through adding functionalities or content to an existing service. This leads to more flexibility when translating ideas into innovations, which is particularly promising in the context of "smart products." Smart products are physical artifacts that have been inherently non-digital but now become increasingly integrated with digital technologies (Yoo et al. 2012). An interesting example has been given by

[2] Please note that it can be difficult to separate digital products and services from the technologies ingrained, as indicated by El Sawy (2003).

the automobile manufacturer Tesla that added autonomous driving features to its cars by merely releasing a software update (Bradley 2016). This case illustrates that even complex products can be infused with digital technologies, which allows for continuous improvements by their producers.

2.1.3 Challenges of Creating Digital Innovations

While companies can alter their digital products and services relatively quickly, the creation and implementation of ideas still require them to invest resources (Svahn et al. 2017). Often, these resources would not only be useful in innovation efforts but in carrying out existing business activities as well. Therefore, organizations need to find a balance between exploring opportunities for innovation to be successful in the long- and simultaneously capturing value in the short-run (Birkinshaw and Gibson 2004). According to van den Ende et al. (2015), this is particularly important in the innovation discovery stage, in which companies need to foster creativity to obtain as many innovative ideas as possible while implementing mechanisms to align them with their strategic goals. Likely, difficulties in achieving this balance are one of the reasons why "organizations struggle with new ideas all the time," as noticed by Henfridsson and Yoo (2014, p. 948).

As a consequence of these competing concerns, managing innovation is a complex and largely intertwined task. Therefore, it requires a holistic strategy that spans the boundaries of different departments and integrates diverse perspectives (Pisano 2015). However, as Pisano (2015) has pointed out, no general approach can be widely applied. Instead, each organization has to develop an individual strategy that considers its particular situation. In this process, companies could profit from an increased knowledge about digital innovations. This is in line with the suggestion of Yoo et al. (2012, p. 1406) who stated that "organizations will have to learn how to compete and thrive in this new world," which is permeated and formed by digital technologies. This thesis aims to support organizations in this process by offering new insights into the discovery and diffusion of digital innovations.

2.2 Enterprise Social Networks

Within this thesis, the discovery of innovations is considered with regard to how ESNs can facilitate the generation of new ideas. Based on Leonardi et al. (2013, p. 2), ESNs can be defined as "platforms that allow workers to (1) communicate messages with specific coworkers or broadcast messages to everyone in the organization; (2) explicitly indicate or implicitly reveal particular coworkers as communication partners; (3) post, edit, and sort text and files

linked to themselves or others; and (4) view the messages, connections, text, and files communicated, posted, edited and sorted by anyone else in the organization at any time of their choosing." Regarding their user interface and features, ESNs are very similar to Online Social Networks (OSNs) like Facebook or Google+. However, in contrast to OSNs, ESNs are solely meant to connect an organization's employees.

To establish a foundation for the ESN-related papers of this thesis, the next two subsections provide an overview of the relevance (2.2.1) and use cases (2.2.2) of ESNs. Afterward, subsection 2.2.3 builds on this background and explains how ESNs foster the creation of innovative ideas and thus can serve an important purpose in companies' discovery of innovations. Please note, while it is beyond the scope of this thesis to provide a comprehensive overview of the ESN literature, a recent review has been offered by Wehner et al. (2017b).

2.2.1 Relevance of ESNs

Today, many software development companies provide ESN implementations (e.g., Facebook offers "Workplace," IBM "Connections," and Microsoft "Yammer"). Furthermore, numerous organizations have recently introduced ESNs. For example, Facebook's ESN "Workplace" has gained around 14,000 businesses as users during the last two years (TechCrunch 2017b). Besides, according to Wehner et al. (2017b), the number of publications referring to ESNs in conference proceedings and scientific journals has continuously increased. Specifically, they found that scholars published over 20 articles per year in 2014 and 2015, whereas there has been merely one publication per year between 2004 and 2007. This keen interest reflects the plurality of research opportunities that emerge from examining the "complex intersection of technological advances, the transformation of organizational cultures and structures as well as the continuous development of employees' expectations and abilities" (vom Brocke et al. 2018, p. 361), which is present in the context of ESNs.

Recent technological advances include the increasing incorporation of ESNs into holistic enterprise platforms (Rode 2016), their integration with third-party applications (TechCrunch 2017a), and the growing involvement of artificial intelligence, for instance in the form of chatbots (TechCrunch 2017a). Transformations of organizations' structures and cultures most notably relate to management's persistent attempts to create an environment that supports the targets of a company as much as possible (Groysberg et al. 2018), which particularly concerns the potential of establishing new ways of collaboration and communication using ESNs. The development of expectations and abilities corresponds, amongst others, to the vast experienc-

es employees gather using OSNs in their private lives (vom Brocke et al. 2018), which likely impacts how they deal with ESNs in the workplace as well.

2.2.2 Use Cases of ESNs

Investigating ESNs is particularly interesting since they can be utilized for various purposes (Richter and Riemer 2013a). Against this backdrop, extant literature found numerous benefits to be associated with the use of ESNs (Wehner et al. 2017a). In the following, this section provides an overview of research on three essential ESN use cases.

First, the use of ESNs can foster employees' performance, which is important since the relation between technology and performance is one of the most debated topics in the IS literature (e.g., Brynjolfsson 1993). In the context of ESNs, several studies have addressed this issue. For instance, based on a quantitative study among 491 employees, Kügler et al. (2015b) found that both intra-team and inter-team ESN use positively influence employees' task performance. More precisely, they revealed that intra-team use asserts a stronger effect on task performance compared to inter-team use. Similarly, Leonardi (2014) provided evidence that ESNs can enhance employees' performance by improving their overview of the company's knowledge and activities, which reduces work duplication. Likewise, Wu (2013) showed that employees can profit from ESNs in the form of increased productivity. Specifically, she illustrated that this is possible due to changes in their network structures, which influence employees' performance through the information they have access to and the communication they can participate in.

Second, the use of ESNs can improve employees' integration and participation within organizations, which has been recently emphasized by vom Brocke et al. (2018). Interestingly, previous research found mixed results in this regard so far. For instance, based on a case study conducted in a financial services institution, Koch et al. (2012) showed that ESNs can create positive emotions among employees by overcoming the borders of their social and work-related lives, which can help to decrease employee turnover. However, they also found that non-users developed negative feeling as they had been excluded from the activities carried out in the system. Similarly, Denyer et al. (2011) have emphasized that ESNs might not be as open and participative as organizations expect since control mechanisms and organizational politics can limit employees' involvement. Nevertheless, more recent research indicates that ESNs can lead to more balanced communication structures as well, thus, giving employees the chance to enlarge their influence within the organization (Riemer et al. 2015c).

Third, the use of ESNs can increase employees' innovativeness, which is relevant for this thesis due to its focus on the discovery of innovations. So far, Kügler et al. (2015b) found that ESN use enhances employees' innovation performance, which means that they create innovative ideas more often. More precisely, they showed that the effect of inter-team ESN use on innovative performance is larger than the corresponding effect of intra-team ESN use. Furthermore, Leonardi (2014; 2015) accounted for ESNs' potential to foster employees' innovativeness by developing CVT. CVT is based on ESNs' unique characteristic of making a company's previously invisible daily communication permanently visible (Kane et al. 2014; Majchrzak et al. 2013a; Treem and Leonardi 2012), which can be illustrated by comparing ESNs to e-mail applications. If two employees communicate via e-mail, a third individual is unable to see the content of these communications (Leonardi 2014). However, if they use an ESN instead, their communications are visible for others, since ESNs are regularly configured to provide all employees access to the content posted on coworkers' profile pages (e.g., Leonardi 2014).

2.2.3 How ESNs Foster Innovations According to Communication Visibility Theory

As two papers included in this thesis are based on CVT, this subsection provides details on the theory's explanation of how ESNs foster the discovery of innovations. Owing to ESNs' communication visibility, CVT argues that employees can become aware of others' communications, which concerns their contents and participants (Leonardi 2014). Employees' communication awareness, in turn, can translate into knowledge about their co-workers (Leonardi 2014), which is referred to as meta-knowledge. According to Ren and Argote (2011, p. 192), meta-knowledge can be defined as individuals' "memory with label and location information about what other members [of a group] know." Meta-knowledge has been shown to enable employees to develop innovative ideas more frequently (Leonardi 2014). Specifically, Leonardi (2014) revealed that employees can use their meta-knowledge to recombine existing into novel ideas more often. Creating innovative ideas through recombination is an important mechanism complementing ideation trough interrogation (i.e., focusing on local and domain-specific instead of diverse information) (Rhee and Leonardi 2018). Consequently, ESNs can substantially contribute to an organization's innovation discovery owing to employees' improved meta-knowledge.

However, acquiring meta-knowledge through communication awareness usually takes time. Accordingly, Leonardi (2015, p. 758) has highlighted that "routine communications seen by third-party observers contain some dribs of information that can only be turned into me-

taknowledge when they are assembled with other dribs of information from different observed communications." As a consequence, it is not sufficient to become aware of a single conversation to develop meta-knowledge (Leonardi 2014). Instead, employees only learn effectively about others if they become aware of a multitude of conversations, which contain a variety of information completing each other (Leonardi 2014; 2015).

Although it takes time to develop meta-knowledge, the changes arising from this process are significant. Based on the case of a large financial services institution, Leonardi (2015) showed that employees could improve their meta-knowledge of "who knows what" by 31% within six months. In the same period, they could likewise increase their meta-knowledge of "who knows whom" by 88%. "Who knows what" and "who knows whom" are the two dimensions of meta-knowledge (Leonardi 2014). Owing to these meta-knowledge advancements, employees likely come up with an increasing number of innovative ideas prospectively. However, while CVT offers vital insights into the role of ESNs in facilitating the discovery of innovations, future research is necessary given the novelty of the theory. Accordingly, Leonardi (2014, p. 814) has pointed out that "a good deal of work is needed to refine this theory, introduce scope, and test its predictions in varied organizational contexts."

The papers included in this thesis relate to Leonardi's call for research. Specifically, Paper A validates and extends CVT. Paper B improves the understanding of employees' information disclosure in ESNs, which is crucial for creating meta-knowledge as described by CVT.

2.3 Data-Driven Business Models

In addition to their discovery, this thesis addresses the diffusion of digital innovations in the particular context of data-driven business models. Therefore, this section introduces background on data-driven business models.

In general, "a business model describes the rationale of how an organization creates, delivers and captures value" (Osterwalder and Pigneur 2010, p. 14). Prior research has specified different components that are aimed at providing a basic structure of the business model concept (e.g., Al-Debei and Avison 2010; Osterwalder et al. 2005). Based on a literature review, Burkhart et al. (2011) showed that a company's offering, market, internal capability, and economic factors cover the vast majority of previous business model component conceptualizations. Referring to the business model research agenda provided by Veit et al. (2014), data-driven business models can be classified as a subtype of digital business models. This thesis utilizes the following definitions for these terms: "A business model is digital if changes in

digital technologies trigger fundamental changes in the way business is carried out and revenues are generated" (Veit et al. 2014, p. 48). Besides, according to paper C, a business model is considered to be data-driven, "if its core business necessarily requires digital data."

Recently, prior research started to debate how data can generate value in data-driven business models (Günther et al. 2017). In this regard, the next subsection (2.3.1) provides details on the pathways of how data might be used to improve existing and create new business models. Afterward, subsection 2.3.2 describes why blurring industry boundaries make data-driven business models a particularly interesting context for examining the diffusion of digital innovations.

2.3.1 How Data Creates Value in Data-Driven Business Models

So far, the literature has highlighted different ways of how data creates value. First, according to Woerner and Wixom (2015), companies could provide new information-based products and services such as raw data or analytical reports. In these cases, companies can monetize their data through selling, wrapping, or bartering, where selling relates to explicitly charging money for the information-based offering, wrapping corresponds to enriching existing products and services with data, and bartering refers to trading data for other products or services (Woerner and Wixom 2015).

Second, a company's data can be utilized to improve existing products, services, and processes (Hartmann et al. 2016). In these cases, the data is not explicitly part of the offering. Instead, it is used in the process of composing valuable products, services, and processes. In particular, these improvements emerge as organizations leverage their customers' data to align their offerings with their individual needs (e.g., Lycett 2013). An example is presented by virtual assistants such as Apple's Siri or Amazon's Alexa, which get better the more data is available about their users, for instance as to their online shopping activities (Dawar and Bendle 2018).

Third, data can be used to develop new products, services, and processes (Hartmann et al. 2016). In these cases, data-driven innovation happens in the form of providing entirely new value propositions (Günther et al. 2017). Still, the data is no explicit part of these offerings. An interesting example of this way of utilizing data is presented by the online streaming service Netflix that leverages data about its users' preferences to inform the process of producing new content (Lycett 2013).

Along these lines, a central driver of data-driven business models is the increasing emergence of "big data" (e.g., Buhl et al. 2013). Big data refers to large amounts of processable data (i.e.,

volume), a high degree of continuous data flows (i.e., velocity), and strong heterogeneity of data structures (i.e., variety) that organizations have to deal with (Lycett 2013). In the last years, big data has frequently been discussed, especially in the context of organizations' value creation. For instance, Günther et al. (2017) provide further information in this regard by offering a recent literature review.

2.3.2 Data-Driven Business Models and the Blurring of Industry Boundaries

Furthermore, the diffusion of data-driven business models is a topic of increasing interest. So far, the literature has emphasized that the rise of digital technologies facilitates the blurring of industry boundaries and fosters new competition (Seo 2017; Yoo et al. 2012; Yoo et al. 2010). This thesis argues that these changes especially apply to data-driven business models. Specifically, as described in the next paragraph, the increasing competition across previous boundaries is triggered in this context as both incumbent organizations and market entrants such as digital start-ups have strong incentives to leverage their data in new ways.

On the one hand, incumbent organizations regularly possess vast amounts of data, which remain unused but could be leveraged as a foundation for data-driven innovations. Often, this concerns data that has been stored as a by-product of previous business activities (Yoo et al. 2012). Emphasizing the wide availability of data in the case of telecommunications companies, Bughin (2016, p. 24) states that "the industry is awash in information." Since early access to data can also cause competitive advantages, as outlined by Porter and Heppelmann (2014) in the context of smart, connected products, creating data-driven business models should be of particular interest for incumbent organizations. On the other hand, the value creation of digital start-ups often inherently builds on utilizing data. Accordingly, Huang et al. (2017) found that data-driven operations are a central reason why start-ups can quickly scale their business. Therefore, digital start-ups should have strong incentives to use their data intensively as well.

As a consequence of these incentives, both incumbent organizations and digital start-ups often invest in data-driven business models, leading to a new state of competition in many markets. For instance, Loebbecke and Picot (2015) have recently pointed to the particular pressure that start-ups can create in this regard. As a market's competitive situation can be relevant for the diffusion of the corresponding innovations (Robertson and Gatignon 1986), it is therefore important to investigate the diffusion of digital innovations in the context of data-driven business models.

However, the literature does not sufficiently consider the increasing blurring of industry boundaries so far, neither for data-driven business models nor the services, which are part of these business models. Accordingly, previous adoption and diffusion theories such as the Innovation Diffusion Theory (Moore and Benbasat 1991; Rogers 2003), the Technology Acceptance Model (Davis 1989; Venkatesh and Bala 2008; Venkatesh and Davis 2000) or the Unified Theory of Acceptance and Use (Venkatesh et al. 2003; Venkatesh et al. 2016) do not reflect that similar services can be simultaneously offered by diverse companies like incumbent organizations and digital start-ups. Therefore, knowledge on how users evaluate services in such situations is missing. In particular, it is unclear which service would be chosen, if users can decide between diverse companies providing it. Given this issue, it is also unknown which services are likely to diffuse successfully, which applies to the corresponding business models as well. Addressing this issue, this thesis includes two papers (i.e., Papers C and D) that are aimed to shed light on the diffusion of data-driven business models and the respective services.

3 Paper A: How Employees Gain Meta-Knowledge Using ESNs

Title

How Employees Gain Meta-Knowledge Using Enterprise Social Networks: A Validation and Extension of Communication Visibility Theory

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Abstract

Employees often lack a comprehensive overview of their coworkers' expertise and connections (i.e., meta-knowledge), which limits the employees' performance. Communication visibility theory suggests that Enterprise Social Networks (ESNs) improve employees' meta-knowledge and, therefore, increase productivity and innovativeness. Our quantitative study validates this novel theory across different contexts and extends it by showing that meta-knowledge not only develops in the long but also in the short-run and that managers gain more meta-knowledge when using ESNs than non-managers. This strongly contrasts with prior literature indicating that managers perceive ESNs' benefits as insufficient. We discuss implications for ESN and transactive memory systems research.

Keywords

Enterprise Social Networks, Communication Visibility Theory, Communication Awareness, Meta-knowledge, Transactive Memory Systems

3.1 Introduction

Today, employees often have difficulties to gain an overview of what their colleagues do and with whom they work. In particular, the increasing division into geographically distributed teams, the rise of virtual collaboration, and the frequent modification of organizational structures contribute to this challenge. However, knowing "who knows what" and "who knows whom" is essential to harness specialized expertise, which can translate into improved performance (e.g., Austin 2003; Leonardi 2014; Lewis and Herndon 2011; Ren and Argote 2011). The knowledge of "who knows what," for instance, involves knowing which coworker has expertise in data analysis. The knowledge of "who knows whom," for example, includes knowing who has close ties with the marketing department.

To enhance their employees' knowledge about one another, many companies have started to introduce Enterprise Social Networks (ESNs). ESNs closely resemble public online social networks, such as Facebook or Google+, with the exception that access to an ESN is typically limited to a company's employees. In total, more than 60% of all organizations have been estimated to utilize ESNs in 2015 (Bughin 2015). Still, the ESN market revenue is expected to grow further with an annual rate of 19.1% (International Data Corporation 2015). Providers of ESNs include companies such as Facebook (with "Workplace"), IBM (with "Connections"), Microsoft (with "Yammer"), and Salesforce (with "Chatter").

From an academic perspective, the knowledge of "who knows what" and "who knows whom" has been labeled meta-knowledge (Leonardi 2014; Ren and Argote 2011). Its development has been extensively discussed in research on transactive memory systems (TMS) (e.g., Brandon and Hollingshead 2004; Lewis and Herndon 2011; Ren and Argote 2011). A TMS refers to the "shared division of cognitive labor with respect to the encoding, storage, retrieval, and communication of information" (Hollingshead 2001, p. 1080). Meta-knowledge is a central element of TMS, as it enables an effective transfer of subject-related knowledge within a TMS (Griffith et al. 2003; Majchrzak et al. 2004). The benefits of a TMS include both improved performance behaviors and outcomes (e.g., Austin 2003; Lewis et al. 2005; Ren and Argote 2011).

Recently, scholars have suggested that ESNs could be well-suited to facilitate TMS that cover entire organizations by improving employees' meta-knowledge (e.g., Fulk and Yuan 2013; Trier and Richter 2015). Leonardi (2014; 2015) has investigated this potential by developing communication visibility theory (CVT). Analyzing a marketing leadership group consisting of 44 employees, he showed that employees' ESN use significantly contributed to their meta-

knowledge—an important insight with respect to the role of IS in fostering TMS. CVT states that employees develop meta-knowledge in ESNs because of these systems' communication visibility, which allows them to become aware of others' communications. This awareness, in turn, can translate into meta-knowledge when employees incrementally extract different bits of information from others' conversations (Leonardi 2015). Against this backdrop, Leonardi (2014) provides evidence that employees' meta-knowledge leads to increased productivity and innovativeness. Although the theory indisputably offers remarkable insights into the unique benefits of ESNs, Leonardi (2014, p. 814) emphasized that "a good deal of work is needed to refine this theory, introduce scope, and test its predictions in varied organizational contexts."

In this study, we address Leonardi's (2014) call for research and extend our knowledge of how ESNs contribute to the creation of meta-knowledge in three ways. First, Leonardi (2014; 2015) has developed CVT in the context of a marketing leadership group of a financial services institution that had 44 employees. Therefore, its generalizability to an organization-wide level and different organizational contexts still needs to be tested. This is also important for TMS research since literature's suggestion that ESNs improve TMS at the organizational level (e.g., Fulk and Yuan 2013; Trier and Richter 2015), has not been tested so far. Therefore, we examine CVT's validity across different departments, companies, and industries.

Second, CVT has focused on the development of meta-knowledge through communication awareness, which has been described as a rather long-term and barely goal-oriented process (Leonardi 2014; 2015). However, research concerned with evaluating ESNs' success (e.g., Herzog et al. 2015; Herzog et al. 2013) should not neglect any benefits of ESNs and therefore ought to consider potential short-term gains in meta-knowledge as well. In fact, goal-oriented behaviors such as actively searching for content (Schlagwein and Hu 2016) or purposefully screening others' profiles (DiMicco et al. 2008; Ellison et al. 2015) could contribute to immediate increases in meta-knowledge. To better understand the ways of gaining meta-knowledge through ESN use, we propose and test a moderated mediation model that includes both an indirect effect, as suggested by Leonardi (2014; 2015), and a direct effect of ESN use on meta-knowledge, which reflects potential short-term consequences.

Third, CVT has not considered individual differences in how employees develop meta-knowledge yet. However, we argue that differences with respect to employees' managerial responsibilities should be particularly interesting to examine because of the still inconclusive findings in previous research. Prior ESN literature suggests that managers often consider their

benefits of using ESNs as insufficient (e.g., Denyer et al. 2011; Han et al. 2015). In contrast, research on managers' information needs and information seeking behaviors (e.g., De Alwis et al. 2006; Wilson 1981) implies that managers could profit even more than others from the information available in ESNs. Given the central role that managers play in facilitating the success of ESNs (e.g., Chin et al. 2015; Han et al. 2015; Van Osch and Steinfield 2016), it is essential to clarify the benefits they can derive from ESNs. Therefore, we investigate individual differences in how employees become aware of others' communication when using an ESN based on their managerial responsibilities. This is also important for the broader TMS literature as this literature indicates that managers' meta-knowledge has consequences that go beyond those of non-managers' meta-knowledge (Heavey and Simsek 2015).

Our quantitative study among 206 employees makes three major contributions. First, we provide evidence for CVT's broad validity across different departments, companies, and industries. This suggests that different organizations can utilize ESNs to foster their employees' productivity and innovativeness owing to an improved meta-knowledge. This result also contributes to TMS research, as it empirically supports suggestions in previous research that ESNs are well-suited to foster employees' organization-wide TMS (e.g., Fulk and Yuan 2013; Trier and Richter 2015). Second, we provide evidence for a direct effect of ESN use on meta-knowledge, which complements its indirect effect transmitted through communication awareness. This implies that meta-knowledge not only develops in the long-run, as suggested by Leonardi (2014; 2015), but also in relatively short time frames, which is essential for developing suitable ESN success measures (e.g., Herzog et al. 2015; Herzog et al. 2013). Third, we provide evidence that managers can develop more meta-knowledge than non-managers by using ESNs. This result contrasts starkly with managers' skeptical attitudes toward ESNs reported on in prior research (e.g., Denyer et al. 2011; Han et al. 2015; Koch et al. 2012), and shows the relevance of sensitizing managers to the inconspicuous nature of meta-knowledge and its benefits. Fostering managers' meta-knowledge not only advances their productivity and innovativeness, but can also help them to improve their units' performance, foster organizational learning, and advance their company's strategic positioning (Rulke et al. 2000).

The remainder of this article is structured as follows: In section two, we provide theoretical background on ESNs and the development of meta-knowledge through them, which is of particular concern to CVT. In section three, we highlight the importance of validating and extending CVT, craft hypotheses, and develop a research model. In section four, we describe our methodology and provide details regarding our survey sample. Section five presents the

results of our study. In conclusion, we discuss theoretical contributions, limitations, possibilities for future research, and practical implications.

3.2 Theoretical Background

3.2.1 Enterprise Social Networks

We define ESNs based on Leonardi et al. (2013, p. 2) as "*platforms that allow workers to (1) communicate messages with specific coworkers or broadcast messages to everyone in the organization; (2) explicitly indicate or implicitly reveal particular coworkers as communication partners; (3) post, edit, and sort text and files linked to themselves or others; and (4) view the messages, connections, text, and files communicated, posted, edited and sorted by anyone else in the organization at any time of their choosing*." In recent years, ESNs have been increasingly adopted by many organizations (Bughin 2015). For instance, Microsoft (2017) reported that their ESN "Yammer" is now used by 85% of the Fortune 500 companies. Similarly, Facebook's "Workplace" had been adopted by 1,000 companies while it still was in its beta-development stage (TechCrunch 2016).

ESNs can be used for a variety of different purposes (Richter and Riemer 2013a) such as broadcasting information (Schlagwein and Hu 2016), supporting employees' communication (Leonardi et al. 2013), managing knowledge (Majchrzak et al. 2013a), fostering collaboration (Dyrby et al. 2014), and connecting employees to one another (Koch et al. 2012). Consequently, organizations might be able to obtain a range of benefits. For instance, prior research has shown that ESN use can lead to improved productivity (Kügler et al. 2015b; Wu 2013), higher innovation performance (Kügler et al. 2015b), positive emotions (Koch et al. 2012), an increase in social capital (Riemer et al. 2015a), as well as more democratic and inclusive communication structures (Riemer et al. 2015b).

However, ESNs' benefits strongly depend on managers' attitudes toward these systems (Koch et al. 2013). If managers do not perceive an ESN to be valuable, they could inhibit its use, and therefore its success. For instance, managers can impede an ESN's introduction or integration into an organization, since they are directly involved in these processes (Chin et al. 2015). Besides, managers can discourage others from using ESNs explicitly by instructing them not to spend too much time on ESNs (Han et al. 2015), or implicitly by giving them the feeling that their ESN activities are not valued (Choudrie and Zamani 2016; Leidner et al. 2010).

3.2.2 Meta-Knowledge and Its Development Through ESNs

Meta-knowledge has been defined as individuals' "memory with label and location information about what other members [of a group] know" (Ren and Argote 2011, p. 192). It is central to the development of TMS among groups of people because it enables an effective transfer of their subject-related knowledge (Griffith et al. 2003; Majchrzak et al. 2004). Based on the shared division of cognitive labor that is enabled through meta-knowledge, a well-developed TMS leads to improved performance behaviors such as team learning and creativity as well as outcomes such as team effectiveness and efficiency (e.g., Austin 2003; Lewis et al. 2005; Ren and Argote 2011).

While TMS research has its origins in the study of couples and smaller groups, the development of TMS at the organizational level involves different challenges (Nevo et al. 2012). Therefore, prior research has emphasized the potential of IS to support its formation (e.g., Lewis and Herndon 2011; Nevo et al. 2012; Ren and Argote 2011). Regarding a TMS' meta-knowledge, Majchrzak et al. (2013b) have reasoned that Wikis enable employees to identify their coworkers' expertise as they show individuals' contributions. In addition, Alavi and Tiwana (2002) have proposed that knowledge management systems offering codified knowledge and information on employees' experience could facilitate users' meta-knowledge. Likewise, Choi et al. (2010) provided evidence that knowledge repositories, bulletin boards, and search engines can improve employees' meta-knowledge.

With respect to ESNs, as a special type of IS, literature has suggested that these systems might foster their users' meta-knowledge as well. For example, Majchrzak et al. (2009) proposed that ESNs could help employees to learn about coworkers' expertise, interests, and work contributions. Similarly, Fulk and Yuan (2013) discussed how the information visible within ESNs could support the development of meta-knowledge. Further, Trier and Richter (2015) noticed that ESNs could influence the TMS processes necessary to create meta-knowledge. Compared to other IS, ESNs could be particularly beneficial with respect to improvements in meta-knowledge, as they make previously invisible routine communication visible (Kane et al. 2014; Majchrzak et al. 2013a; Treem and Leonardi 2012). In fact, when employees communicate using ESNs, their conversations are usually visible to everyone in the organization, since most ESNs are configured to give all users access to content posted on a person's wall (Leonardi 2014). However, sound empirical proof of ESNs' potential to facilitate employees' meta-knowledge is still missing.

Initial proof for a positive link between ESN use and meta-knowledge was offered by Leonardi (2014; 2015) who developed CVT to explain that the use of ESNs indeed facilitates TMS development by increasing employees' meta-knowledge. Specifically, Leonardi (2015) argued that employees develop meta-knowledge in ESNs by reading others' conversations and, in this way, becoming *aware* of what their conversations are about. Therefore, individual's communication awareness is a central construct of CVT, which mediates the effect of ESN use on meta-knowledge. It has been defined by Leonardi (2015, p. 747) as "*awareness of ambient communications occurring amongst others in the organization.*" In line with the two meta-knowledge dimensions (i.e., "who knows what" and "who knows whom"), two dimensions of communication awareness are part of CVT, namely employees' awareness of a) the content of coworkers' messages, and b) their coworkers' connections.

Note that gaining meta-knowledge based on communication awareness is a rather long process. Leonardi (2015, p. 758) explains that "*routine communications seen by third-party observers contain some dribs of information that can only be turned into metaknowledge when they are assembled with other dribs of information from different observed communications.*" Therefore, becoming aware of the content of a single conversation is usually not sufficient to acquire meta-knowledge (Leonardi 2014). Consider the following example: If an employee observes a single conversation in which a coworker discusses a particular topic, it might be hard to assess this coworker's expertise regarding the topic in question. Similarly, the relationship between this coworker and a peer who is part of that conversation is normally unclear based on a single conversation. However, when more conversations become visible, different bits of information can complement each other and enable employees to make meaningful inferences (Leonardi 2014; 2015).

Although CVT is of high theoretical and practical value, Leonardi (2014) has pointed out that it needs validation and refinement. Responding to this call, we develop a research model below that we have used to validate and extend our understanding of how ESNs foster employees' meta-knowledge.

3.3 Hypotheses Development

3.3.1 ESN Use, Communication Awareness, and Meta-Knowledge

As a first and basic step, we aim at testing CVT across different departments, companies, and industries. Therefore, we formulate a research model that considers the relationships among

the theory's existing concepts, namely ESN use, communication awareness, and meta-knowledge.

CVT's first theoretical argument concerns the *relationship between communication awareness and meta-knowledge*. Leonardi (2015) has found that employees' awareness of the content of coworkers' messages influenced their knowledge of "who knows what" and that their awareness of coworkers' connections affected their knowledge of "who knows whom." Explaining why communication awareness leads to meta-knowledge, Leonardi (2015) argued that routine communications involve several cues about others' knowledge (Campbell et al. 2003). Employees can aggregate these cues to a proper perception of "who knows what" if different fragments of information involved in the observed cues complement each other (Leonardi 2015). Consequently, the more communications employees become aware of, the more information fragments they have available to combine them into new knowledge of "who knows what." In a similar fashion, employees can develop knowledge of "who knows whom." As these arguments should not be restricted to the organizational context in which employees work, we assume that the relationships between communication awareness and meta-knowledge also hold in contexts that differ from Leonardi's case.

The second argument of CVT concerns the *relationship between ESN use and communication awareness*. Leonardi (2014) argued that the permanent visibility of others' conversations offered by ESNs enables employees to become aware of these communications. Specifically, ESNs' communication visibility refers to two aspects. On the one hand, it involves message transparency, which means that ESNs make the content of others' messages widely accessible (Leonardi 2015). If the content of others' conversations is accessible, employees can view and develop awareness of it. On the other hand, communication visibility involves network translucence, which means that ESNs make employees' social networks apparent (Leonardi 2015). If others' social networks are apparent, employees can view them and develop awareness of their coworkers' connections. The longer and more frequently employees use an ESN, the more they see both the content of others' messages and their social networks, which should increase their communication awareness. As different ESNs share the characteristic of communication visibility, employees should be able to develop communication awareness irrespective of the organizational context in which they work.

So far, CVT has focused on these two arguments that suggest an indirect relationship between ESN use and meta-knowledge, mediated by communication awareness. Thereby, developing meta-knowledge through communication awareness has been characterized as time-

consuming and rarely goal-oriented (Leonardi 2014). However, we argue below that employees' ESN use also exerts a direct effect on their meta-knowledge through three more goal-oriented and less lengthy activities.

First, employees can utilize ESNs to search for content actively and, this way, purposefully read through existing conversations to gain meta-knowledge quickly (Schlagwein and Hu 2016). For instance, an employee could search for an expert concerning new technology. While scanning several communications, the employee could identify a peer as the go-to expert based on how regularly this peer communicates about the technology in question. This way, the employee's meta-knowledge improves neither through a long-term process nor through incidental awareness as suggested by Leonardi (2014; 2015). Second, ESN users can not only view others' communications but also actively engage in discussions by posting content themselves (Van Osch et al. 2016). As a participant in a conversation, an employee does not need to become incidentally aware of what others are discussing to acquire meta-knowledge. Instead, the employee should be able to directly develop meta-knowledge by asking coworkers involved in the conversation about their expertise or contacts. Third, employees can use ESNs to communicate their expertise and connections using their ESN profiles explicitly (e.g., DiMicco et al. 2008; Ellison et al. 2015). These profiles enable others to immediately learn about the profile owner's expertise, as well as contacts, and hence increase their meta-knowledge. Given this reasoning, we argue that employees' ESN use also exerts a direct influence on employees' meta-knowledge that operates independently from and in parallel to communication awareness.

Taken together, our arguments suggest that both a direct effect between ESN use and meta-knowledge and an indirect effect transmitted through communication awareness exist. Considering both dimensions of communication awareness and meta-knowledge, we therefore propose:

H1: *Employees' ESN use positively influences their knowledge about "who knows what" through both a direct effect and an indirect effect transmitted by their awareness of the content of their coworkers' messages.*

H2: *Employees' ESN use positively influences their knowledge about "who knows whom" through both a direct effect and an indirect effect transmitted by their awareness of their coworkers' connections.*

3.3.2 The Moderating Effect of Employees' Managerial Responsibility

As a second step, we extend CVT by considering individual differences in how employees develop meta-knowledge in ESNs. Specifically, we compare managers with non-managers. Clarifying managers' particular meta-knowledge gains in ESNs is essential for two reasons. First, as mentioned, managers' perceptions of ESNs' benefits can substantially impact the success of these systems (Koch et al. 2013). Second, TMS literature indicates that managers' meta-knowledge has consequences that go beyond those of non-managers' meta-knowledge (Heavey and Simsek 2015). For instance, managers' meta-knowledge can help them to improve their units' performance, foster organizational learning, and advance their company's strategic positioning (Rulke et al. 2000).

Besides, previous research put forward contrasting arguments regarding the benefits managers can obtain from using ESNs. Prior ESN literature suggests that the benefits which managers can derive from ESNs are insufficient. For instance, based on interviews with managers of a telecommunications company, Denyer et al. (2011) found that managers hardly take time to contribute to such systems. One of the interviewed managers illustrated this issue by emphasizing that these contributions are "the sort of thing that is put in the edge of the leaders' diaries and it's the thing that always gets dropped off" (Denyer et al. 2011, p. 386). Similarly, Han et al. (2015) reported that managers prioritize other activities over the use of ESNs even if successful business cases for utilizing ESNs exist. One reason for managers' resistance is their concern that ESNs are mainly a waste of time given the discussion of non-work activities in these systems (Koch et al. 2012; Leidner et al. 2010). Based on these findings, it appears that managers are less likely to profit from the use of ESNs.

However, research on managers' information needs and information seeking behaviors suggests otherwise. In general, managers are in charge of developing a company's goals, acquiring resources, supporting their implementation, and monitoring and controlling their progress (Garvin 1998). Doing their job requires managers to maintain a broad overview of the company's matters. Consequently, managers have particular information needs and engage in information seeking behaviors that exceed those of non-managers (e.g., De Alwis et al. 2006; Wilson 1981). In fact, Pfeffer and Salancik (2003) even argued that the activity of "management" itself can be referred to as information gathering. Similarly, Hales (1986) stated that monitoring, filtering, and disseminating information is one of managers' main tasks. Against this backdrop, a vital part of managers' information gathering is listening to others (Garvin 1998). Managerial listening has many benefits such as recognizing employees' ideas (Tagiuri

1995) or integrating employees within the company (Alvesson and Sveningsson 2003). Accordingly, Helms and Haynes (1992, p. 17) emphasized that "only through effective listening can a manager know what needs to be communicated" and that "organizational capability depends on the listening skills of management."

Following the latter line of argumentation that shows managers' need to gather information and listen to what is happening in the company, we argue that they allocate more attention to the communication of others in an ESN, compared to non-managers. If managers pay more attention to others' conversations in an ESN, their ESN use should result in higher communication awareness. Higher communication awareness, in turn, should lead to higher meta-knowledge. Therefore, we hypothesize that the mediated effects of ESN use on meta-knowledge transmitted through communication awareness are moderated by an employee's management responsibility.

H3: *The positive effect of employees' ESN use on their knowledge about "who knows what" is stronger for managers compared to non-managers, because of a stronger relationship between ESN use and communication awareness.*

H4: *The positive effect of employees' ESN use on their knowledge about "who knows whom" is stronger for managers compared to non-managers, because of a stronger relationship between ESN use and communication awareness.*

Figure 1 illustrates our research model.

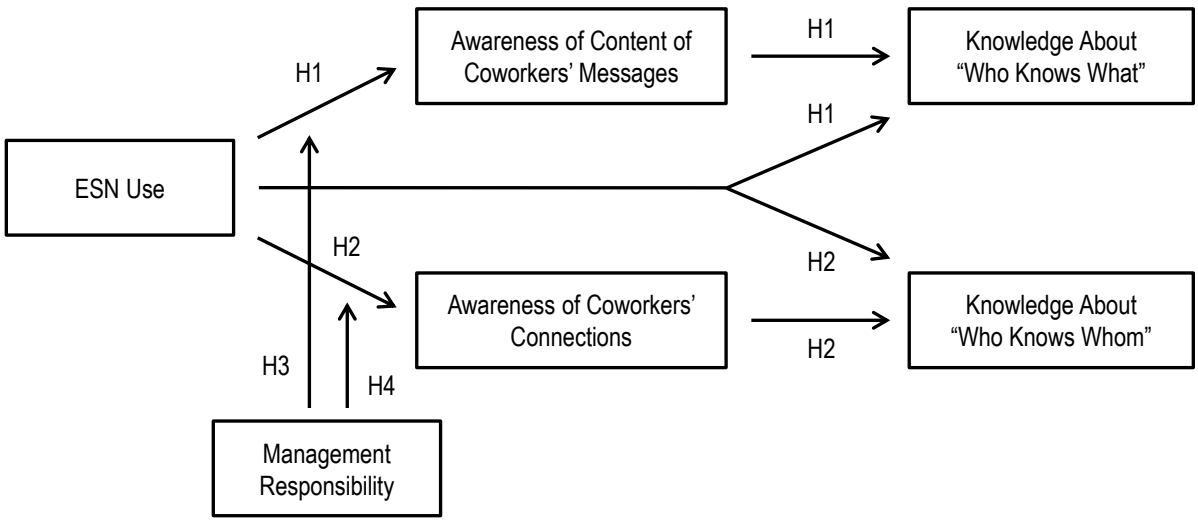

Figure 1. Research Model

3.4 Methodology

3.4.1 Data Collection and Sample

To test our research model, we conducted a cross-sectional survey among working professionals from different departments, companies, and industries who had access to an ESN. To recruit our participants, we consulted the services of a professional survey firm which had access to a panel of working individuals. In order for a panel member to qualify as a participant for our study, three selection criteria applied: first, the individual had to be working on mostly non-physical tasks. Second, the individual had to have access to an ESN. Third, the individual had to work in a company with at least 500 employees, because ESNs are said to unfold their main potential in companies where employees are locally distributed (Ehrlich and Shami 2010) and where organizational structures are complex (Leonardi et al. 2013).

Sex	Female	72 (35.0%)	**Firm Size** (Number of Employees)	501 – 1,000	2 (1.0%)
	Male	134 (65.0%)		1,001 – 5,000	70 (34.0%)
Age	18 – 33	40 (19.4%)		5,001 – 20,000	54 (26.2%)
	34 – 44	43 (20.9%)		20,001 – 100,000	25 (12.1%)
	45 – 55	81 (39.3%)		> 100,000	55 (26.7%)
	56 – 65	40 (19.4%)	**Industry** (Multiple Choice)	Automotive	17 (8.3%)
	> 65	2 (1.0%)		Banking & Insurance	21 (10.2%)
Management Responsibilities	No	134 (65.0%)		Chemicals & Pharma	11 (5.3%)
	Yes	73 (35.0%)		Communication	13 (6.3%)
Department	Communications	14 (6.8%)		Consumer Goods	8 (3.9%)
	Finance & Controlling	23 (11.2%)		Electrics & Electronics	7 (3.4%)
	Human Resources	15 (7.3%)		Engineering	18 (8.7%)
	IT	33 (16.0%)		Healthcare	8 (3.9%)
	Marketing	2 (1.0%)		IT	20 (9.7%)
	Production	18 (8.7%)		Service Providers	20 (9.7%)
	Purchasing & Sales	31 (15.0%)		Transportation	19 (9.2%)
	Research & Development	13 (6.3%)		Utility	8 (3.9%)
	Others	57 (27.7%)		Others	54 (26.2%)

Table 1. Sample Descriptives

Eligible respondents were contacted by the survey firm, while we hosted the survey—thus assuring all participants' anonymity. All data was collected during the first quarter of 2017. We worked closely with the survey firm to achieve a well-distributed sample in terms of age, sex, management responsibility, company size, industries, and departments in which the indi-

viduals were working. Thereby, we assumed that managers actually use ESN. While prior literature has indicated that managers often consider their benefits of using ESNs as insufficient, it is unlikely that most managers entirely refrain from using these systems. As argued above, managers have particular information needs, which can be addressed by using ESNs. Therefore, managers' attitudes toward ESNs should vary along a continuum ranging from positive to negative. Overall, the survey firm invited 10,457 employees to participate in our study, of which 2,219 answered the screening questions. Applying the selection criteria described above, we immediately screened out 1,550 participants. Further, we dismissed data from 150 participants due to missing values. As distracted participants can cause critical issues in survey studies (Maniaci and Rogge 2014; Meade and Craig 2012), we further removed 313 participants who either failed attention checks, exhibited excessive straight-lining, completed the survey in an unrealistic amount of time, or provided contradictory responses. Consequently, our final sample consisted of 206 participants working in various organizational contexts. Specifically, we collected data from individuals employed in smaller (501 – 5,000 employees, 35.0%), medium (5,001 – 20,000 employees, 26.2%) and large (> 20,000 employees, 38.8%) companies. Further, we addressed a wide variety of employees operating in different departments such as IT (16.0%), purchasing and sales (15.0%), or finance and controlling (11.2%). Finally, our sample also covers a wide range of distinct industries including banking and insurance (10.2%), IT (9.7%), and service providers (9.7%). Table 1 provides a descriptive overview of our participants.

3.4.2 Measurements, Control Variables, and Empirical Pretest

All scales are listed in Appendix A1. Whenever possible, we relied on established scales from previous research. Accordingly, ESN use was measured using a reflective three-item scale for social ESN use introduced by Kügler and Smolnik (2014). To measure the dimensions of employees' communication awareness (i.e., regarding the content of coworkers' messages and coworkers' connections), new items had to be developed. In particular, the new items were based on the two-item scales offered by Leonardi (2015) that did not satisfy recommendations of using at least three items in survey studies (e.g., Hoyle 2012). Accordingly, based on Leonardi's (2015) items, we generated a pool of items that captured the meaning of communication awareness as outlined by Leonardi (2015). To ensure high content validity, we thoroughly discussed all newly-developed items among the co-authors and with professionals with extensive ESN-related expertise to improve their wordings iteratively. These efforts resulted in reflective three-item scales for each awareness dimension. Further, we used the scale

provided by Kanawattanachai and Yoo (2007) to measure employees' meta-knowledge about "who knows what" as Leonardi (2015) and Lewis (2003) did not offer meta-knowledge scales that fulfilled the requirements of quantitative studies. For measuring employees' meta-knowledge of "who knows whom," we adapted the items by Kanawattanachai and Yoo (2007) since no appropriate scale was available for this purpose. Again, we discussed the newly-developed items among the co-authors and with professionals to ensure their content validity. Finally, employees' managerial responsibility was measured by a single item that determined whether participants did or did not have such responsibilities.

As for control variables, we considered three groups of characteristics related to 1) the individuals we surveyed, 2) the organizations in which these individuals worked, and 3) the ESNs that were implemented in these organizations. Since our study tested CVT across different departments, companies, and industries, controlling for organizational contexts and their ESN implementations was essential. Regarding *individuals' characteristics*, we followed Leonardi (2015) and controlled for job tenure, the number of ESN users working in close proximity, and the interactions with ESN users beyond the system. Further, we included employees' age as a control variable, as individuals of different ages could differ in their information processing capabilities (Prensky 2001), which are important for employees' communication awareness and the development of meta-knowledge in ESNs. As there is evidence for differences between women's and men's behaviors in social networks (e.g., Muscanell and Guadagno 2012), we integrated sex as a control variable as well. Besides, we controlled for employees' managerial responsibility, as managers could inherently possess more meta-knowledge than non-managers (Jackson and Klobas 2008). However, increased meta-knowledge should neither prevent them from following conversations in ESNs, nor make such behavior expendable, since managers have information needs that exceed those of non-managers (e.g., Wilson 1981). Regarding *organizational characteristics*, we considered a company's geographical distribution and its number of employees to be relevant to the amount and diversity of the communication occurring in an ESN. Additionally, we incorporated employees' identification with the community, which has been defined as "an individual's sense of belonging and positive feeling toward a virtual community" (Chiu et al. 2006, p. 1877). Such identification is likely to influence employees' interaction, in our case within the ESN. Finally, we controlled for a company's innovative climate, defined as "shared perceptions […] concerning the practices, procedures, and behaviors that promote the generation, introduction, and realization of new ideas" (Van der Vegt et al. 2005, p. 1172). Considering organization climate is important, as it affects what employees focus on at work (Schneider et

al. 1994), which can be decisive for employees' awareness and meta-knowledge. Regarding *ESN-related characteristics*, we controlled for when the ESN had been introduced in the participant's company, and when our participant had started to use the system, because employees' behavior in ESNs can change over time (Engler et al. 2015) and meta-knowledge requires time to develop. Lastly, we controlled for the share of employees intended to use the ESN and the extent to which employees on average indeed did so (not to be confused with the ESN use of the surveyed employee), as this would affect how much of the company's communication is visible, and both awareness and meta-knowledge are said to vary in this regard (Leonardi 2015). We linked all control variables to our communication awareness and meta-knowledge constructs.

Since our measurement instrument included several newly-developed items, we performed a quantitative pretest to ensure the validity and reliability of these scales. Therefore, we recruited participants via the authors' professional networks, and via a professional online social network such as LinkedIn. We asked all participants with access to an ESN (n = 155) to answer a questionnaire that included our newly-developed scales. Although the pretest revealed good properties concerning all standard quality criteria of our measurements (i.e., internal consistency reliability, indicator reliability, convergent validity, and discriminant validity), it still helped to fine-tune the new items before our main data collection took place.

3.5 Data Analysis and Results

To test our model, we utilized partial least squares structural equation modeling (PLS-SEM), which is widely used in IS research and was implemented in our study by the software SmartPLS3 (Hair et al. 2016). Hair et al. (2016) and Rigdon et al. (2017) have emphasized that the use of PLS-SEM, compared to covariance-based SEM, is particularly suited for research that tends to be exploratory. Besides, it is well qualified for testing mediation and moderated mediation as suggested by Preacher and Hayes (2004; 2008) and Hayes (2015). As our study extends a novel theory and contains mediation and moderated mediation hypotheses, PLS-SEM fits our purposes well. Going further, we first elaborate on the measurement model, before presenting our structural model.

3.5.1 Measurement Model

To assess the quality of our measurement model, we computed different quality criteria. Regarding the model's internal consistency reliability, we calculated Cronbach's alpha and the composite reliability measure for each reflective multi-item scale. All values met the required

thresholds of .7 (Hair et al. 2016; MacKenzie et al. 2011). Concerning the model's indicator reliability, it has been proposed that each indicator's loading on the associated construct should exceed the threshold of .7 (Hulland 1999), which was given in our study. Further, we accounted for convergent validity by checking whether each construct's average variance extracted (AVE) exceeded the threshold of .5 (Bagozzi and Yi 1988). Again, our measurement raised no concerns. To assess discriminant validity, we applied the Fornell-Larcker criterion which requires that the square root of the AVE of a construct exceeds this construct's bivariate correlation with any other construct (Fornell and Larcker 1981), which was given for all variables. Based on simulation studies, Henseler et al. (2015) showed that the Heterotrait-Monotrait-Ratio (HTMT) exceeded traditional assessments of discriminant validity in terms of precision, and can be regarded as a rather strict criterion. Therefore, we assessed HTMT values which were lower than .85 for all construct pairs, suggesting excellent discriminant validity (Hair et al. 2016). To finally address potential concerns of multicollinearity, we calculated variance inflation factors (VIFs) for all possible combinations of constructs. All values were well below the threshold of 5 (Hair et al. 2016), ranging between 1.08 and 3.44. Accordingly, we concluded that multicollinearity should not be of concern in our study. The appendix provides an overview of major measurement criteria, as well as the correlations of the study's constructs.

We followed different procedures to address the potential for common method bias (CMB) in our data (Podsakoff et al. 2003). First, we assured all participants that their data would be analyzed and stored anonymously. Next, we asked them to respond spontaneously and honestly, and explained that there were no right or wrong answers. In addition, we used three statistical procedures to assess whether our results might be biased by common method variance. First, we applied Harman's single factor test (Podsakoff et al. 2003). An exploratory factor analysis revealed that no single factor accounted for the majority of the variance occurring in our model. Second, we used a marker variable approach as proposed by Lindell and Whitney (2001). A particular item, measuring a company's "relevance of digitalization" was used as a marker variable, which should not be theoretically related to employees' ESN use, their awareness, or their meta-knowledge. A correlation analysis revealed that there were no significant correlations between the marker variable and our model variables (the average correlation was .04). Further, a comparison of the zero-order and partial correlations, in which the marker variable had been partialled out, revealed no significant differences. Third, we followed Liang et al. (2007) and added an unmeasured common method variable to our model. This test revealed that the average indicator variance caused by the substantive constructs was

.81. In contrast, the method variable caused less than 1% of the variance. Accordingly, the ratio between variance caused by substantive constructs and the method was around 270:1. Moreover, all but one of the method factor's loadings were insignificant. Overall, these analyzes consistently suggested that CMB should not have significantly affected our results.

To account for a possible non-response bias, we followed Armstrong and Overton (1977) and compared the first 25% of our respondents with the last 25% using t-tests. Particularly, the last 25% refer to individuals that answered the questionnaire with a large delay after being invited to participate. As we could not observe significant differences between these two groups, it is unlikely that a non-response bias is an issue in our data.

3.5.2 Overview of Structural Model

We calculated the significances of our models' path coefficients by conducting the PLS bootstrapping procedure with 5,000 samples. Figure 2 provides an overview of the results. Below, we first elaborate on the paths separately and describe the model's predictive power and relevance. Subsequently, we discuss our mediation and moderated mediation hypotheses.

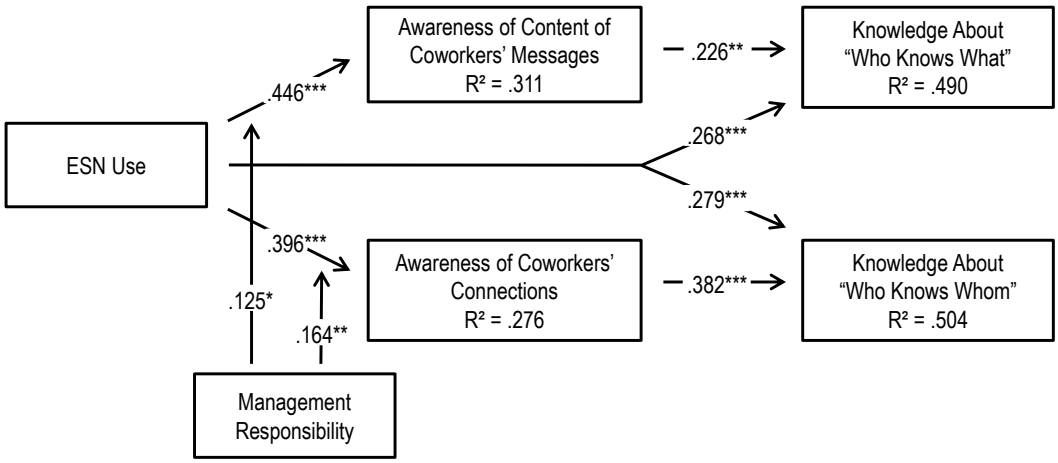

Figure 2. Model Results

Based on the PLS bootstrapping results, we found that all paths included in the model were significant. The paths' p-Values are provided in Table 2. Further, we assessed R^2 values to evaluate the model's predictive power. Regarding employees' meta-knowledge, the R^2 value was .490 for the knowledge of "who knows what" and .505 for the knowledge of "who knows whom." Further, the R^2 values for employees' awareness were .311 regarding the content of coworkers' messages and .276 regarding coworkers' connections. Next, we assessed the predictive relevance (Q^2) of our structural model by using the blindfolding procedure. Following Henseler et al. (2009), a set of exogenous variables is relevant in predicting an endogenous

variable if the Q^2 value is larger than zero. Since all Q^2 values of our model are clearly above this threshold, namely .204 for awareness of the content of coworkers' messages, .182 for awareness of coworkers' connections, .356 for knowledge of "who knows what," and 0.405 for knowledge of "who knows whom," we conclude that predictive relevance is present in our model. Regarding our control variables, significant relationships are described in Appendix A5.

P#	Path and Direction	Coefficient	p-Value
1	ESN Use (+) → Knowledge about "Who Knows What"	.268	.000
2	ESN Use (+) → Knowledge about "Who Knows Whom"	.279	.000
3	ESN Use (+) → Awareness of Content of Coworkers' Messages	.446	.000
4	ESN Use (+) → Awareness of Coworkers' Connections	.396	.000
5	Awareness of Content of Coworkers' Messages (+) → Knowledge about "Who Knows What"	.226	.001
6	Awareness of Coworkers' Connections (+) → Knowledge about "Who Knows Whom"	.382	.000
7	ESN Use x Managerial Responsibility (+) → Awareness of Content of Coworkers' Messages	.125	.043
8	ESN Use x Managerial Responsibility (+) → Awareness of Coworkers' Connections	.164	.009

Table 2. Path Coefficients and p-Values

3.5.3 Mediation and Moderated Mediation Analysis

To test our mediation and moderated mediation hypotheses, we further performed mediation, moderation, and mediated moderation analyzes. Regarding the mediating effects, we examined whether the indirect effects (i.e., the effects of ESN use on meta-knowledge transmitted through communication awareness) were significant. Table 3 shows the results of our mediation analysis. As the 95% confidence intervals do not include the value of zero, we can conclude that both indirect effects are significant at the .05 significance level. As the direct effects of ESN use on meta-knowledge (shown in Table 2) were also significant, both mediating effects represent complementary mediations (Zhao et al. 2010). Therefore, we found support for H1 and H2.

Indirect Path	Indirect Effect	95% Confidence Interval
ESN Use → Knowledge about "Who Knows What"	.101	[.046, .176]
ESN Use → Knowledge about "Who Knows Whom"	.151	[.086, .233]

Table 3. Results of Mediation Analysis

Next, we analyzed the moderating effects more closely to examine our moderated mediation hypotheses. As described above, both effects were significant. Concerning the moderators' effect sizes, Hair et al. (2016) argued that the values of .005, .010, and .025 can be regarded as realistic thresholds to interpret their relevance in explaining a dependent construct. We

calculated an f^2 value of .022 for managerial responsibility's influence on the relation between ESN use and awareness of the content of coworkers' messages, and a value of .035 for its influence on the relation between ESN use and awareness of others' connections. Therefore, we conclude that these effects have a medium respectively large effect size. To support the interpretation of these moderation effects, we graphically visualized them in Figure 3. We used one standard deviation below and above the mean to represent low and high values of ESN use, according to recommendations of Aiken et al. (1991) and Dawson (2014).

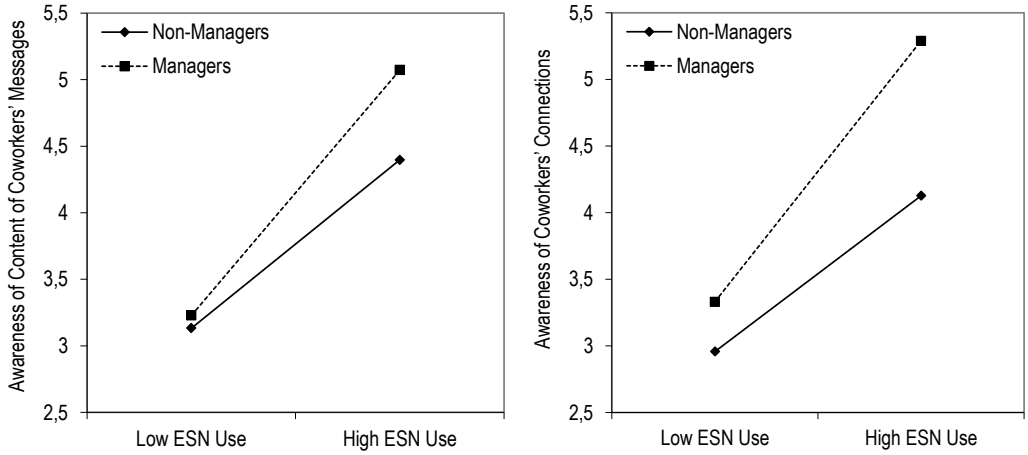

Figure 3. Interaction Plots

As part of the moderation analysis, we also conducted a multigroup analysis to see how the paths between ESN use and communication awareness differ concerning their coefficients and significances depending on employees' managerial responsibility. The results in Table 4 show that the effects of ESN use on both awareness dimensions are smaller for non-managers, than for managers. All relationships were significant.

Path	Coefficient		p-Value	
	Non-Managers	Managers	Non-Managers	Managers
ESN Use → Awareness of the content of coworkers' messages	.325	.593	.002	.000
ESN Use → Awareness of coworkers' connections	.292	.568	.004	.000

Table 4. Results of Multigroup Analysis Regarding the Moderated Paths

Finally, we tested for moderated mediation that "*occurs when the strength of an indirect effect depends on the level of some variable, or in other words, when mediation relations are contingent on the level of a moderator*" (Preacher et al. 2007, p. 193). As this is the case in our model, we examined whether employees' managerial responsibility significantly influences the indirect effect of ESN use on meta-knowledge that is transmitted through communication

awareness. To do so, we assessed the index of moderated mediation, which represents "a direct quantification of the linear association between the indirect effect and the putative moderator of that effect" (Hayes 2015, p. 3). If the index of moderated mediation is significantly different from zero, we can conclude that the indirect effect systematically varies depending on the moderator (Hayes 2015). Table 5 shows the index of moderated mediation and the 95% confidence intervals. As the confidence intervals do not include the value of zero, we can conclude that employees' managerial responsibility moderates the indirect effect of ESN use on their knowledge of "who knows what" at the .05 significance level. Similarly, employees' managerial responsibility moderates the indirect effect of ESN use on their knowledge of "who knows whom." Therefore, we also found support for H3 and H4.

Indirect Path	Index of Moderated Mediation for Management Responsibilities	95% Confidence Interval (Bias-Corrected)
ESN Use → "Knowledge about Who Knows What"	.028	[.005, .070]
ESN Use → Knowledge about "Who Knows Whom"	.063	[.018, .132]

Table 5. Results of Moderated Mediation Analysis

3.6 Discussion

Employees' meta-knowledge is essential to harness specialized expertise in organizations, and so to improve performance (e.g., Austin 2003; Leonardi 2014; Lewis and Herndon 2011). While CVT presents a sound theoretical foundation to explain how ESNs improve employees' meta-knowledge, Leonardi (2014) has emphasized the need to test the theory across different contexts and to refine it. Responding to this call, we conducted a quantitative study among 206 employees working in various departments, companies, and industries. Our results show that 1) CVT holds across different contexts, 2) ESN use influences employees' meta-knowledge through both a direct and an indirect effect and 3) employees' managerial responsibility moderates the indirect effects, as managers develop more communication awareness when using ESNs than non-managers do.

3.6.1 Theoretical Contributions

Our validation and extension of CVT contributes to extant research in several ways. First, while Leonardi (2014; 2015) analyzed the benefits of ESNs in a marketing leadership group of a financial services institution, our study is the first that has applied and tested CVT across different organizational contexts. As our results support Leonardi's (2014; 2015) findings beyond his particular case, we empirically confirm CVT's external validity. This is particularly important for the broader TMS research, which has suggested that ESNs offer great poten-

tial for fostering *organization-wide* TMS (Fulk and Yuan 2013; Trier and Richter 2015). While this assumption has not been verified yet, our findings provide evidence that ESNs indeed facilitate organization-wide TMS by improving employees' meta-knowledge throughout organizations.

Second, CVT has focused on the development of meta-knowledge through communication awareness—a process that is time-consuming and rarely goal-oriented (Leonardi 2014). However, ESN research indicates that meta-knowledge can develop in the short-run through more goal-oriented activities, such as actively searching for content or purposefully screening others' profiles, as well. By testing a direct effect of ESN use on meta-knowledge that reflects possible short-term consequences and complements its indirect effect transmitted by communication awareness, we show the importance of such goal-oriented activities for the more immediate formation of meta-knowledge. This finding helps to develop enhanced frameworks for evaluating the success of ESNs (e.g., Herzog et al. 2015; Herzog et al. 2013) that consider not only the long-term creation of meta-knowledge, but also its more immediate development. Further, it informs research on the process of TMS development (e.g., Brandon and Hollingshead 2004; Lewis 2004). In particular, future research considering the role of IS in forming organization-wide TMS can build on our finding that ESNs contribute to meta-knowledge in the short and long-run.

Third, our study shows that managers gain more meta-knowledge than non-managers when using ESNs. This finding contradicts managers' skeptical attitudes toward ESNs that have been reported in prior literature (e.g., Denyer et al. 2011; Han et al. 2015; Koch et al. 2012). In particular, our results imply that the employees said to be the most skeptical about the benefits of ESNs, controversially, gain more meta-knowledge than others by using these systems. Against this backdrop, an essential question is why many managers seem not to recognize the particular benefits they could derive from ESNs. One attempt to answer this question is based on the nature of meta-knowledge. Meta-knowledge is usually tacit, which means it is deeply rooted in individuals' actions and thus hard to grasp (Nonaka 1994). Therefore, managers might not recognize the value of the meta-knowledge they have. Particularly, managers' numerous tasks (Hales 1986) could contribute to this issue because they leave them little time to reflect on how benefits emerged. Besides, meta-knowledge develops through more means than ESNs only, for instance, if managers collaborate with others on a project (Ren and Argote 2011). Therefore, managers might not know exactly how they obtained meta-knowledge and to what extent ESNs contributed.

Our finding that managers obtain more meta-knowledge than others in ESNs is also important for TMS research. So far, prior literature has not considered that gains in meta-knowledge through IS use could vary among different employees. However, such differences determined by employees' managerial responsibilities are essential, as managers' meta-knowledge is likely to have consequences that go beyond those of non-managers' meta-knowledge (Heavey and Simsek 2015). For instance, managers' meta-knowledge can help them in improving their units' performance, fostering organizational learning, and supporting a company's strategic positioning (Rulke et al. 2000). Consequently, ESNs are expected to unleash benefits that exceed managers' productivity and innovativeness.

Our evidence about managers' particular benefits further enables a more thorough interpretation of Leonardi's (2015) results. Leonardi (2015) reported a 31% increase in employees' knowledge about "who knows what" and an 88% increase in their knowledge about "who knows whom" owing to the introduction of an ESN. However, Leonardi's study was based on data from employees involved in a leadership program. Therefore, all participants had managerial responsibilities. In light of our findings, Leonardi's (2015) results represent an upper boundary of the meta-knowledge that employees can derive in ESNs.

Our result concerning the differences in employees' meta-knowledge development also complements Leonardi's (2014, p. 813) proposition that "enterprise social networking technologies can lead to metaknowledge that is […] more similar across coworkers." Specifically, our study suggests that managers, who already might possess a greater store of meta-knowledge than others (Jackson and Klobas 2008), can develop more meta-knowledge in ESNs. Therefore, the divide in and differences between managers' and non-managers' meta-knowledge could also increase through ESNs. Fortunately, such differences can be beneficial, as teams with unevenly distributed meta-knowledge can achieve performance advantages compared to teams with evenly distributed meta-knowledge (Mell et al. 2014). These advantages can occur since individuals with superior meta-knowledge can operate as catalysts for exchanging and integrating information.

3.6.2 Limitations and Future Research

This section points to limitations of our study and discusses avenues for future research. A first limitation concerns our cross-sectional data set, which does not account for changes in employees' ESN use, their communication awareness, and meta-knowledge over time. Although we controlled for both the beginning of an ESN's introduction and employees' start of

ESN use, future research could investigate the long-term effects of using an ESN based on longitudinal data sets with lagged or panel data.

A second limitation is associated with the measurements related to employees' meta-knowledge. As we surveyed employees across different departments, companies, and industries, we could not effectively verify whether our participants actually possessed the meta-knowledge as indicated. However, we believe that our results are unlikely to be biased in this regard since we guaranteed our participants anonymity to ensure that the questionnaire was answered thoroughly and filtered out low-quality responses. Still, future research could verify our results by using more objective measures for employees' meta-knowledge.

Moreover, our study's participants might not be representative of all kinds of employees. As all employees surveyed in our study worked in Western Europe, our results are limited to this cultural context. Therefore, future research could validate our results using data from different cultural contexts.

Several other opportunities for future research exist. For instance, examining the content that employees communicate in ESNs could be informative. So far, we do not know how different types of content contribute to the development of meta-knowledge. For example, distinguishing between routine and non-routine communication content could be valuable. Additionally, the design of recommendation algorithms in ESNs could be an intriguing area to study. If future research succeeds in developing algorithms that support the visibility of the "right" fragments of information for fostering the formation of relevant meta-knowledge, organizations could increasingly be able to improve employees' productivity and innovativeness.

3.6.3 Practical Implications

Our study has several practical implications. First, our results indicate that ESNs can increase employees' meta-knowledge beyond the particular case of a marketing leadership group of a financial services institution, as analyzed by Leonardi (2014; 2015). Therefore, different companies should be able to profit from ESNs in terms of increased meta-knowledge. Companies that have not implemented ESNs yet should consider introducing an ESN to foster their employees' meta-knowledge. Companies that have already implemented ESNs should ensure that their employees use the systems regularly to unleash their full benefits.

Second, our findings show that the benefits of ESNs can be realized in both the short and the long-run. Consequently, companies should explicitly consider how long their ESNs have been in use when they evaluate their success. While the full potential unfolds in the long-run, com-

panies should already be able to measure first benefits after a short period of time. This could be an additional argument for companies to invest in implementing and promoting ESNs, for instance using change management initiatives that elucidate benefits or integrate an ESN into existing processes. Further, our study can benefit companies as it suggests which activities cause short-term improvements of meta-knowledge in ESNs. Specifically, we suggest the use cases of searching for content (Schlagwein and Hu 2016), engaging in conversations (Van Osch et al. 2016), and screening others' profiles (e.g., DiMicco et al. 2008; Ellison et al. 2015). By communicating the potential of these use cases to their employees, companies can facilitate the short-term improvement of meta-knowledge.

Third, our findings reveal that managers gain more meta-knowledge in ESNs than non-managers do. However, in many cases managers still seem to resist to actively use ESNs (Denyer et al. 2011; Han et al. 2015). If companies can succeed in changing their managers' skeptical attitudes, payoffs are expected to be high. In particular, prior research has indicated that the impact of managers' meta-knowledge exceeds the impact of non-managers' meta-knowledge (Heavey and Simsek 2015). For instance, managers' meta-knowledge is unique as it is supposed to improve the performance of managers' units, foster organizational learning, and support a company's strategic positioning (Rulke et al. 2000). Still, the question remains: How can companies change their managers' negative attitudes and motivate them to participate more actively in ESNs? If managers are not yet using ESNs at all, companies could try to identify and address potential preconceptions that might withhold managers from starting to use ESNs. For instance, communication on non-work related topics (Leidner et al. 2010) could raise concerns that should be handled, for example, by emphasizing that conversations with leisure-related content can contribute to the formation of meta-knowledge as well (Huang et al. 2015). If managers have already started to use but still do not fully engage in ESNs, companies could try to sensitize them regarding the inconspicuous nature of meta-knowledge. Since meta-knowledge is usually tacit, it is hard to recognize (Nonaka 1994). Therefore, managers might not consciously perceive the existence and benefits of their meta-knowledge unless they are made aware of this particular potential.

3.6.4 Conclusion

The purpose of this paper was to validate and extend our knowledge of how ESNs increase employees' meta-knowledge based on CVT, research on ESNs, and literature on managers' information needs and behaviors. Whereas CVT was developed in the context of a leadership program of a financial services institution, our study is the first that considers employees

across different departments, companies, and industries and confirms the theory's broad validity. Besides, we extend CVT in two important ways. First, we show that meta-knowledge develops through more goal-oriented activities in the short-run, which complements the rarely purposeful and long-lasting process of creating meta-knowledge through communication awareness in the long-run. Second, we provide evidence that managers can develop more meta-knowledge when using ESNs, than non-managers. This insight starkly contrasts with findings of managers' skeptical attitudes toward ESNs reported in previous studies. We hope that this study will serve as a springboard for future research to improve our understanding of ESNs and helps practitioners in realizing these systems' comprehensive benefits.

4 Paper B: Analyzing Employees' Willingness to Disclose Information in ESNs

Title

Analyzing Employees' Willingness to Disclose Information in Enterprise Social Networks: The Role of Organizational Culture[3]

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Abstract

Due to the rise of social media, many companies have started to implement enterprise social networks (ESNs). Compared to existing systems supporting communication and collaboration in organizations, ESNs can foster employees' productivity and innovativeness by making previously invisible communication among employees visible. However, this visibility can prevent employees from disclosing information within ESNs. As the success of ESNs depends on users' contributions, it is crucial to understand which factors influence employees' behavior in this regard. In this research, we investigate the role of organizational culture in fostering employees' trusting and mitigating their risk beliefs, two factors we transfer from research on Online Social Networks (OSNs) and hypothesize to be highly relevant for information disclosure in ESNs. Based on data obtained from 282 employees, we find support for our hypotheses and illustrate that group and development culture significantly affect employees' trusting and risk beliefs, and their willingness to disclose information. Our results imply that organiza-

[3] Please note that the paper has been originally written in British English. However, for consistency reasons, it has been changed to American English in this thesis.

tions should carefully assess employees' trusting and risk beliefs as well as their culture to account for possible obstacles preventing employees' information disclosure.

Keywords

Enterprise Social Networks, Organizational Culture, Employee Privacy

4.1 Introduction

In order to transfer the benefits of social media to the organizational context, many companies have started to implement ESNs (Steinhueser et al. 2015), which offer social functionalities in an intra-organizational setting. Along these lines, both practitioners and scholars highlight the potential that is associated with ESNs (e.g., Bughin et al. 2011; Leonardi 2014; Leonardi 2015). However, it seems that many companies still struggle with the challenge that their employees are rather reserved towards these systems (Kiron et al. 2013; Morrison and Parker 2011). In contrast to other enterprise systems supporting communication and collaboration in organizations, prior research has argued that ESNs significantly differ by making invisible communication among employees visible (e.g., Leonardi 2014; Leonardi 2015; Leonardi et al. 2013). This, in turn, can improve employees' innovativeness and productivity (Leonardi 2014; Leonardi 2015). However, these benefits can merely be achieved if employees are willing to disclose information in these systems.

Studies in the context of OSNs have explored the factors which influence individuals' willingness to disclose information. In this context, users' trusting and risk beliefs have emerged as significant determinants of information disclosure (e.g., Krasnova et al. 2010; Krasnova et al. 2012; McKnight et al. 2011; Sun et al. 2015). However, the organizational context significantly differs from the public context. While users of OSNs communicate with friends and families, users of ESNs interact with colleagues or managers. Hence, the nature of users' relationships in ESNs is different compared to OSNs. Consequently, employees could be reserved with regard to disclosing information as information might get misused later on. While prior research has examined different factors relevant for employees' behavior in ESNs (e.g., Chin et al. 2015; DiMicco et al. 2008; Kügler et al. 2015a), trusting and risk beliefs, highly relevant factors in OSNs, have not been analyzed yet. Thus, to verify if extant theory on OSNs can be transferred to the intra-organizational context, our first research question is:

Do employees' trusting and risk beliefs affect their willingness to disclose information in ESNs?

In order to account for the unique characteristics of the organizational context, we investigate a particularly important aspect – a company's organizational culture. Organizational culture reflects common patterns of assumptions (Schein 1990), shared values, and beliefs (Deshpande and Webster 1989). It can have a substantial impact on a company (Schein 2004) and fundamentally affect employees' attitudes and behaviors (Schein 1990). In this regard, we argue that organizational culture also affects employees' trusting and risk beliefs and therefore their willingness to disclose information in an ESN. Thereby, organizational culture can be conceptualized through the widespread competing values framework (CVF) (Denison and Spreitzer 1991; Quinn and Rohrbaugh 1983). The CVF distinguishes between organizational cultures that are either characterized by a high level of flexibility or a high level of control. As ESNs support rather unstructured and less predefined use cases (McAfee 2009; Richter and Riemer 2013b) and are often aimed at fostering innovations (Kügler et al. 2015b), we argue that culture types emphasizing flexibility (namely group and development culture) are especially relevant for the success of ESNs. Accordingly, our second research question is:

How do organizational cultures characterized by flexibility (group and development culture) influence employees' trusting and risk beliefs associated with ESNs?

We conducted a study among 282 employees from different companies and reveal that intra-organizational trusting and risk beliefs are highly relevant to explain why some employees are reluctant to disclose information in ESNs. Our analysis also shows the importance of culture types emphasizing flexibility (group and development culture) which affect employees' trusting and risk beliefs. In this regard, we identified two distinct mechanisms: while group culture directly influences employees' trusting and risk beliefs, the effect of development culture is transferred through a company's error aversion culture. This organizational characteristic reflects the extent to which employees are worried about making mistakes and establish behaviors to avoid them (Van Dyck et al. 2005).

Our study makes important contributions to research and practice. From a theoretical perspective, we transfer existing findings that explain individuals' information disclosure from the public to the intra-organizational context. By considering employees' trusting and risk beliefs, we extend existing studies concerned with employees' information disclosure in ESNs. Next, we reveal how a company's organizational culture affects employees' trusting and risk beliefs and therefore their willingness to disclose information in ESNs. Specifically, we disentangle two distinct mechanisms: a direct effect of group culture on trusting and risk beliefs and an indirect effect of development culture via error aversion culture. Thereby, we address an ex-

isting call for research that asks for studies regarding the incorporation of cultural factors in analyzing ESN usage (Wehner et al. 2017b). From a practitioner's perspective, our findings help companies to understand which factors may encourage and discourage their employees from participating in ESNs. Therefore, our results can help to foster the success of ESNs.

4.2 Theoretical Foundation

In the following subsections, we first provide background on the nature of ESNs. Second, we review existing work on information privacy that explains individuals' information disclosure in OSNs. Third, we introduce the concept of organizational culture and elaborate on its types.

4.2.1 Definition and Characteristics of Enterprise Social Networks

We define ESNs based on Leonardi et al. (2013, p. 2) who state that ESNs "allow workers to (1) communicate messages with specific coworkers or broadcast messages to everyone in the organization; (2) explicitly indicate or implicitly reveal particular coworkers as communication partners; (3) post, edit, and sort text and files linked to themselves or others; and (4) view the messages, connections, text, and files communicated, posted, edited and sorted by anyone else in the organization at any time of their choosing." ESNs are characterized by a high visibility of previously invisible communication among employees in terms of the communication partners and content (e.g., Leonardi 2014; Leonardi 2015; Leonardi et al. 2013). Accordingly, conversations among employees, which were once conducted personally or via e-mail, now become visible (Leonardi 2014; Leonardi et al. 2013).

Regarding their benefits, ESNs have been shown to improve employees' productivity and innovativeness: For instance, Riemer et al. (2015a) found that employees who regularly used ESNs exhibit a higher job performance in comparison to other employees using ESNs less often. Likewise, Kügler et al. (2015b) revealed that ESNs enhance employees' task and innovative performance, whereby the extent of these performance improvements depends on the type of usage (i.e., intra-team vs. inter-team usage). Along these lines, Leonardi (2014; 2015) provided additional evidence that ESNs improve employees' productivity (i.e., by reducing work duplication) and innovativeness (i.e., by enabling them to recombine existing ideas in new ways). Regarding these potential benefits, prior research also remarked that different ways exist in which ESNs might be utilized, depending on an employee's current context (Richter and Riemer 2013a). In fact, ESNs are not limited to specific use cases and can be used for multiple purposes (Richter and Riemer 2013b). Thus, ESNs offer (but presumably

also require) a higher level of flexibility compared to traditional enterprise systems designed to support communication and collaboration.

Up to now, few studies exist that examine the factors which influence employees' behaviors in ESNs. Along these lines, Chin et al. (2015) conducted a qualitative study in multinational service firms and found that technological (e.g., platform quality), organizational (e.g., top management support), social (e.g., critical mass of other users) and individual aspects (e.g., time) can affect employees' behaviors. Besides, DiMicco et al. (2008) emphasized the meaning of employees' possibilities to advance their careers, to position themselves for a project and to connect on a personal level to others as main determinants of using ESNs. Finally, Kügler et al. (2015a) showed that collaboration norms are an important factor when regarding employees' contributions in ESNs. In addition to these studies, Mettler and Winter (2015) have provided an initial step to explicitly examine employees' attitude towards disclosing information in enterprise social systems. While their result that employees' privacy concerns influence their sharing attitude presents a significant finding, we argue that more research is necessary to understand employees' information disclosure in ESNs.

4.2.2 Information Privacy Research and Information Disclosure in OSNs

In recent years, the development of new technologies enabling the collection and analysis of extensive amounts of information has driven wide-ranging discussions about privacy. While existing research examines privacy in diverse settings, many scholars have focused on OSNs. The analysis of OSNs is interesting since providers are usually dependent on the users' willingness to disclose information (Loiacono 2015). For instance, an OSN provider needs to collect information to earn money by establishing personalized advertisement (Berger et al. 2014). Accordingly, many studies are concerned with the factors that are associated with the users' willingness to disclose personal information in OSNs (e.g., Krasnova et al. 2010; Krasnova et al. 2012; McKnight et al. 2011; Sun et al. 2015).

Reviews of the information privacy literature have emphasized central constructs by creating integrated frameworks (e.g., Dinev et al. 2015; Li 2011; Smith et al. 2011). These frameworks especially point to the importance of privacy concerns, trusting beliefs, and risk beliefs to explain individuals' behavior. In this particular study, we aim at transferring these findings to the context of ESNs, since they share the same characteristics with regard to the persistent communication visibility. As Mettler and Winter (2015) have investigated the role of employees' privacy concerns for their information disclosure, our study focuses on the role of trusting and risk beliefs. Indeed, in the context of OSNs, trusting beliefs (e.g., Krasnova et al.

2010; Krasnova et al. 2012; McKnight et al. 2011) and risk beliefs (e.g., Krasnova et al. 2010; Sun et al. 2015) have both emerged as predictors of individuals' information disclosure behaviors.

In line with prior research (e.g., Gefen et al. 2003b; Malhotra et al. 2004), we refer to a user's trusting beliefs as the expectation that others, the user decides to trust, will not behave opportunistically by exploiting the user's information disclosure. In this regard, existing research has shown that users' trusting beliefs are positively associated with their willingness to disclose information (e.g., Krasnova et al. 2012; Malhotra et al. 2004). Further, we define users' risk beliefs in line with prior research (e.g., Featherman and Pavlou 2003; Malhotra et al. 2004) as the expectation for potential losses when disclosing information. Referring to the connection between risk beliefs and individuals' behavior, research on OSNs found a negative relationship between these constructs (e.g., Krasnova et al. 2010; Sun et al. 2015). Pointing to Krasnova et al. (2010), we define information disclosure as the extent to which individuals are providing information while participating in a social network. Additionally, existing research has also investigated the relationship between trusting and risk beliefs. According to Malhotra et al. (2004), the trust-risk framework (Mayer et al. 1995; McKnight et al. 1998) builds the theoretical foundation to connect both constructs as it describes that trusting believes represent a crucial factor in determining individuals' behavior under circumstances in which risk beliefs are in place (Luo 2002). Along these lines, prior research has shown the importance of the trust-risk-framework in the organizational as well as in the individual context (Malhotra et al. 2004).

4.2.3 Organizational Culture as a Characteristic of the Organizational Context

In this research, we account for the influence of a company's organizational culture on employees' willingness to disclose information, which represents a contextual difference to OSN studies. Organizational culture affects all parts of an organization (Schein 1990) and causes wide-ranging consequences (Schein 2004). Drawing on Hartnell et al. (2011, organizational culture especially affects employees' attitudes such as job satisfaction (e.g., Kirkman and Shapiro 2001), companies' operative effectiveness like their innovativeness (e.g., Naranjo-Valencia et al. 2011), and companies' financial effectiveness such as their profitability (e.g., Narver and Slater 1990). According to the complex nature of organizational culture and the fact that it incorporates diverse ideas from various disciplines such as sociology, psychology, and business studies (Schein 1990), it is difficult to find a clear definition (Straub et al. 2002). To describe what constitutes organizational culture, previous literature has highlighted differ-

ent aspects like shared patterns of assumptions (Schein 1990), collectively accepted meanings (Pettigrew 1979), and shared values and beliefs (Deshpande and Webster 1989). Further, existing research also points to more tangible aspects such as symbol, rituals (Hofstede et al. 1990), or myths (Pettigrew 1979).

In the context of enterprise social systems, scholars have suggested that organizational culture may be relevant for these systems (Seo and Rietsema 2010). In their exploratory study, Seo and Rietsema (2010) have found that companies who seek to leverage Web 2.0 technologies for their organizations need to establish a culture, which is characterized by flexibility, trust, and openness. Similarly, Kügler et al. (2015a) examined the influence of organizational climate, which is related to organizational culture, and employees' contributive use of ESNs. Specifically, they found that collaboration norms influence employees' behavior, while general trust showed no significant influence. However, empirical evidence regarding the effect of organizational culture is still required.

In this research, we conceptualize organizational culture based on the widely used competing values framework (CVF) (Denison and Spreitzer 1991; Quinn and Rohrbaugh 1983). This framework has frequently been applied by studies that have examined the antecedents and outcomes of organizational culture (e.g., Iivari and Huisman 2007; McDermott and Stock 1999; Moorman 1995). The CVF distinguishes four types of organizational culture based on two dimensions: first, the organization's focus towards an internal or an external perspective and second, the organizational structure referring to emphasize flexibility or control (Quinn and Rohrbaugh 1983). The resulting four types of organizational culture are group, development, rational, and hierarchical culture (Denison and Spreitzer 1991). To describe each type, we will briefly discuss relevant attributes (based on Cameron and Quinn 2011; Denison and Spreitzer 1991; Quinn and Rohrbaugh 1983):

Group culture is characterized by a strong internal focus. Thus, it is oriented towards the own organization rather than concentrating on the market or environment. Furthermore, it emphasizes flexibility rather than control. Accordingly, its key values refer to trust, participation, belonging and commitment. Two substantial targets of organizations with a strong group culture are the development of human resources and the maintenance of the group. *Development culture* is characterized by a strong external focus. Thus, it is oriented towards the market and the organization's environment rather than towards the own company. It emphasizes flexibility rather than control. Its key values refer to growth, creativity and the continuous adaption to external requirements, which are strongly related to the market and the environment. There-

fore, employees in such organizations are likely to follow promising visions and to take risks in order to achieve them. In this regard, they also provide entrepreneurial skills within their companies. *Rational culture* is characterized by a strong external focus and the emphasis of control. Therefore, its main values refer to productivity and performance. In this regard, the achievement of well-defined goals plays a major role in such organizations. Accordingly, employees primarily concentrate on competition and optimizing their work routines. *Hierarchical culture* is characterized by a strong internal focus and the emphasis of control. Its main values refer to security and order by strictly following regulations and rules. Accordingly, employees in such organizations can be described as rather conservative. Following this aspect, they are focused on ensuring stability. While the CVF portrays these types of organizational culture, it is important to notice that organizations in practice cannot be represented by a single type of culture (Denison and Spreitzer 1991). Instead, an organization will be rather described through a combination of these types, in which one type may be dominant (Cameron and Quinn 2011).

4.3 Hypotheses Development

4.3.1 Trusting and Risk Beliefs and Employees' Information Disclosure

As mentioned above, existing literature on OSNs has shown that both trusting (e.g., Krasnova et al. 2012; McKnight et al. 2011) and risk beliefs (e.g., Krasnova et al. 2010; Sun et al. 2015) directly influence user's willingness to disclose information in these settings. Since we aim to explain employees' willingness to disclose information in the organizational context, discussion is necessary whether these relationships can be transferred. Whereas both individuals in the context of OSNs and employees in the context of ESNs might feel uncomfortable when disclosing information, possible consequences strongly differ. While the disclosure of information in OSNs might cause problems for individuals' social status or relationships with friends or family, employees' information disclosure in ESNs could lead to career setbacks or dismissals.

However, the trust-risk framework presents a generic foundation, which has also been used to explain employee-employer relationships in settings other than employees' disclosure of information in ESNs (e.g., Mayer et al. 1995; McKnight et al. 1998). Given this strong theoretical foundation, we argue that the relationships between trusting (e.g., Krasnova et al. 2012; McKnight et al. 2011) resp. risk beliefs (e.g., Krasnova et al. 2010; Sun et al. 2015) and users'

willingness to disclose information in OSNs should also hold for the intra-organizational context. Hence, we hypothesize:

H1: Employees' trusting beliefs are positively associated with their willingness to disclose information within an ESN.

H2: Employees' risk beliefs are negatively associated with their willingness to disclose information within an ESN.

Beside possible influences of users' beliefs on their willingness to disclose, existing literature has also investigated the relationship between trusting and risk beliefs (Malhotra et al. 2004). Similar to prior empirical results, we argue that employees' perception towards the trustworthiness of their employers influences their risk beliefs. Specifically, if employees feel that their employers act on behalf on their employees' interests and that the employer is honest in handling their information, it is likely that employees would not expect their employers to act opportunistically when using information disclosed in an ESN (e.g., an employee would not be blamed for a prediction that does not come true). Thus, employees are likely to have reduced risk beliefs regarding the information disclosure. We hypothesize:

H3: Employees' trusting beliefs are negatively associated with their risk beliefs with regard to disclosing information within an ESN.

4.3.2 Flexible Cultures and Their Influence on Trusting and Risk Beliefs

In order to examine the influence of organizational culture on employees' trusting and risk beliefs, we focus on culture types characterized by an orientation towards flexibility instead of control (i.e., group and development culture). Flexible cultures emphasize change and spontaneity—an orientation which fits the nature and purposes of ESNs: as mentioned before, ESNs aim to support rather unstructured tasks and rarely predefined usage scenarios (Herzog et al. 2015; McAfee 2009; Richter and Riemer 2013b). Besides, culture types highlighting flexibility are especially important when considering organizational change that accompanies with the introduction of an ESN (e.g. changed communication and collaboration patterns, the establishment of new workflows, or altered interaction between different management levels). As employees working in companies with a high group or development culture have a particular mind-set when it comes to change (Denison and Spreitzer 1991; Quinn and Rohrbaugh 1983), they are able to adapt to it more quickly. Thus, we expect that this mind-set will also be reflected in employee's attitude towards an ESN as the ESN causes and is part of the organizational change. Referring to these reasons, we argue that culture types highlighting flex-

ibility will have a particular influence on how employees behave in an ESN. While it could be assumed that rational and hierarchical culture (i.e., the remaining types offered by the CVF) might exert effects, which are exactly inversely related to those of group and development cultures, both conceptual and empirical studies argue otherwise (e.g., Iivari and Huisman 2007; McDermott and Stock 1999; Moorman 1995; Quinn and Rohrbaugh 1983). Therefore, we did not include additional hypotheses for these types. Still, we controlled for both rational and hierarchical culture.

Going further, we differentiate between a direct and an indirect mechanism how organizational culture affects trusting and risk beliefs. Below, we argue that group culture exerts a direct effect, whereas development culture has an indirect effect on trusting and risk beliefs.

According to the CVF, group culture emphasizes values such as participation, belonging, and commitment (Denison and Spreitzer 1991). These values are the foundation for several behaviors like open communication (Hartnell et al. 2011) and strong teamwork (Cameron and Quinn 2011). As a consequence, employees in a group culture are intensively and consciously cooperating with each other. Thereby, they are developing common goals and a strong team spirit. We argue that, in such a culture, an opportunistic behavior is less likely to occur. This should cause employees to develop strong trusting beliefs in general, but also in our particular case of disclosing information in ESNs.

H4: The extent to which group culture is present is positively associated with employees' trusting beliefs regarding their disclosure of information within an ESN.

Concerning employees' assessments of potential losses (i.e., risk beliefs), their strong involvement (Cameron and Quinn 2011) and belonging to a company (Denison and Spreitzer 1991) are crucial in a group culture. We argue that employees, who develop common goals in a group, experience failure and losses as a group as well. In other words: negative events experienced by a certain employee will be perceived as negative events happening to the whole group. Therefore, employees in a strong group culture should have no interest in harming each other, since this would, in turn, harm the group they are members of. Thus, employees should perceive a lower potential for losses in a group culture:

H5: The extent to which group culture is present is negatively associated with employees' risk beliefs regarding their disclosure of information within an ESN.

Since hierarchical culture emphasizes an internal focus like group culture, we controlled for its direct influence on employees' trusting and risk beliefs. In contrast to the direct effect of

group culture, we propose that development cultures should affect employees' trusting and risk beliefs through an indirect mechanism. This distinction can be explained by the difference in focus of group and development cultures. While group cultures emphasize an internal orientation towards the own organization, development cultures are more concerned with an external perspective concentrating on the market and the organization's environment (Quinn and Rohrbaugh 1983). Accordingly, the core values of a development culture are growth, creativity, and the continuous adaption to external requirements (Denison and Spreitzer 1991). Unlike a group culture, the values of a development culture are not directly linked to employees' trusting and risk beliefs.

Instead, another phenomenon can be observed in development cultures, which should indirectly affect employees' trusting and risk beliefs: employees working in companies with a strong development culture are focused on developing innovative products and services (Naranjo-Valencia et al. 2011). Thereby, companies are fostering their employees' entrepreneurial behaviors within the company (Cameron and Quinn 2011). Employees practicing these entrepreneurial activities are used (and required) to apply trial and error approaches (Garvin and Levesque 2006), take risks (Hartnell et al. 2011), and utilize mistakes to learn (Politis 2005). Accordingly, we argue that employees in organizations with a strong development culture should be less afraid of making errors in their daily work routines. This should prevent what literature refers to as an "error aversion culture" (Van Dyck et al. 2005). An error aversion culture is present when employees within an organization strongly fear and try to avoid mistakes (Van Dyck et al. 2005). As a consequence, we propose:

H6: The extent to which development culture is present is negatively associated with an error aversion culture within an organization.

As rational and development culture have an external focus in common, we controlled for rational culture's effect on error aversion culture. A company's error aversion culture presents a general concept that describes an environment in which work and projects are carried out (Van Dyck et al. 2005). Accordingly, we argue that when ESNs are introduced within an organization and employees are requested to disclose information within a system, their attitudes and behaviors regarding this system will be influenced by this environment as well. Employees working in a strong error aversion culture develop negative feelings since they are constantly worried about making mistakes (Van Dyck et al. 2005; Van Dyck et al. 2010). As is known from research in psychology, individuals' emotional states significantly influence how they process information and arrive at evaluations of target entities (Bagozzi et al. 1999).

Specifically, prior research has shown that individuals will evaluate a stimulus more positively if they experience positive feelings and more negatively if negative feelings are present (e.g., Forgas and Bower 1987; Isen et al. 1978; Schwarz and Clore 1983). In addition, negative emotions experienced by an individual also trigger a more skeptical mode of information processing (Pham 2007). Consequently, negative feelings caused by a strong error aversion culture should also affect individuals' trusting and risk beliefs with regard to an ESN. Therefore, they are more likely to develop lower trusting and higher risk beliefs regarding the disclosure of information in ESNs:

H7: The extent to which error aversion culture is present is negatively associated with employees' trusting beliefs with regard to disclosing information within an ESN.

H8: The extent to which error aversion culture is present is positively associated with employees' risk beliefs with regard to disclosing information within an ESN.

4.4 Methodology

4.4.1 Data Collection and Sample

We conducted a survey among employees from German companies. Since not every company has implemented an ESN, employees should imagine that their companies had provided access to a company-wide ESN, which they should use to communicate with their colleagues. We described this system as being similar to familiar OSNs such as Facebook. We further reported that the system would offer employees the possibilities to maintain an individual profile, to share content with others, and to comment on the contents shared by others. While these possibilities already require employees to disclose information, we fostered additional variance in participants' trusting and risk beliefs, as well as their willingness to disclose information by displaying half of the participants, which were randomly chosen, an additional statement. This statement informed them that their employers demanded them to disclose additional information within the ESNs. Particularly, they were required to engage in exchanges with others on project-related issues, work-related news, and current developments and therefore explicitly asked to disclose additional information compared to the other participants.

We sent out invitations to a mailing list including approx. 8,000 employees from different companies and about 650 members of a professional OSN. In total, 525 participants accessed the first page of our survey and 333 completed it (response rate: 3.85 %). Excluding those participants with missing values, we ended up with 282 responses. Table 6 provides descriptive statistics of our sample.

Gender	Female	26.2 %	**Firm Size** (Number of Employees)	< 250	7.8 %
	Male	73.8 %		250 - 500	3.9 %
Age	< 21	0.4 %		501 - 1,000	1.8 %
	21 – 33	33.0 %		1,001 - 5,000	24.5 %
	34 – 44	33.0 %		5,001 - 20,000	19.9 %
	45 – 55	28.7 %		20,001 - 100,000	18.4 %
	56 – 65	4.6 %		> 100,000	23.8 %
	> 65	0.4 %	**Industry** (Multiple Choice)	Automotive	11.7 %
Degree of Managerial Responsibility	Low	59.6 %		Banking & Insurance	13.5 %
	Medium	31.9 %		Chemicals & Pharma	9.6 %
	High	8.5 %		Communication	19.2 %
Area of Activity	Communications & Marketing	16.0 %		Consumer Goods	9.2 %
	Finance & Controlling	4.6 %		Electrics & Electronics	14.9 %
	Human Resources	2.8 %		Healthcare	3.9 %
	IT	43.6 %		Engineering	8.9 %
	Production	2.5 %		Service Providers	14.2 %
	Purchasing & Sales	6.7 %		Transportation	8.2 %
	Research & Development	6.0 %		Utility	3.5 %
	Others	17.4 %		Others	17.7 %

Table 6. Descriptive Sample Characteristics (n = 282)

4.4.2 Measurement and Scales

In order to measure our study variables, we relied on established scales. We followed Malhotra et al. (2004) to inquire employees' willingness to disclose information as well as their trusting and risk beliefs. We used scales provided by Iivari and Huisman (2007) to assess organizational culture and relied on Van Dyck et al. (2005) to measure error aversion culture. Since some of these items were originally developed in a public context, we slightly adapted their wordings to fit the organizational context. For example, we instructed our participants to focus on information relevant to use ESNs when answering questions regarding their willingness to disclose information, while Malhotra et al. (2004) originally used the scales to analyze different types of information in the context of discount club websites. To ensure a high level of comprehensibility, we validated our survey items during two workshops with domain experts. Appendix A6 provides an overview of all items.

We included the following control variables in our theoretical model: first, as discussed in chapter 3, we controlled for rational and hierarchical culture. Second, we controlled for two individual characteristics as literature has shown that both age (Pfeil et al. 2009) and gender (McKnight et al. 2011) can affect users' behaviors in OSNs. To analyze the obtained data using structural equation modeling, we used SmartPLS and conducted the bootstrapping with 5,000 samples to calculate the significances of the path coefficients (Hair et al. 2011). Going

further, we first evaluate the measurement model to ensure appropriate measurement. Next, we assess the structural model in the results section. Regarding measurement quality, we assessed indicator reliabilities, internal consistency, convergent validity, and discriminant validity. As for indicator reliability, each indicator's loading on the construct should be greater or equal than the threshold of .7 (Hulland 1999). According to this cut-off, we dropped two items (regarding error aversion culture resp. hierarchical culture) that exhibited loadings below this threshold. Further, the square root of each item's loading should be greater than .5, which shows that the construct explains more than 50 % in the item's variation (Hair et al. 2014). Regarding internal consistency, all constructs exceeded the threshold of .6 for composite reliability (Bagozzi and Yi 1988). Assessing Cronbach's Alpha (CA) values, the lowest value was .804. In addition, all constructs fulfilled the requirements regarding their average variance extracted (AVE). While literature proposes that the AVE of a construct should be greater than .5 (Bagozzi and Yi 1988), all measured constructs showed values greater than .71. In order to evaluate discriminant validity, we used the Fornell-Larcker criterion, which states that the square root of AVE for each construct should be higher than all correlations with other constructs (Fornell and Larcker 1981). Second, we verified that all indicators loaded higher on their respective construct than on others (Chin 1998). Both procedures indicated that discriminant validity was present in our data. Table 7 provides an overview of the measurement quality.

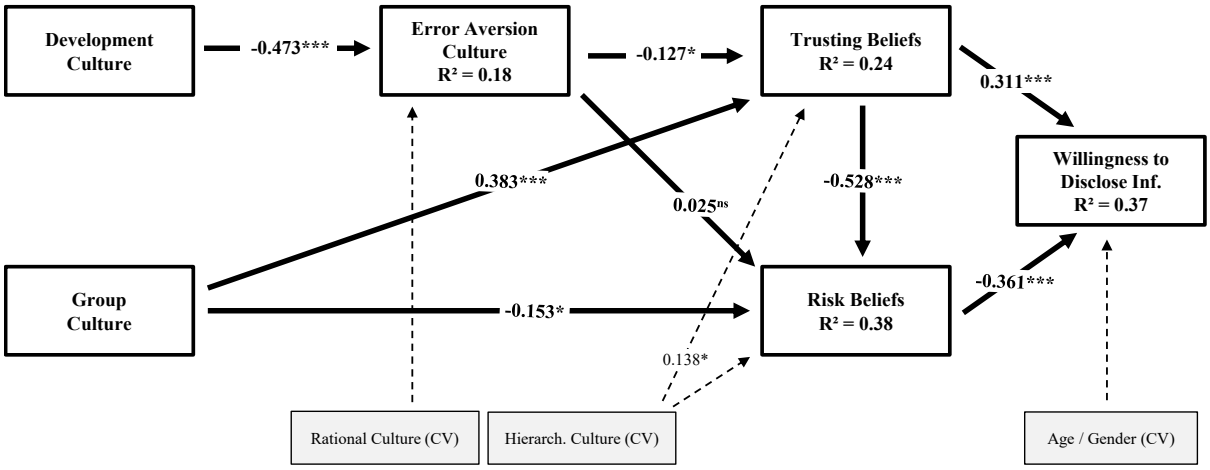
#	Construct	Loadings	Indicator Reliability	CA	CR	Correlation to Construct # / Square root of AVE (bold)					
						1	2	3	4	5	6
1	Group Culture	.722-.912	.521-.832	.804	.882	**.846**					
2	Development Culture	.812-.896	.659-.803	.823	.893	.526	**.858**				
3	Error Aversion Culture	.947-.959	.897-.920	.899	.952	-.291	-.412	**.953**			
4	Trusting Beliefs	.901-.949	.812-.901	.913	.946	.457	.200	-.235	**.923**		
5	Risk Beliefs	.905-.926	.819-.857	.907	.942	-.393	-.143	.195	-.596	**.918**	
6	Willingness to Disclose Inf.	.938-.974	.880-.949	.958	.973	.244	.011	-.066	.539	-.544	**.960**

Table 7. Assessment of Measurement Model (CR = Composite Reliability)

Drawing on Armstrong and Overton (1977), we compared the answers of the last 25 % of our respondents with the answers of the first 25 %. T-tests comparing both groups showed no significant differences, indicating that non-response bias should not be an issue. In addition, we conducted Harman's single factor test to test for common method bias (Podsakoff et al. 2003). The first factor resulting from an exploratory factor analysis accounted for 26.5 % of the total variance indicating that it is unlikely that our results are biased in this regard.

4.5 Results

Figure 4 provides an overview of our model testing results. They highlight the importance of organizational culture for explaining employees' trusting and risk beliefs and therefore their willingness to disclose information in ESNs. Accordingly, seven of our eight hypotheses were supported by our results.



*p < 0.05; p** < 0.01; p*** < 0.001; Bootstrapping with 5,000 samples; CV = Control Variable; n = 282

Figure 4. Results of the Empirical Analysis

We found support for our first two hypotheses, which propose that both employees' trusting (H1) and risk beliefs (H2) influence their willingness to disclose information. The link between employees' trusting beliefs and their willingness to disclose information was positive and significant ($\beta = .311$, $p < .001$), confirming H1. In addition, risk beliefs were negatively associated with willingness to disclose ($\beta = -.361$, $p < .001$), supporting H2. Our results also provide empirical support for H3 that proposes an effect of employees' trusting beliefs on their risk beliefs. Specifically, we found that trusting beliefs were negatively associated with risk beliefs ($\beta = -.528$, $p < .001$).

To assess the influence of a company's group culture, our results confirm the suggested direct effect on trusting beliefs (H4) as well as the direct effect on risk beliefs (H5). Precisely, group culture was positively associated with employees' trusting beliefs ($\beta = .383$, $p < .001$) and negatively associated with employees' risk beliefs ($\beta = -.153$, $p < .05$). By comparing the path coefficients of these relationships, it can be recognized that the group culture's effect on trusting beliefs is stronger than its corresponding effect on risk beliefs. Nevertheless, the data supports our hypotheses that group culture is relevant to explain both employees' trusting and risk beliefs.

We further hypothesized that a company's development culture is relevant for employees' trusting and risk beliefs through an indirect mechanism. First, we suggested that a company's development culture would affect its error aversion culture (H6). Confirming this hypothesis, we found that a company's development culture is negatively associated with its error aversion culture ($\beta = -.473$, $p < .001$). Next, we proposed that a company's error aversion culture would influence employees' trusting (H7) and risk beliefs (H8). In this regard, we found mixed results: while a company's error aversion culture is negatively associated with employees' trusting beliefs ($\beta = -.127$, $p < .05$), the link between error aversion culture and employees' risk beliefs was not significant ($\beta = .025$, $p > .05$).

We further assessed the R^2 values and the predictive relevance (Q^2) of our structural model. In general, a certain set of exogenous variables is relevant in predicting a particular endogenous variable if the Q^2 value is greater than zero (Henseler et al. 2009). Since all of our endogenous variables provide Q^2 values greater than zero (i.e., $Q^2_{\text{Error Aversion Culture}} = .148$, $Q^2_{\text{Trusting Beliefs}} = .192$, $Q^2_{\text{Risk Beliefs}} = .295$, $Q^2_{\text{Willingness to Disclose}} = .335$), we conclude that our model offers predictive relevance. Additionally, the relevance of our results is also supported by the R^2 values. We compared our R^2 values ($R^2_{\text{Trusting Beliefs}} = .24$, $R^2_{\text{Risk Beliefs}} = .38$, $R^2_{\text{Willingness to Disclose}} = .37$) with those reported by similar studies examining individuals' willingness to disclose information. As prior research has reported both higher (e.g., Krasnova et al. 2010; Malhotra et al. 2004; Sun et al. 2015) and lower R^2 values (e.g., Krasnova et al. 2012; McKnight et al. 2011), we conclude that the R^2 values seem appropriate.

Finally, we conducted a multi-group analysis to account for possible differences between two groups of our sample, namely the employees who already have access to an ESN and those who have not. The analysis reveals that only two paths of our model are significantly different in this regard: While the influence of error aversion culture on trusting beliefs is stronger for employees with access to an ESN, the effect of risk beliefs on willingness to disclose information is weaker compared to employees without access to an ESN. However, the latter relation still holds for employees with an ESN. Consequently, our results are barely influenced by employees' experiences with an ESN.

4.6 Discussion

Our results revealed insights about how employees' willingness to disclose information within ESNs is formed. Specifically, we showed that employees' trusting and risk beliefs are significantly influencing their willingness to disclose information within an ESN and that group

and development culture, in turn, affect employees' trusting and risk beliefs. With regard to the importance of development culture, we identified that its effect occurs via a company's error aversion culture.

4.6.1 Theoretical Contributions

Our study makes three theoretical contributions: first, we transferred existing findings on the determinants of individuals' willingness to disclose information to a new context – the intra-organizational context. Originally, these findings were produced in the context of OSNs such as Facebook (Krasnova et al. 2010; Krasnova et al. 2012; McKnight et al. 2011; Sun et al. 2015). By exploring that the corresponding relationships also hold for the intra-organizational context, we help to extend prior research on understanding employees' willingness to disclose information in ESNs. Specifically, our focus towards employees' trusting and risk beliefs complements a first study by Mettler and Winter (2015) who concentrated on the importance of employees' privacy concerns.

Second, our results reveal *that* organizational cultures emphasizing flexibility (group and development culture) significantly affect employees' trusting and risk beliefs and therefore their willingness to disclose information in ESNs. Thus, we showed that organizational culture is a central factor differentiating the organizational context from public settings explored in previous studies (e.g., Krasnova et al. 2010; McKnight et al. 2011). Our findings are in line with prior research, which states that organizational culture causes wide-ranging effects (Schein 2004) and influences employees' behaviors (Schein 1990). In our study, we show that these outcomes include employees' willingness to disclose information in ESNs. Thereby, cultures emphasizing flexibility relate to the specific characteristics of ESNs as they support rather unstructured and less predefined use cases (McAfee 2009; Richter and Riemer 2013b) and therefore require flexibility. Referring to prior literature on ESNs, we complement prior studies by Seo and Rietsema (2010) and Kügler et al. (2015a) that conclude that organizational circumstances can significantly influence employees' behavior in ESNs. While Kügler et al. (2015a) found that organizational climate (in terms of collaboration norms) is important in the context of ESNs, we provide evidence for the effects of organizational culture. Further, we add to literature that is generally concerned with employees' behavior in ESNs (e.g., Chin et al. 2015; DiMicco et al. 2008) by revealing that organizational culture plays a major role in this regard.

Third, we provide evidence for *how* organizational culture affects trusting and risk beliefs by disentangling two distinct mechanisms: while group culture is directly associated with trust-

ing and risk beliefs, we have identified that the effect of development culture is transferred by a company's error aversion culture. In this regard, error aversion culture reflects possible fears that might reduce employees' trusting beliefs and therefore hinder them to disclose information in ESNs. Consequently, we sensitize future research endeavors focusing on organizational culture regarding its complex mechanisms towards employees' trusting and risk beliefs.

4.6.2 Practical Contributions

From a practical perspective, we contribute by supporting companies in understanding what employees may encourage or discourage to disclose information in ESNs. Thereby, we tackle the challenge that many employees are rather reserved towards participating in ESNs Kiron et al. 2013; Morrison and Parker 2011). By considering our results, companies can purposefully account for their employees' trusting and risk beliefs as well as their organizational culture. As we have connected both employees' beliefs and organizational culture, we help to establish a comprehensive perspective. Going further, we specify concrete recommendations for practice.

Since we have shown that employees' trusting and risk beliefs are directly associated with their willingness to disclose information, a first recommendation includes the systematic assessment of these beliefs. This way, companies can analyze if these beliefs might prevent their employees from disclosing information in ESNs. If such an assessment reveals that employees have strong risk beliefs, companies can try to compensate these risk beliefs by fostering trust. Further, organizations can elaborate on its culture to investigate if it represents an inhibiting factor regarding positive beliefs.

Assuming that a company is currently thinking about the adoption of a new ESN, a structured analysis of its culture may prevent its management from introducing a system, which may not exploit its full potential in the short-run. While one consequence addressing this dilemma would be to decide against the adoption of the system, another possibility could include a cultural change. Specifically, companies could attempt to establish values such as belonging and commitment to strengthen its group culture or try to develop incentives encouraging entrepreneurial activities to reinforce its development culture (Denison and Spreitzer 1991; Quinn and Rohrbaugh 1983). As we identified that error aversion culture transfers the effect of development culture, companies could also try to walk up to their employees in order to mitigate their anxieties of making mistakes. However, it is important to note that changing organizational

culture requires years of work and therefore could not be an appropriate mean if the only reason is introducing an ESN.

4.6.3 Limitations and Future Research

This section points to limitations and areas for future research. A first limitation concerns our data collection. As discussed in our multi-group analysis, we surveyed both employees with and without experience in using an ESN. While the analysis shows that few differences exist, the consideration of non-experienced employees might still affect our results. Yet, the comparison of employees' perceptions with regard to their experiences with an ESN might be a promising area for future research. Besides, the generalizability of our findings is limited by our focus on German companies. Therefore, future research could contribute by leveraging different cultural populations. In addition, many of our participants worked in IT divisions (43.6 %) and therefore might not represent average employees. Moreover, we have observed some moderately high cross-loadings regarding our measurement items. This reflects empirical results from existing studies, which also report such correlations and cross-loadings – especially between different types of organizational culture (e.g., McDermott and Stock 1999; Moorman 1995). While improving the measures for organizational culture is outside the scope of this research, future research could contribute by developing improved measurement approaches.

Besides, future research could contribute by explicitly examining employees' attitudes towards the disclosure of different categories of information. Finally, we have to consider the constant dynamics occurring in organizations. To date, ESNs are still relatively new to most companies. As a result, employees' attitudes towards these systems and their according behaviors may change in the future, when they get used to these kinds of systems. On a related note, new generations of employees, who have grown up with OSNs, join organizations, and further factors might become salient when explaining employees' behaviors. Hence, future research could extend our findings by seeking to understand how mechanisms explaining employees' willingness to disclose information change over time.

5 Paper C: Understanding the Anatomy of Data-Driven Business Models

Title

Understanding the Anatomy of Data-Driven Business Models – Towards an Empirical Taxonomy

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Abstract

As a consequence of the increasing digitization, massive amounts of data are created every day. While scholars and practitioners suggest that organizations can use this data to develop new data-driven business models, many organizations struggle to systematically develop such models. A fundamental challenge in this regard is presented by the limited research on data-driven business models. Accordingly, the goal of this research is to better understand data-driven business models by identifying key dimensions that can be used to distinguish them and to develop a taxonomy. As our taxonomy aims to guide future studies in a way that ultimately serves organizations, it is based on dimensions regarded to be most relevant from the practitioners' perspective. To develop this taxonomy, we utilize an established empirical approach based on a combination of multidimensional scaling (MDS), property fitting (ProFit), and qualitative data. Our results reveal that the most important dimensions distinguish data-driven business models based on the data source utilized, the target audience, and the technological effort required. Based on these dimensions, our taxonomy distinguishes eight ideal-typical categories of data-driven business models. By providing an increased understanding

regarding the topic, our results form the foundation for subsequent investigations in this new field of research.

Keywords

Data-Driven Business Models, Big Data, Digitization, Taxonomy, Multidimensional Scaling

5.1 Introduction

As a consequence of the increasing digitization, massive amounts of data are created every day. Both scholars and practitioners suggest that this trend towards "big data" could be an important source for companies to create new business value and to develop innovative business models (e.g., Chen et al. 2012; Lycett 2013; Manyika et al. 2011; Woerner and Wixom 2015). However, since the process of business model innovation is rather unstructured (e.g., Schneider and Spieth 2013), the development of new business models based on data still remains a challenging endeavor. A fundamental reason for this challenge refers to the limited knowledge regarding data-driven business models. As previous research suggests, such new business models could significantly change the way organizations create value and therefore differ substantially from traditional ones (e.g., Bharadwaj et al. 2013; Veit et al. 2014). Following this perspective, we argue that it is crucial to provide a solid foundation for future research on this topic. Consequently, this research intends to better the understanding of data-driven business models by identifying key dimensions that can be used to develop a taxonomy in this regard.

Taxonomies are "systems for grouping objects of interest […] based on common characteristics" (Nickerson et al. 2013, p. 338). Thus, taxonomies help to structure a phenomenon and create a foundation for further research in this direction. According to the "science of diversity" (McKelvey 1978; McKelvey 1982), a solid understanding regarding the similarities and distinctions of objects is a crucial requirement to enable further research on these objects. Likewise, we argue that it is equally problematic for our research community trying to engage in collective research efforts and make generalized statements about data-driven business models, if there is a lack of common understanding. A central task for developing taxonomies is the selection of dimensions that are used to distinguish the considered objects. Usually, there are many possible dimensions that can be chosen to arrive at such a distinction. In order to identify the most relevant dimensions in a given context, it is crucial to clearly define the purpose of the taxonomy (Nickerson et al. 2013). The purpose of our research is to identify those dimensions considered to be the most relevant from a practitioners' perspective given

that our taxonomy intends to guide future studies with the target of ultimately serving organizations.

In order to develop our taxonomy, we utilize an established empirical approach based on a combination of multidimensional scaling (MDS), property fitting (ProFit), and qualitative data (e.g., Padgett and Mulvey 2007; Posey et al. 2013; Robinson and Bennett 1995). In accordance with our research goal, we rely on data obtained from business model experts, as this group of people faces the challenge of developing new business models in their companies. In a first step, these experts need to assess the similarities of different data-driven business models. Afterwards, their similarity ratings are used to create a model of their cognitive mind sets. Thereby, we obtain dimensions relevant for distinguishing different business models and then associate meaningful labels to these dimensions. Our results reveal that the three most important dimensions distinguish data-driven business models according to the data source utilized (non-user data vs. user data), the target audience (consumer-focus vs. organization-focus), and the technological effort required (low vs. high). Based on these dimensions, our taxonomy distinguishes eight ideal-typical categories of data-driven business models.

Our research makes important contributions to research and practice. From a theoretical perspective, we provide an increased understanding regarding data-driven business models by identifying relevant dimensions by which these models can be distinguished. In the spirit of the "science of diversity" (McKelvey 1978; McKelvey 1982), our results form the foundation for subsequent investigations in this new field of research. For instance, future studies concerning the design of new methods to support the development of data-driven business models could build on our results considering the differentiation dimensions to structure the topic. As these differentiation dimensions relate to both data-related (e.g., big data) and business model research, we also address calls for more integrated investigations of these areas (e.g., Buhl et al. 2013; Loebbecke and Picot 2015; Veit et al. 2014). From a practitioner's perspective, our research helps to understand data-driven business models by highlighting eight ideal-typical categories and the dimensions differentiating them. Consequently, organizations can develop new business models in a more structured manner as these categories help to inspire the innovation process and to define a target state. By diving deeper into relevant categories, organizations may also learn about category-specific challenges and existing practices to address them.

The remainder of this paper is structured as followed: in the next section, we will provide an overview of the theoretical background relevant for this study. We will then present the meth-

odology used in our research and describe each step of our data collection and analysis in detail. In the subsequent section, we present the results of our study and finally conclude by discussing its results, implications, and limitations and offer suggestions to further investigate this topic.

5.2 Theoretical Background

In the following subsections, we provide an overview of two streams of research that constitute a relevant background for the presented study: 1) literature concerned with current developments on the topic of "big data" and 2) research related to business models. As outlined below, both areas are increasingly concerned with the joint topic of data-driven business models.

5.2.1 How Big Data May Foster Business Model Innovation

The term "big data" refers to the emergence and use of massive amounts of data in nearly every part of our lives. This trend thereby describes both the quantitative raise of existing kinds of data and the availability of new kinds of data like those created by social media use (e.g., Woerner and Wixom 2015). Big data is commonly conceptualized by the three dimensions volume, velocity, and variety (e.g., Chen et al. 2012; Lycett 2013). As the mere availability of more data does not necessarily imply better data quality or an improved organizational performance (Buhl et al. 2013), the exact scope of this definition is not crucial. Instead, it is rather important to investigate how data can create new business value (Lycett 2013) and how this development may lead to the transformation of organizations (Goes 2014).

Three major areas of research that suggest how big data may create value and have an impact on organizations can be distinguished: first, organizational decision making and strategizing may become even more data-driven as it is today (Chen et al. 2012). This also refers to the challenge of how established management practices can be improved with new kinds of data (e.g., Bhimani 2015; Constantiou and Kallinikos 2014) and how companies in general are required to establish a data-driven organizational culture (Davenport 2006; Sharma et al. 2014). Second, big data allows the improvement of existing products and services as well as the development of new ones (e.g., Davenport et al. 2012). Thereby, a major obstacle refers to the challenge that certain business potentials may not be generalizable across industries. Existing literature highlights several examples along these lines, but struggles to find common mechanisms that can be widely applied in organizations at a more general level (e.g., Chen et

al. 2012; Davenport 2006). Third, organizations may develop new business models on the foundation of their data, which we will discuss in the following.

Big data has the potential to foster business model innovation in organizations (e.g., Buhl et al. 2013; Loebbecke and Picot 2015; Manyika et al. 2011). Yet, little empirical research has been conducted on this topic. Furthermore, no comprehensive overview of different possibilities and best practices regarding data-driven business model innovation exists. Nevertheless, several suggestions about how big data could be utilized for such innovative business models are put forward. According to Woerner and Wixom (2015), one possibility to innovate business models is to monetize data by selling raw data, enhanced data, or data-driven reports. In this case, traditional companies could establish new types of products and services, where the data itself is a part of the offering. Another aspect in creating data-driven business models refers to new dynamics in "the interplay between the offering and the customer" (Lycett 2013, p. 382). By collecting and analyzing consumer data, organizations can customize existing products to perfectly match customer demands. A third approach that affects new business models relates to the development of new business ecosystems (Woerner and Wixom 2015). Based on the data-driven interconnectedness of diverse entities in a market, increasing possibilities exist to integrate and unite business partners or customers in future business models.

(Big) data-driven business models are becoming a topic of increasing interest, as it has been suggested that innovating traditional business models from a data-driven perspective is necessary to be successful in the long-run (Buhl et al. 2013; Loebbecke and Picot 2015). In this context, Loebbecke and Picot (2015) refer to the high pressure that results from new start-ups entering existing markets due to potentially low barriers for new players. Therefore, research needs to assess the potential of new data-driven business models (Buhl et al. 2013) in order to deepen the understanding of how companies can change their business models to realize the potentials of big data along with gaining competitive advantage. In order to follow these calls for research, it seems crucial to first arrive at a shared understanding of what is meant by data-driven business models.

5.2.2 Business Model Research

In recent years, the business model concept has gained growing attention in academic literature, which is reflected in a rising number of publications (Zott et al. 2011). To date, there is no consistent definition of the term "business model", which has led to discussions regarding the existing definitions (e.g., Al-Debei and Avison 2010; Burkhart et al. 2011; Zott et al. 2011). In the following, we refer to the definition by Osterwalder and Pigneur (2010, p. 14),

who state that "a business model describes the rationale of how an organization creates, delivers and captures value."

Several studies are dedicated to the question which components are parts of a business model (e.g., Al-Debei and Avison 2010; Hedman and Kalling 2003; Osterwalder et al. 2005). In general, many possibilities to delineate the components of a business model exist. Osterwalder et al. (2005) describe a business model as a combination of nine elements: value proposition, target customer, distribution channel, customer relationship, value configuration, core competency, partner network, cost structure, and revenue model. In contrast, Hedman and Kalling (2003) choose to identify a business model by the components of customers, competitors, offering, activities and organization, resources, suppliers, and process. To gain a consensus from the diverse components offered in existing research, Burkhart et al. (2011) conducted a literature review to identify four groups of components that are common for the majority of approaches to conceptualize business models at a general level (see Table 8).

Component	Description
Offering factors	"Describe how the company creates value for its stakeholders"
Market factors	"Express for whom the company creates values"
Internal capability factors	"Deal with the internal activities and competences of the company"
Economic factors	"Bundle all economic-related aspects of the company"

Table 8. Consensus of Business Model Components (Burkhart et al. 2011, p. 10)

With regard to the increasing availability of potentially valuable data, researchers have argued that new technological developments can be an essential trigger affecting established business models (e.g., Veit et al. 2014). This aspect supports the proposition that companies need to adjust their business models in order to be successful in the long-run (Hanelt et al. 2015). This is particularly relevant for digital business models that can build on the large amounts of data, which arise due to the omnipresent digitization (Veit et al. 2014). Hartmann et al. (2014) have undertaken a first step to investigate the peculiarities of data-driven business models. In their working paper, they analyze these business models regarding the role of different data sources and key activities. Despite this first step, further research is required that provides guidance on how these new business models can be developed and how their success can be fostered (George et al. 2014).

Furthermore, extant research has emphasized the challenge of analyzing business models in the context of specific domains. As a consequence, various scholars have developed specific business model taxonomies in order to account for the particular characteristics of the considered domain (e.g., Burkhart et al. 2011; Pateli and Giaglis 2004). For example, Schief and

Buxmann (2012) examined the peculiarities of business models in the software industry considering the specific characteristics of software compared to other products. Likewise, one aim of the present taxonomy is to consider the specific characteristics of data-driven business models and therefore to extend the more generic business model literature in this direction.

Ultimately, both research streams on big data as well as business models are increasingly influenced by each other. This is remarkable as researchers from both fields have suggested that new data-driven business models could be an essential source for organizations to create new value. Consequently, we argue that there is a need for more integrated investigations of data-driven business models. Using experts' perceptions of data-driven business models to develop a taxonomy presents an important step to provide a relevant foundation supporting further research endeavors. As there is currently no precise definition of the term "data-driven business model", we introduce the following definition: "A business model of an organization is data-driven, if its core business necessarily requires digital data.[4]"

5.3 Methodology

In general, the purpose of a taxonomy is to group "objects of interests […] based on common characteristics" (Nickerson et al. 2013, p. 338). We refer to these characteristics as dimensions by which objects of interest can be differentiated. Thus, a taxonomy supports researchers to differentiate individual objects and to understand their relationships. This is helpful to examine complex topics and to potentially reveal new research areas (Nickerson et al. 2013).

In this research, we develop a taxonomy of data-driven business models. Our methodology is based on an established procedure, which involves a combination of multidimensional scaling (MDS), property fitting (ProFit), and qualitative data. Several previous studies have successfully used this procedure to develop taxonomies in contexts such as the technological influence on service interactions (Padgett and Mulvey 2007), security behaviors (Posey et al. 2013), or workplace behaviors (Robinson and Bennett 1995). The main advantage of this pluralistic approach lies in the combination of qualitative and quantitative analyzes and therefore a better understanding of the examined research area by not focusing on a single approach (Orlikowski and Baroudi 1991). Furthermore, in contrast to other approaches for developing taxonomies, this pluralistic approach involves a solid empirical basis used to identify relevant dimensions to group the objects of interest.

[4] While the trend of "big data" fosters the development of new business models, some data-driven business models might not require fulfilling the definition of a big data-driven business model. "Small data" can be used to create new business models as well and our study seeks to incorporate these business models.

MDS is a powerful "set of mathematical techniques that enable researchers to uncover the 'hidden structure' of data bases" (Kruskal and Wish 1984, p. 5). In our case, we uncover the structure (i.e., dimensionality) within a population of data-driven business models. The foundation to develop a taxonomy using MDS relies on the elicitation of mental perceptions of individuals regarding the similarities among objects of this population (Schiffmann et al. 1981). The obtained similarity ratings are then used to produce a representation of the data that builds the basis for identifying and labelling the dimensions underlying this representation (Kruskal and Wish 1984; Schiffmann et al. 1981). Simply put, MDS allows researchers to investigate how people differentiate a set of objects (Posey et al. 2013). Relying on external sources for comparing the objects of interest has the additional benefit that a potential bias towards the researchers' subjectivity during the analysis can be reduced (Robinson and Bennett 1995).

Going forward, we strictly adhere to this established process which involves five subsequent steps: (1) selecting data-driven business models; (2) acquiring similarity ratings; (3) determining the structure and dimensionality of the experts' perceptions using MDS; (4) identifying common characteristics based on qualitative data; (5) mapping of the characteristics to the dimension using a ProFit analysis.

5.3.1 Selecting Data-Driven Business Models

The first step aims at building a record of data-driven business models that represents the population of the objects of interest (i.e., data-driven business models). This record should be as exhaustive as possible in order to cover all existing kinds of data-driven business models. For this purpose, we chose to extract data from a database of start-ups, as innovative business models are often launched in start-ups before they are introduced in established organizations. Specifically, we retrieved data from "CrunchBase". CrunchBase gathers data on innovative companies using a crowdsourcing approach with a strong focus on start-ups as it maintains a large partnership program with more than 2,000 participants from the start-up community (e.g., accelerators, venture funds, and university programs) (Crunchbase 2016d). According to the crowdsourcing approach, different groups of people (e.g., the user community or partnering organizations) can participate and improve or extend the database (Crunchbase 2016a). Up to now, CrunchBase counts 10,000 individual contributors per month that have produced more than 500,000 datasets. These datasets are accessed by more than 2 million unique visitors per month (Crunchbase 2016b). To ensure high data quality, CrunchBase provides sever-

al mechanisms: user authentication, algorithmic and personal reviews, and error reporting features (Crunchbase 2016c).

CrunchBase uses categories to organize registered start-ups. One specific start-up can be assigned to several categories. In order to identify data-driven business models, two IS researchers independently went through the list of existing categories and tagged data-related categories to find a consensus. To validate the relevance of the chosen categories, we analyzed the first 20 start-ups (sorted by relevance for the according category) to decide whether or not a certain category should be included. Based on this procedure, we considered the following six categories of start-ups: big data, big data analytics, business analytics, predictive analytics, analytics, and data mining.

Using this set of categories we extracted the 50 most relevant start-ups of each category, resulting in an initial record of 300 start-ups. We ensured that every start-up included was based on a data-driven business model by comparing available information (collected from CrunchBase as well as the website of the start-up) with our definition of a data-driven business model. To ensure a high amount of objectivity, two IS researchers reviewed the start-ups independently. According to this procedure, 253 business models were dismissed, as the core of their activities obviously did not require data. After a consensus was found, we started to analyze the resulting 47 data-driven start-ups regarding duplicate business models. Thereby, we examined if two or more businesses in this record were based on a similar business model. Subsequently, the two IS researchers first coded outstanding similarities and afterwards discussed, which start-ups could be discarded. We finally ended up with 33 distinct data-driven business models that were examined in the subsequent steps.[5]

5.3.2 Acquiring Similarity Ratings

In a second step, we gathered similarity ratings that form the foundation to extract the taxonomy's dimensionality using MDS in step three. As a purpose of our research is to ultimately help practitioners concerned with the development of new business models, we consulted experts from this domain. Considering their perceptions builds the foundation for future research to help this group of interest. Consequently, we searched for business model experts that also provide entrepreneurial experiences as they had to assess business models of start-ups. We addressed both founders of existing start-ups as well as professionals with a strong focus on business models. Since entrepreneurs are frequently confronted with the challenge to

[5] A list of all data-driven business models is available in the appendix.

improve and innovate their business model, they should provide extensive knowledge in this area. With regard to other business model professionals, we limited the search results to those who had an explicit record of entrepreneurial activities to ensure a high quality of our sample.

We collected similarity ratings for each pair of data-driven business models. As the comparison of each possible pair by a single expert is not appropriate in terms of cognitive load, we followed Posey et al. (2013) and asked each expert to compare one specific data-driven business model with all remaining ones. Accordingly, 33 experts were involved in comparing all possible combinations of business models. Overall, we collected 1,055 similarity ratings from these experts regarding the presented business models. Experts' age ranged from 20 to 50 resulting in an average of 32.07 years of age (SD = 7.75). The business models were presented using a short text-based description adapted from the information available on CrunchBase and the specific website of the start-up. To ensure that each description contained sufficient information about the business model, we followed Burkhart et al. (2011) who proposed offering factors, market factors, internal capability factors, and economic factors as common features of every business model. To avoid a bias in the experts' similarity ratings, we did not explicate which business model components were used. The similarity ratings were provided using nine-point bipolar scales ranging from 1 = "not at all similar" to 9 = "very similar." For the qualitative part of the study, experts were asked to reflect on the criteria they used to compare the business models and enter these reflections into a text field after their similarity assessments.

5.3.3 Determining the Structure and Dimensionality of Experts' Similarity Perceptions

In the third step, the data obtained from the previous step was analyzed using MDS. Specifically, we applied the PROXSCAL implementation included in SPSS. To calculate the structure of the experts' perceptions using the similarities, it is first necessary to decide how many dimensions should be used. Research on MDS proposes that interpretability is an important criterion that affects the choice of a reasonable number of dimensions (Kruskal and Wish 1984; Schiffmann et al. 1981). Therefore, most researchers use a maximum number of three dimensions (e.g., Padgett and Mulvey 2007; Posey et al. 2013; Robinson and Bennett 1995) as it is hardly possible to interpret a higher dimensionality. To decide whether three or fewer dimensions should be chosen, the stress index can be used to further guide this decision. The stress index states how well the similarity ratings can be matched to a certain dimensionality (Robinson and Bennett 1995). Therefore, it is required to minimize this stress index. In our case, we obtained the lowest stress level for a three-dimensional solution (.06 < .11 < .28).

The second part of this step implies the graphical mapping of the experts' perceptions. Thus, MDS was used to calculate a position for every business model regarding the three dimensional space (coordinates for each dimension x, y, z). Thereby, MDS tries to locate all business models in a way that achieves the best fit with the empirical similarity ratings.

5.3.4 Identifying Common Characteristics Based on Qualitative Data

The two subsequent steps were aimed at interpreting and labelling the three dimensions that explain the similarities and differences of the business models in the data. To later obtain meaningful labels, the procedure consults the qualitative data to extract those attributes that were used by the experts to arrive at their similarity ratings (Posey et al. 2013). In order to identify these attributes, all three authors studied the qualitative data in two steps: first, the authors independently coded the data and thereby created separate lists of attributes. The following example (see Table 9) illustrates how an expert's statement was used to extract different attributes:

Exemplary statement	*"[I compared the business models based on the] target group (consumers, companies) to which the business is selling a product or service."*
Resulting attributes	"The offering is not relevant for consumers." vs. "The offering is relevant for consumers."
	"The offering is not relevant for organizations." vs. "The offering is relevant for organizations."

Table 9. Coding Example

Attribute	Left Anchor	Right Anchor
REL_C	"The offering is not relevant for consumers."	"The offering is relevant for consumers."
REL_O	"The offering is not relevant for organizations."	"The offering is relevant for organizations."
COST_C	"The offering is available for free for consumers."	"The offering is not available for free for consumers."
COST_O	"The offering is available for free for organizations."	"The offering is not available for free for organizations."
TECH	"The business model requires small technological efforts."	"The business model requires high technological efforts."
U_DATA	"The business model is not based on user data."	"The business model is based on user data."
ADV	"The business model is not based on advertisement."	"The business model is based on advertisement."
SALE	"The business model is not based on the sale of data."	"The business model is based on the sale of data."
SERV	"The business model is not based on offering a service."	"The business model is based on offering a service."

Table 10. Attributes Extracted from the Qualitative Data Provided by the Experts.

Afterwards, potential differences were discussed in order to arrive at a single list of attributes. If two attributes were highly similar, they were merged. This resulted in 16 attributes. In a second step, the authors independently counted the occurrences of these attributes in the data to determine their relevance. To deal with possible subjectivities, the resulting frequencies of all three authors were added up to arrive at a joint ranking. As the next step associates the

attributes extracted from the qualitative data with the dimensions resulting from MDS, the resulting set of attributes needs to be reduced for feasibility reasons for ProFit analysis (Posey et al. 2013; Robinson and Bennett 1995). We selected the nine most frequently mentioned attributes that resulted from the coding process which are displayed in Table 10.

5.3.5 Mapping Attributes and Dimensions Using ProFit Analysis

ProFit analysis is based on multiple regressions to determine how well an object's location within the n-dimensional space (obtained by MDS) explains its value for each of the relevant attributes. To obtain the business models' values for the attributes extracted in the previous step, it was required to collect an additional round of data. We therefore asked 16 expert raters (i.e., 11 IS researchers and five research assistants trained on the topic) to evaluate all data-driven business models regarding each attribute identified. These raters have a profound background in the field of information technology and intensively cooperate with the local start-up center that fosters entrepreneurial activities. As they are confronted with the development of innovative business models in this regard, the raters are also well educated with respect to this topic.

As all attributes should be rated for every business model, we presented and surveyed each attribute on a 7-point bipolar scale as shown in Table 10. Thus, we collected scores for each attribute for every business model from all raters, which resulted in over 500 ratings for each attribute. These ratings allow subsequent regression analyzes for the attributes regarding their relationship with the business model locations. One separate regression was computed for each attribute in relation to its position in the space created by MDS (Padgett and Mulvey 2007; Posey et al. 2013; Robinson and Bennett 1995). Particularly, attributes were used as the dependent variables and the coordinates of the business models' positions (x,y,z) were used as independent variables. Table 11 shows the results of these regressions.

						Correlations					
Attribute	**R^2**	**F**	**Dim 1**	**Dim 2**	**Dim 3**	**REL_C**	**REL_O**	**COST_C**	**TECH**	**U_DATA**	**ADV**
REL_C	.22	4.07*	-.00	-.54**	-.02						
REL_O	.27	4.89**	.05	.48**	.32*	-.50**					
COST_C	.17	3.15*	-.32	-.37*	.04	.28	-.28				
TECH	.28	5.24**	.27	-.19	-.49**	.16	-.24	-.81			
U_DATA	.48	10.97***	.66***	-.25	.19	.26	-.29	-.98	.18		
ADV	.28	5.12**	.14	-.45**	-.36*	.51**	-.49**	-.12	.15	.19	
SERV	.20	3.64*	.31	.26	.33*	-.39*	.48**	-.20	.11	.20	-.37*
***p < .001, **p < .010, *p < .050.											

Table 11. Results of the Property Fitting Analysis

Two of the initial nine attributes were excluded in the process (COST_O and SALE) as they had no significant relationship with any dimension resulting from MDS (COST_O: F = 2.24 with p = .11; SALE: F = .74 with p = .54). Regarding the remaining attributes, two were significantly related to more than one dimension (REL_O; ADV). In this case, we analyzed the corresponding regression weights to determine, to which dimension the attribute was related more strongly. Below, we describe how these results were finally used to arrive at meaningful labels for the dimensions obtained from MDS.

First dimension: data source (non-user data vs. user data)

In order to interpret the first dimension, we focused on the attribute U_DATA, because it was the only attribute that had a significant relationship with this dimension. As this attribute explains a high amount of variance and has the highest regression weight in this analysis (ß = .66), it was clear that this attribute appropriately describes the first dimension. Another indicator for the usefulness of this attribute relates to fact that it is not significantly correlated with another attribute. Thus, the first dimension can be clearly distinguished from the others. Since the associated attribute was surveyed using the bipolar scale "The business model is not based on user data" vs. "The business model is based on user data", we label this dimension "data source". The continuum of this dimension is therefore described using the extrema "non-user data" vs. "user data". To illustrate the characteristics of this dimension, we will provide two examples for each extreme point from our population of business models.

Based on the experts' ratings, "Company 3" had the highest score on this first dimension (.825) and therefore provides a good example for a company that is based on a non-user data-driven business model. Specifically, the company sells access to past and current high quality satellite images that can be used for different organizations, for example, to analyze the workload for providers of logistics services as they can assess how many trucks are currently located within a certain part of a harbor area. Obviously, the company is completely independent from user data as it relies entirely on satellite image data. In contrast, "Company 9" that had a score of -.829 on the first dimension runs a localized search engine that is entirely dependent on user data in form of their search queries and profiles. This dependency relates to the fact, that the provided user data builds the foundation to earn money by selling personalized advertisement.

Second dimension: target audience (consumer-focus vs. organization-focus)

Compared to the first dimension, four attributes were significantly related with the second dimension (REL_C; REL_O; COST_C; ADV). According to the highest regression weights,

this second dimension was strongly associated with ratings whether business models were relevant for consumers or organizations (REL_C, ß = -.54; REL_O, ß = .48). Since the dimension's relationships with these attributes are of opposite signs, dimension two indicates whether the business model's audience has a consumer-focus or an organizational-focus. Furthermore, this dimension also distinguishes business models in respect of whether the offering was a paid service for consumers (COST_C) and whether the business model was based on advertisement (ADV). This is reasonable as manifestations on these attributes should strongly depend on whether the business model is targeted at organizational customers or end users. Note that no significant correlation between COST_C and ADV could be observed in the data. This makes sense as businesses models targeted at consumers can be based on a service fee and advertising simultaneously. Likewise, there was no significant correlation between a business model's relevance for consumers (REL_C) and the costs for consumers (COST_C). This accounts for the possibility that consumer-oriented services within our population of business models were both available for free or for a charge. In sum, this dimension can be labelled "target audience", which varies from consumer-focused to organization-focused business models. As in the previous subsection, we will provide two examples of particular business models that are located near the extreme points of the dimension.

"Company 29" with a value of -.705 on this dimension is entirely focused on consumers as it offers personal health assistance that enables users to get an answer to their medical questions. Accordingly, everything this company does is aligned to serve consumers in a certain way. Therefore, they provide adaptive algorithms that are continuously getting better to intelligently support the users. In contrast, "Company 23" that scored .933 on this dimension, sells insights from legislative and regulatory data to foster transparency in the political and legal system. Accordingly, this offering is focused on helping organizations that are working in highly regulated environments like the financial sector. Therefore, the offering can be considered as largely irrelevant for consumers.

Third dimension: technological effort (high vs. low)

Four attributes were significantly related to dimension three (REL_O; TECH; ADV; SERV). Considering the regression weights, the technological effort of a business model is the most important attribute for this dimension (TECH, ß = -.49). We labelled this dimension accordingly referring to the amount of technological effort required to provide the service (e.g., data collection, transformation, integration, analysis). Based on this label, it seems curious at first that a business model's relevance for organizations (REL_O) and the dependency on adver-

tisement (ADV) were also significantly related to this dimension. Looking into the population of our business models, business models targeted at organizations often required less technological effort as they often offered data or data-based insights without complex processing to their organizational customers who might use these data or insights in their own processes. For consumer-focused business models, no such relationship could be observed which could explain why the business model's relevance for consumers was not associated with dimension three. In a similar fashion, advertisement often requires high technological effort as personalization algorithms are based on a rather complex integration and analysis of different kinds of data.

The fourth attribute associated with dimension three refers to the question whether a business models' offering was based on providing services. This attribute seems problematic for the purpose of differentiating the three dimensions as its regression weights were almost equal for all three dimensions (the significance levels of the coefficients for the first two dimensions were slightly above 5% level). Therefore, we excluded this attribute from our analysis and interpretation of the dimensions. In sum, we interpreted dimension three as the amount of "technological effort" involved in the data-driven business model. Note the negative sign of the regression coefficient which means that a high value on dimension three refers to little amount of technological effort involved and vice versa.

In order to illustrate the dimension label, we discuss two examples of particular business models with high absolute scores on dimension three. "Company 6" with a score of -.675 on this dimension offers a service for consumers that helps them to buy flight tickets at the best price. Therefore, the company uses massive amounts of pricing data gathered from the Internet to automatically predict the development of ticket prices to support consumers. Accordingly, this offering requires high technological efforts to predict accurate results using intelligent algorithms. In contrast, "Company 32" that scored .900 on dimension three offers a simple register of health clubs in a database that helps business owners to promote their health club and consumers to find an appropriate one. Thereby, rather little technological efforts are necessary.

5.4 Results

To sum up, the most relevant dimensions to distinguish data-driven business models according to the perspective of business model experts refer to the data source utilized, the target audience, and the technological effort required. Every dimension is shaped using two extreme

points. Specifically, a data-driven business model can be based on non-user or user data, can focus on consumers or organizations, and can require a high or low technological effort. Using this differentiation, eight ideal-typical categories result. In order to foster a deep understanding, we provided several examples from our data record to illustrate how particular business models regarding these extreme points could look like. In order to present our findings, we provide a visualization using a decision tree that is shown in Figure 5.

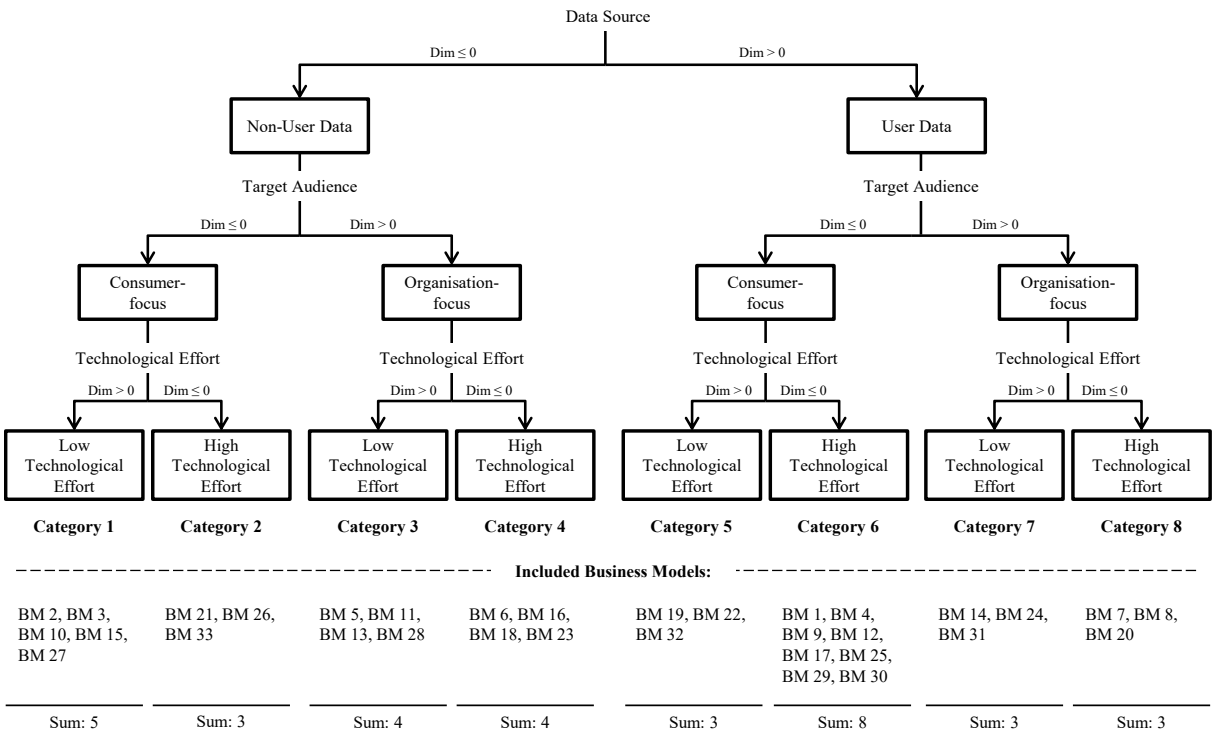

Figure 5. Taxonomy of Data-Driven Business Models Illustrated Using a Decision Tree.

We also use this visualization to provide a mapping of the particular business models to the categories of our taxonomy. This was done by analyzing the position of each business model regarding the three dimensions. We want to emphasize that, obviously, hybrid business models exist with values on the dimensions in between the extrema. For example, a business can provide a service for both consumers and organizations. At this point, we focus on the identification of ideal-typical categories and therefore concentrate on highlighting the meaning of the different endpoints but acknowledging the possibility of hybrid scenarios. As the business models are distributed rather equally across the classes, the dimensions resulting from this research are suitable to distinguish the record of business models. The minimum number of business models in category is three, the maximum is eight. In order to analyze the most important categories regarding our taxonomy, we take a further look at category six, which contains the highest number of business models according to our taxonomy. This category can be described by the following characteristics: the business model is based on user data and fo-

cuses on offering a product or a service to consumers. Furthermore, it requires a high technological effort. Building on these characteristics, we can find offerings created with complex algorithms on the basis of big user data. An example for this category is "Company 4" that computes a data-driven credit score for consumers on the basis of social media data provided by them. As a result of an intelligent usage of this data, the credit score can be calculated in a few minutes and is independent from a lot of critical information that is required in traditional credit scores.

5.5 Discussion

5.5.1 Theoretical Contributions

By revealing the perception of business model experts and the most important dimensions to distinguish data-driven business models, this research contributes by providing a foundation for this increasingly relevant research area. Therefore, in the spirit of Posey et al. (2013), we focus on the "science of diversity" that investigates a population of objects by highlighting and understanding the similarities and differences of the objects in question (McKelvey 1978; McKelvey 1982). In contrast, the "science of uniformity" seeks to discover the "universal laws governing the behavior, function, and processes of a population of objects" (McKelvey 1982, p. 12). As the "science of uniformity" obviously depends on the "science of diversity", our approach is crucial to further study data-driven business models. Accordingly, the presented results may form the foundation for various theory building efforts regarding data-driven business models as we help to create a common understanding based on which important attributes and categories of data-driven business models should be considered. While this common understanding is essential for the consideration of several research questions, we will highlight two particular aspects.

We argue that our resulting dimensions emphasize the importance of an integrative consideration of data-related (e.g., big data) and business model research as we revealed relevant dimensions from both research areas. Therefore, we empirically support the literature's suggestion that it is essential to combine relevant insights from both areas (e.g., Buhl et al. 2013; Loebbecke and Picot 2015; Veit et al. 2014). Thereby, our results can help to instantiate general business model representations that typically do not consider any technical or data-driven aspects (e.g., Al-Debei and Avison 2010; Hedman and Kalling 2003; Osterwalder et al. 2005). Consequently, data-specific attributes (e.g., the data source and its corresponding characteristics) may be integrated into established representations.

Moreover, our results can be a useful foundation to guide design science research efforts that develop entirely new methods, which support organizations in identifying new business models (Gregor and Hevner 2013). While literatures points to the relevance of business model innovation (e.g., Hanelt et al. 2015), existing methods (e.g., Gassmann et al. 2015; Osterwalder and Pigneur 2010) might be too abstract to guide business model developers to work in data-driven areas. In contrast, our study is based on business model experts' perception of data-driven business models. Therefore, we argue that this perspective is particularly valuable as new methods drawing on these results can consider the experts' way of thinking about data-driven business models and hence, help to support them in the best possible way.

5.5.2 Practical Contributions

Our study strongly builds on the perceptions and experiences of business model experts and we argue that this focus on the experts' mind-set leads to a high practical relevance of our results. Indeed, one of the initial aims of this study was to support this group of people in their daily activities. As discussed before, the development of new data-driven business models may be very beneficial for organizations to create new value. While most organizations lack a fundamental understanding of this new topic, we contribute to practice by providing an overview of eight ideal-typical categories of data-driven business models and the dimensions distinguishing them. Thereby, we help to establish a fundamental understanding that allows organizations to purposefully develop data-driven business models in a more structured manner. This is especially relevant as the business model innovation process is usually rather unstructured (e.g., Schneider and Spieth 2013). Accordingly, our results support organizations in identifying a possible target state (i.e., a possible business model) by giving an overview of different kinds of data-driven business models and thereby showing organizations which paths they can follow. In addition to guiding the organization's own path to develop a new data-driven business model, the proposed taxonomy can also be used to segment the market by identifying comparable providers or possible competitors.

As soon as an organization has identified in which category it aims to develop a data-driven business model, the organization can benefit from looking at other companies whose business models fall into the same category. In this way, the organization can get inspired by the examples of others and analyze how the corresponding providers handle category-specific challenges. For instance, an organization might want to develop a business model that can be characterized by the utilization of user data, a consumer-focus, and high technological effort. Examples of this category are services that provide personalized content using complex rec-

ommendation algorithms, such as Netflix. Netflix offers personalized movie and TV show recommendations based on an extensive analysis of viewing preferences. These personalized offerings face the significant challenge that a user may become isolated from content that does not fit to his or her profile (i.e., filter bubble). Therefore, an organization developing its business in this category can try to learn how to handle this challenge by analyzing how these existing companies operate. Accordingly, such comparisons point to areas of expertise, which are required depending on the type of business model that is intended to be developed.

5.5.3 Limitations and Future Research

In this section we will discuss the limitations of our research and point to avenues for further research. One limitation concerns the population of business models considered in this research. On the one hand, it seems possible that the chosen data source (i.e., CrunchBase) does not cover all types of data-driven business models as it focuses on start-ups. Hence, traditional companies may have different business models requiring resources that cannot be provided by start-ups. On the other hand, our definition of data-driven business models excludes those business models that do not necessarily require digital data. Consequently, there might be businesses that use data in complementary business functions, which are not regarded in this study. Therefore, future research could examine data-driven business models in a broader context and analyze if additional types of business models emerge. Furthermore, it is also possible that new kinds of data-driven business models will be developed in the future that are not considered in our sample to date. As a consequence, it could be helpful to validate our results using different populations of data-driven business models. In addition, developing taxonomies is associated with the challenge to trade-off between generic and specific dimensions. Relying on established methods, our study has extracted rather generic dimensions. Therefore, future research may contribute by further exploring these dimensions.

6 Paper D: The Nature of Enterprise-Service-Fit

Title

The Nature of Enterprise-Service-Fit in the Context of Digital Services

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Abstract

Many different companies compete with each other to offer users similar digital services. For instance, traditional banks compete with companies like Apple or Google in providing digital payment services. These companies strongly differ in their strengths and weaknesses, and we argue that users might evaluate the same service differently depending on the company providing it. We introduce the concept of "enterprise-service-fit" and argue that it is beneficial if users perceive a company's resources to fit a service's requirements. Using a grounded theory approach, we explore what constitutes enterprise-service-fit in the context of digital services and discover five dimensions on which a company's resources might fit a service's requirements. We also offer some preliminary insights regarding potential consequences of fit. We contribute to research concerned with users' evaluations of digital services that has so far overlooked an interaction between company and service characteristics.

Keywords

Enterprise-Service-Fit, Digital Services, Service Adoption, Grounded Theory

6.1 Introduction

In today's digital economy, we can choose from a wide range of digital services that support us in the course of our daily lives. Apple's well-known slogan "There's an app for just about anything" perfectly illustrates this rich supply of digital services. Interestingly, in the market for digital services, we can observe that highly different companies compete with each other by offering quite similar services to potential users. Consider the example of digital payment services: in 2015, Ana Botín (executive chair of Santander) reflected on the increasing competition that traditional banks face nowadays given that technology companies have started to enter their market: "if you think about the big guys now, it is not the banks, it is these four large tech companies [Amazon, Apple, Facebook, and Google]" (ComputerWeekly 2015). Indeed, when considering digital payment services, we can choose from a variety of providers such as traditional banks but also technology companies such as Apple or Google (McKinsey 2014).

While digital payment services are just one example of highly different companies competing with each other when offering similar digital services, other markets and industries go through similar changes. To name just a few examples: television is no longer in the hands of incumbent media companies but is disrupted by companies such as Netflix or Amazon, supermarket chains increasingly face competition with companies like Amazon in providing food delivery services, and navigation systems are offered not only by companies with a longstanding history in this market but also by firms like Google or Apple.

But how do individuals arrive at an assessment which company's service might be superior to that of a different provider? To once again consult the abovementioned example, digital payment services require profound technology expertise which seems to be the strong suit of inherently digital companies such as Apple or Google. And indeed, we can observe many people in our everyday lives using payment services provided by these companies (e.g., Apple Pay or Google Wallet). But on the other hand, these companies are new to the payments business where learning by doing does not seem to be an option. Accordingly, choosing these companies seems counterintuitive from the standpoint that traditional banks and payment providers have a strong history and rich experiences in this rather complex business.

In this research, we argue that an individuals' evaluation of a given digital service depends on the company behind it. Although insights, how such evaluations can depend on a company's characteristics, are abundant in technology adoption research (e.g., Gefen et al. 2003a; Gefen et al. 2003b; Pavlou 2003), this literature suggests that company's characteristics affect users'

beliefs and behaviors *independently* of the service in question. In contrast, we advocate that users' evaluations of digital services depend on an *interaction* between a company's resources and a service's requirements. We bring forward the idea that perceptions of how a company's resources *fit* the service in question are relevant for users evaluating a potentially interesting service. We refer to this idea as *enterprise-service-fit*.

To the best of our knowledge, extant IS research has overlooked the possibility that a company's characteristics interact with a particular service's characteristics to influence a user's evaluation of the service. Therefore, our study is exploratory in nature and aims at understanding what constitutes enterprise-service-fit in the context of digital services. We raise the following research question:

RQ: How can enterprise-service-fit be conceptualized in the context of digital services?

Faced with a lack of insights on the nature of enterprise-service-fit in the context of digital services, we performed a grounded theory study based on 37 interviews with potential users of these services. As a result, we define *enterprise-service-fit* as an individual's perception of how well a service's requirements are aligned with the resources available to the company providing the service. Thereby, we define a company's resources as "assets and capabilities that are available and useful in detecting and responding to market opportunities or threats" (Wade and Hulland 2004, p. 109). Our results reveal five dimensions of enterprise-service-fit, which are concerned with 1) customer data, 2) non-customer data, 3) service functionalities, 4) domain-specific expertise, and 5) technological expertise. Besides, we provide preliminary evidence regarding possible consequences of enterprise-service-fit which helps to link the concept to existing theory. Finally, we offer an initial exploration of contextual factors that might influence how enterprise-service-fit operates.

Our research makes significant contributions to theory and practice. From a theoretical perspective, we offer a newly developed construct, namely enterprise-service-fit, that helps understanding how individuals evaluate digital services in the light of different providers. Along these lines, we identify five dimensions of enterprise-service-fit that account for the particular characteristics of digital services. Besides, we provide preliminary evidence of how enterprise-service-fit can be related to existing theory on users' evaluations of digital services. From a practical perspective, our research supports companies in their assessments, which digital services might be more or less successful in a specific enterprise context.

The remainder of this paper is structured as follows: in section two, we present theoretical background on the concept of fit between organizations and its offerings as well as an over-

view of theory concerned with users' evaluations of digital services. Next, we describe the methodology and the results of our grounded theory study. We conclude by integrating our results with existing theory and elaborating on the contributions and limitations of our research.

6.2 Theoretical Background

In this section, we introduce theoretical background on the concept of fit and provide a brief summary of research that has investigated users' evaluations of digital services.

6.2.1 The Concept of Fit

The concept of fit has been examined in different streams of research, such as strategic management (e.g., Drazin and Van de Ven 1985; Venkatraman and Camillus 1984), marketing (e.g., Aaker and Keller 1990; Song et al. 2010; Völckner and Sattler 2006), or information systems research (e.g., Goodhue and Thompson 1995; Zigurs and Buckland 1998). In general, fit means that two or more variables match, are aligned, or congruent with each other (Venkatraman 1989). A state of fit can lead to improved outcomes. While the idea of fit between a company and its offerings has not been regarded in IS literature yet, research on strategic management emphasized the importance of a strategic fit (e.g., Porter 1996; Zajac et al. 2000), which means that a company's resources should be aligned with its products or services (Andrews 1980). Complementing this organization-focused perspective, marketing research has analyzed fit between a company and its offerings using a more customer-centric lens in the area of brand extensions. As our study is concerned with the role of fit in individuals' evaluations of digital services, we provide more details on the customer-centric perspective present in brand extension research below.

Brand extensions occur when products or services are added to a brand, which are targeted at markets not yet associated with the brand in question (Keller and Aaker 1992). Against this background, many studies have shown that new products and services are more successful if customers perceive a fit between these new offerings and the brand (e.g., Aaker and Keller 1990; Völckner and Sattler 2006; Völckner and Sattler 2007). Along these lines, different kinds of fit were found to influence the success of a brand extension. In particular, a product-category-fit refers to the perceived similarity between a new product's category and the product categories the company is already active in (Czellar 2003). Besides, a brand-level-fit describes the extent to which a brand image is reflected in the extension category (Czellar 2003), which is also referred to as brand concept consistency (Park et al. 1991). By now,

brand extension studies largely focused on non-digital products and services such as Heineken extending their brand from beer to also include wine (Aaker and Keller 1990). In contrast, digital services have not been investigated so far, except in one study by Song et al. (2010) who confirmed the importance of a fit between a company's existing and new offerings in the context of a search engine's brand extensions.

However, the lack of studies on brand extensions (and therefore on the role of fit between a company and its offerings) in the signifying context of digital services seems surprising, and we argue that research in this area is much needed. Likewise, Keller (2016, p. 11) reflects on the need for future brand research as follows: "Perhaps the most fundamental issue to consider is how the role of brands and branding has changed in today's *dynamic and fast-moving digital world*" (emphasis added). He further argues: "With so many new and different consumer and firm capabilities, marketers need to rethink virtually all of their beliefs and practices […]." In a similar vein, Völckner and Sattler (2007) underline that brand extension research is subject to considerable contextual influences. Therefore, we should not assume that existing brand extension research can satisfactorily explain individuals' evaluations of digital services regarding a fit between a company and its offerings, which we refer to as enterprise-service-fit. Indeed, digital services might be a particularly interesting context to investigate enterprise-service-fit in, given that highly different companies, such as inherently non-digital companies (e.g., traditional banks) and digital companies (e.g., Google or Apple) increasingly compete with each other by offering similar services.

6.2.2 Research on Individuals' Evaluations of Digital Services

We now provide a brief overview of literature concerned with individuals' evaluations of digital services. Two streams of research are particularly relevant: technology adoption and information privacy research.

Research on IS adoption follows a long tradition and is concerned with the questions when, why, and how individuals decide to adopt and use a technology. Several theories have been developed, advanced, and applied over the last decades. Prominent examples are the Technology Acceptance Model (Davis 1989; Venkatesh and Bala 2008; Venkatesh and Davis 2000), the Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003; Venkatesh et al. 2016), and the Innovation Diffusion Theory (Moore and Benbasat 1991; Rogers 2003). Many have built on these theories, for instance, by integrating the concept of user satisfaction into the Technology Acceptance Model (Wixom and Todd 2005).

To date, research on IS adoption has extensively studied how users' perceptions of technology characteristics or those of the company offering the technology affect users' evaluations and adoptions of technology. For instance, studies have emphasized the importance of perceived usefulness and perceived ease of use as important determinants of users' technology acceptance (e.g., Davis 1989; Davis et al. 1989; Venkatesh and Davis 2000). Others have studied how users' perceptions of the company providing the technology influence individuals' adoption decisions. In this regard, users' perceptions of a company's trustworthiness (e.g., Gefen et al. 2003b; Suh and Han 2003), reputation (e.g., Morgan-Thomas and Veloutsou 2013), or the risk to transact with the company (e.g., Pavlou 2003) were shown to affect adoption decisions significantly. Interestingly, none of these previous studies has considered the possibility that the characteristics of a particular service and the company behind it might interact to affect users' beliefs and behaviors.

Research on information privacy has investigated the question how individuals' privacy-related beliefs might affect their willingness to use services, which require personal information about them. Concepts such as individuals' privacy concerns (e.g., Hong and Thong 2013; Malhotra et al. 2004; Smith et al. 1996) and the trade-off between benefits and risks when disclosing personal information (e.g., Dinev and Hart 2006) have been used to explain individuals' information disclosure while using these services. Similar to IS adoption and use research, information privacy studies have examined the influence of both company and service characteristics on users' privacy concerns and therefore on their willingness to use a service (Li 2011; Smith et al. 2011). However, a consideration of how a company's and a service's characteristics have to fit together and how this fit might influence users' beliefs about a service, is missing from the information privacy literature as well.

In summary, both streams have so far neglected a potential interaction between a company's resources and a service's requirements for individuals' evaluations of digital services. As a result, the nature and possible consequences of enterprise-service-fit in the context of digital services are unclear.

6.3 Methodology

To explore the idea of enterprise-service-fit, we decided to use a grounded theory approach (Glaser 1978; Glaser and Strauss 1967). This approach aims at systematically developing theory from data (Glaser and Strauss 1967), which we deemed appropriate, given the lack of research on the nature of enterprise-service-fit in the context of digital services. Grounded

theory requires the researcher to stay open and "discover what is going on, rather than assuming what should go on" (Glaser 1978, p. 159). It thereby helped us to avoid force-fitting data into pre-existing categories as we explored the nature of enterprise-service-fit.

The idea of *fit* played the role of a seed concept in our study. Seed concepts are "hunches and sources of ideas that do not come from the data" (Urquhart 2013, p. 131). Seed concepts are accepted in Grounded Theory because they can "help a researcher to select an area of enquiry and define the topic" (Urquhart et al. 2010, p. 362). Other than that, we started our study with virtually no predetermined ideas to stay sensitive to what is happening in the data (Glaser 1978).

6.3.1 Data Collection and Theoretical Sampling

We collected data by conducting 37 semi-structured interviews with potential users of digital services. Interviews followed a coarse protocol as shown in the Appendix. Although presented in two separate subsections here, data collection and analysis were *closely interlinked* and proceeded in a highly iterative fashion, which is central to grounded theory studies (Glaser 1978; Glaser and Strauss 1967). We frequently met to discuss themes and ideas emerging from analyzing the latest interviews and to continuously refine the interview protocol to pursue interesting themes and to identify potential target participants that seemed most promising to interview next. This sampling strategy is referred to as *theoretical sampling* and presents a central element of developing grounded theory (Glaser and Strauss 1967). Specifically, we purposefully sampled our participants regarding their age, their gender, and their level of technology affinity to cover different perspectives towards digital services. Overall, our data was collected between June and November 2016.

Over the course of the last ten interviews, we recognized that no new codes emerged and that additional data revealed no new insights. This indicated that we had reached a point of *theoretical saturation* as we started seeing "similar instances over and over again" (Glaser and Strauss 1967, p. 61). Consequently, we ended our data collection after 37 interviews. The interviewees' age ranged from 17 to 74 years resulting in an average of 31.5 years. 15 of the participants were female, 22 were male. All participants were active smartphone users, which we deemed as relevant, given that many digital services are provided as mobile apps. Still, our participants differed with regard to how often they usually tried new apps which allowed us to incorporate both the perspectives of more and less experienced app users.

To explore the relevance of an enterprise-service-fit, we presented our interviewees the concept of a digital "smart travel assistant service," which we explicitly describe at the end of this section. Participants should imagine this smartphone service being offered by two particular companies to create two different enterprise-service constellations and elicit participants' thoughts and evaluations of these constellations. The companies were chosen in a way that should represent the common situation in which similar digital services are offered by a) an established non-digital company which tries to extend its offerings to digital areas and b) an established digital company trying to enter the traditional companies' markets (as companies like Google, Apple, or Amazon often do).

Therefore, we chose a real and well-known transportation company "TransCom" (synonym) with a long history and experience in this business and a real digital company "TechCom" with a strong technological background and a wide portfolio of other digital services. This constellation is quite common in today's market for digital services. For example, traditional banks are competing with companies like Apple or Google in offering digital payment services. Similarly, supermarket chains try to enter the digital market but face increasing competition from companies such as Amazon. Another example is presented by the hotel industry, in which established hotel chains face a strong competition with companies like Airbnb.

With regard to the "smart travel assistant service," we explained our participants that the general idea of this service was to provide users with a) information and recommendations regarding places, cities, and countries the user might visit (e.g., sightseeing), b) travel planning (e.g., the quickest routes vs. the ones with more beautiful landscapes), and c) options for ticket purchases. To use this service, users were told that the service needed access to GPS data offered by their smartphones.

6.3.2 Coding and Data Analysis

In order to analyze our data, all interviews were recorded and transcribed immediately, which resulted in almost 300 pages of single-spaced text. Data analysis was supported by the software package MAXQDA 12. We applied an *iterative coding approach*, which consists of three coding techniques: we used open coding to generate an initial set of codes that described our interpretations of what was going on in the data (Glaser 1978). This included *constant comparisons* of each incident with existing categories and data (Glaser and Strauss 1967). As we analyzed more and more interviews, we recoded our data several times, merged and divided codes to represent the data in the best possible ways. Along these lines, we used extensive

memo writing (over 200 memos) helping us to systematically collect and clarify ideas (Glaser 1978).

Next, we applied a selective coding approach that aimed at concentrating on common and conceptually interesting themes (Glaser 1978). In our case, this resulted in focusing on codes that were significantly related to our core theme of enterprise-service-fit. During this process, we discovered interactions between companies' resources and service requirements, which we coded as fit dimensions. In the last step, we engaged in theoretical coding, which is concerned with the relationships between the most interesting codes under study (Glaser 1978). Accordingly, we looked for connections between the fit dimension codes and relevant codes regarding potential consequences of fit. To do so, we *constantly compared* the codes that originated from our data with constructs of established theories on individuals' evaluations of digital services.

Throughout the whole process, we regularly discussed open questions which often led to new ideas and a deeper understanding of our data. Additionally, we collected early feedback from both potential customers of the travel assistant service and companies that were interested in understanding how digital services are evaluated by users. Specifically, we presented our preliminary results to our participants to check if they felt that our results represented their thinking appropriately. Likewise, we discussed our results in workshops with two companies, which were interested in how customers might evaluate digital services, to obtain their feedback and to better understand practical implications of our research.

6.4 Results

6.4.1 Conceptualization of Enterprise-Service-Fit

Five different dimensions of enterprise-service-fit emerged from our data. Most generally speaking, the extent of fit in each dimension depends on two factors: a) the resources a company has from the users' perspective (i.e., company-related component) and b) what the service requires from the users' perspective (i.e., service-related component). In a similar manner in which task-technology-fit means that a technology "has" what is "required" for a task (e.g., Goodhue and Thompson 1995), we define enterprise-service-fit in the context of digital services *as an individual's perception of how well a service's requirements are aligned with the resources available to the company providing the service*. In the following, we will provide more details on each of the five dimensions.

The *first dimension* we found represents a fit between *available and required customer data*. We define this fit dimension as the extent to which the personal user data required by the service is already available within the company. One interviewee stated that TechCom already accesses his GPS data through the operating system of his smartphone and additional location-based services. Therefore, he argued that the disclosure of GPS data in the introduced service did not represent an obstacle to use the service:

> "Well, I use a smartphone from TechCom, so my current location is available for them anyway, since GPS is activated by default to use their maps service and similar stuff. Therefore, I would say that it doesn't matter if TechCom uses my location for this travel assistant service as they already know where I am. So I don't lose any more of my privacy." (i34)[6]

The following quote by a different participant describes a misfit in this dimension as the GPS data demanded by the service is not available to TechCom for this particular user. Given this misfit, the user would be required to disclose additional data, which negatively influenced his perception of the service:

> "I would rather choose a service provided by the other companies to avoid that my whole data goes to TechCom. I mean, TechCom knows a lot about me already: they know a lot about my smartphone usage. So the GPS data [requested by the service] would come on top of that – as well as all of the data, which are then created regarding my travel activities." (i32)

The *second dimension* that emerged from our data represents a fit between *available and required non-customer data*. We define this fit dimension as the extent to which non-customer data that is required to provide a service is already available within a company. By non-customer data, we refer to data that is not personal information of the customer who evaluates the service in question. Non-customer data is often collected by a company when offering other products and services. For instance, TransCom collects large amounts of data regarding the timing and schedules of their transportation services. Another example for non-customer data relevant in our context was map data owned by TechCom, which could show how different points of interest in a city are connected through bicycle routes. In the following quote, the interviewee explained that the map data available to TechCom could improve the travel assistant service:

[6] We use the IDs (1 – 37) for our participants.

> "If I had to decide, I would choose to use the service provided by TechCom. […] I think the reason is that TechCom is quite good at knowing what is where given their map services and everything. […] I think they already possess a big amount of data." (i36)

Another participant similarly highlighted that the availability of more service-relevant data could lead to advantages when providing this service. When asked about TechCom's advantages when providing the travel assistant service compared to the other companies, the interviewee reported:

> "Given that TechCom owns an enormous amount of data, they should be able to provide a better service I think, simply because of this abundance of data they have." (i7)

Following our understanding of non-customer data, it also includes the data that has been generated by other individuals in the context of different services or products offered by a company. For instance, such data could occur in the form of individuals' reviews about particular places of interest or profiles covering their behavior (e.g., which routes they frequently travel). Accordingly, the following participant emphasized the value of integrating different pictures, reviews, and recommendations provided by individuals using the maps service of TechCom:

> "Going back to the example of TechCom's maps service, there are different tourist attractions and user photos, reviews, and further information related to them. Therefore, I believe that [the smart travel assistant service provided by TechCom that uses this information] would be rather up-to-date and better." (i30)

Similarly, another interviewee highlighted the potential that could arise when a company can build on comprehensive insights regarding their users' preferences obtained through analyzing the data that has been collected in existing services:

> "As TransCom collects data of many passengers, they have a large aggregated data pool, which enables them to discover particular user preferences that can be used to provide better additional services. These services, in turn, are probably valuable for another large group of users." (i19)

The *third dimension* of fit is related to *existing service functionalities* and the *functional requirements of the new service*. Existing service functionalities are features already implemented in other digital services of a company. We define this fit dimension as the extent to which the functionalities required in a new service already exist in other services of the company. Accordingly, participants assumed that it is beneficial for a company if it can reuse

these existing functionalities. The following quote offers an example that a route planning functionality available to TechCom could be integrated into the travel assistant service:

> "This can certainly be an advantage for TechCom, if their products are linked somehow. For instance, if I could use this traveling service to travel from A to B and then I could open the maps app, which has already downloaded an offline map of this city – different services could be integrated." (i33)

The *fourth dimension* is concerned with *available and required domain-specific expertise*. We define this fit dimension as the extent to which the domain-specific expertise that is necessary to provide a service is already available to a company. In this respect, participants argued that they would rather use a service offered by a company if they perceived that the company would have the domain-specific expertise necessary to provide a high-quality service. For instance, one interviewee explained which domain-specific expertise he expected from both TechCom and TransCom and which service he would rather use as a result:

> "I'd choose TransCom for anything related to traveling. […] For things related to searching such as looking for a restaurant, shopping, or products, I would certainly use a service provided by TechCom." (i24)

Similarly, another participant highlighted the potential advantage that TransCom could have regarding all knowledge specific to traveling:

> "Well, I guess that TransCom has a greater knowledge related to traveling. I think this is an advantage for them [when providing the introduced service]." (i15)

Finally, the *fifth dimension* is related to the fit between the *available and required technological expertise*. Accordingly, we define this fit as the extent to which the technological expertise that is necessary to provide a service is already available to a company. Similar to the previous fit dimension, individuals perceive it as an advantage if they think that a company already has the required technological expertise for providing a particular service. Therefore, this dimension, for instance, captures if a company can handle a service's complexity regarding the collection, processing, analysis, and presentation of large amounts of data. Our results indicate that individuals consider if the technological expertise of a company is sufficient to provide a certain service. The following interviewee perceived a rather high complexity when talking about the travel assistant service. Accordingly, she reported that TechCom should be better in handling this complexity than TransCom:

> "If the service is about filtering relevant things out of large amounts of data, I believe that TechCom would be more capable of doing so compared to TransCom, as they already deal with great amounts of data." (i19)

Likewise, another interviewee explained that TransCom's core business does not involve offering digital services. Therefore, he stated:

> "I mean traveling is definitely TransCom's business. But apps or data-related services – that's the core business of TechCom and they are more experienced in this regard. They know how to effectively provide data [to users]." (i23)

Taken together, the analysis of our data revealed five dimensions of enterprise-service-fit that were relevant for participants' perceptions of digital services. Table 12 sums up the five dimensions of fit and offers additional quotes for each dimension.

6.4.2 Exploring Possible Consequences of Enterprise-Service-Fit

Going further, we provide preliminary results how enterprise-service-fit could relate to existing theories or concepts with regard to individuals' evaluations of digital services. Note that our study is exploratory in nature – a theory-generating study – and that we, therefore, report on what emerged from the data. We do not seek to offer a complete and comprehensive framework of the consequences of enterprise-service-fit.

In case participants perceived an enterprise-service-fit with regard to the *available and required customer data*, two possible consequences were reported: first, participants told us that they were less concerned about their privacy, if the company offering the service already possessed the data requested by the service. For instance, one participant stated:

> "[I wouldn't have any concerns to provide my personal data in this service] as TransCom already has a lot of my data, including my bank account." (i19)

Based on our data, it seemed that a high enterprise-service-fit regarding the available and required customer data reduces individuals' *specific privacy concerns*, which represent "a person's privacy concerns in a given […] context, such as information requests by a particular website" (Li 2011, p. 466). In contrast, interviewees who perceived lower levels of fit in this dimension consistently reported higher specific privacy concerns. For instance, the following participant was worried about the increase in transparency when providing a company with additional data:

> "TechCom gets more and more of my data. Over time, you become somewhat transparent for this company. When I would choose to rather share this part [traveling] of my life with TransCom, this transparency would be distributed a little more." (i23)

Second, besides its effect on individuals' privacy concerns, participants also mentioned that a high level of fit in this dimension would be beneficial for the service's *ease of use* as they could save effort entering their personal data over and over again. Ease of use is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis 1989, p. 320) and represents a major factor in adoption research (e.g., Davis 1989; Davis et al. 1989; Venkatesh and Davis 2000). The following quote highlights the benefits of reusing a user account already existing at a company for a new service:

> "I already have a user account at TransCom. It means that it's easier to use the service […]. So I would rather choose the service provided by TransCom. Using the service offered by TechCom would mean that I would have to enter my data once again." (i29)

Regarding the second fit dimension (i.e., fit between available and required non-customer data), we observed that the availability of relevant non-customer data was perceived as helpful by the interviewees. It meant that the service could provide them with better travel-related information if this non-customer data could add value to the service. According to our results, a high fit in this dimension was positively associated with the perceived *information quality* of the service. Information quality has been defined in terms of the completeness, accuracy, format and currency of information and shown to affect individuals' adoption decisions (Wixom and Todd 2005). For example, a participant emphasized how TechCom could leverage available map data to provide users with better information within the traveling assistant service:

> "I just believe that TechCom has more data so they could provide a higher-quality service with more background information. […] things about the landscape and other things, for instance." (i22)

Likewise, another interviewee suggested that TransCom could offer a traveling assistant service with better information about traveling delays, having first-hand access to this information:

> "TransCom could be faster than others, since I would get the information [using the service] immediately from the source as compared to a third-party company that probably gets their data from TransCom anyway." (i28)

Remarkably, being able to provide a better information quality given the fit between available and required non-customer data is of particular importance, since a company's non-customer data can include enormous amounts of data obtained from different sources (involving individuals' use of existing products and services). Accordingly, when asked if the service provided by TechCom could be better due to the amount of data available, a participant emphasized that utilizing TechCom's data would be beneficial as it has been generated by numerous individuals, which implies large improvements in the information quality:

> "Yes, definitely [the service provided by TechCom could be better due to their enormous amounts of data]. As TechCom uses their [virtual personal assistant] and other services to track [their users'] locations and transfers this information to their servers, they permanently know where people are. This is fully enabled by the smartphones based on [TechCom's operating system] and the people using TechCom's maps service." (i31)

As described, the third dimension accounts for a fit between existing functionalities already implemented in other services and the functional requirements of the new service. We found that participants expected a higher *usefulness* of a service if a company was able to reuse existing functionalities in the particular service. Thereby, existing functionalities must be relevant for the digital service in question. In the context of consumer services, perceived usefulness has been defined as "the extent to which an individual perceives a [service] to be useful in performing […] tasks" (Kumar and Benbasat 2006, p. 428). A higher usefulness may be a result of both the availability of more functions (as additional functions could be integrated with little effort) and the quality of these functions (as reuse could lead to a higher maturity). The following quote provides an example of this relationship:

> "Intuitively, I would expect that TechCom's service would be richer and better integrated with their existing services such as their maps service. […] I think that their service would […] offer more functionality." (i30)

As shown before, the fourth dimension illustrates the need for a fit between the available and required domain-specific expertise. Our data showed that interviewees associated a high domain-specific expertise with regard to the domain of the particular service (e.g., traveling) with the ability to build a better service in terms of a higher usefulness. Accordingly, this indicates that perceptions of fit with respect to the domain-specific expertise resulted in a higher *perceived usefulness* of a service in this domain.

Fit No. and Definition	Example Quotes	Example Quotes for Possible Fit Consequences
Fit 1: **extent to which the personal user data required by the service is already available within the company.**	"This company already has a lot of my personal data, for instance from their search engine or other services. So, it's not an additional company that […] I provide my data with [when I use the service]. Instead, this company already has my data and now just uses it in a different way." (i11) "TransCom anyway sees which tickets I buy because of my customer account. They know where I'm going. I mean they have to know it, because I buy tickets from them. […] I don't want to give my data to TechCom in addition [by using their service]." (i1)	**a) Fit is associated with less *specific privacy concerns*.** "Consider that TransCom already knows where you're going. In fact, if I've bought a ticket using their service, then they know I'm on my way. […] Thus, I wouldn't be too concerned that they know a lot more about me in addition to what they already know if I'd use the new service." (i13) **b) Fit is associated with a higher *ease of use*.** "If I already have disclosed my data to a company, then I would try to use many of their services to avoid disclosing my data to additional companies. […] For example, I don't use ten different payment services, once I've started using one of them. This would take too much effort." (i33)
Fit 2: **extent to which non-customer data that is required to provide a service is already available within a company.**	"I believe that TechCom would have an advantage [when providing this service]. They've already collected a lot data about the world for their maps service. TransCom would have to start afresh since they haven't done anything like that before." (i12) "If TransCom offers such a service, then they can provide me with all of their offerings. But in case of a start-up, I'm not sure if they could provide me with all transportation possibilities [within this service], since some companies might keep their data for themselves." (i17)	**a) Fit is associated with a higher *information quality*.** "I think that they could likely provide me with a lot more and more accurate information [within the travel assistant service] than the TransCom, given the amount of data TechCom has." (i13)
Fit 3: **extent to which the functionalities required in a new service already exist in other services of the company.**	"I think that TechCom has a great advantage [offering the travel assistant service] due to their maps service. They could say: 'You're here' and then the maps service can help you navigating." (i27) "I would choose the service from TechCom, because I think they are experienced with everything that has to do with location and maps and they can draw on many of their existing services." (i11)	**a) Fit is associated with a higher *perceived usefulness*.** "With regard to traveling, I can't think of anything particular, where TechCom would have an advantage over TransCom. But maybe for navigation, because their maps service already has some functionalities in this regard." (i15)
Fit 4: **extent to which the domain-specific expertise that is necessary to provide a service is already available to a company.**	"If the service is not about knowledge related to traveling, I wouldn't choose TransCom, because I would think that they lack that knowledge." (i15) "TransCom's expertise is not in the area of making recommendations about anything else, which is not their products or services." (i16)	**a) Fit is associated with to a higher *perceived usefulness*.** "I think that TransCom could provide a better service. […] They are closer to the customers, they know this area better. […] They are just closer to the problems of the customers. [They know about] why people are traveling. What are their complaints? What are they missing during their travels? I think they are closer." (i35)
Fit 5: **extent to which the technological expertise that is necessary to provide a service is already available to a company.**	"When it comes to artificial intelligence, things like recommendations based on my data […] I believe that TechCom clearly has a greater expertise in this area. […] I could definitely imagine that [the presented service would be better when provided by TechCom.] " (i33) "In terms of such a service, it's crucial for me to quickly and clearly […] access the data. […] If you are unexperienced, then you are not going to do this as well as others who already have this experience due to the fact that they have already tried these things." (i34)	**a) Fit is associated with a higher *information quality*.** "I don't think they [TransCom] could provide the data in a current and timely fashion. […] I don't think that they could provide real-time information at the right time and at the right place. I don't think that they are able to do this from a technological standpoint." (i8) **b) Fit is associated with a higher *system quality*.** "They have a strong [technological] expertise in different areas and TransCom does not. […] Thus, I believe […] that the service is possibly more stable and reliable." (i30)

Table 12. Dimensions of Enterprise-Service-Fit and Its Possible Consequences

The following quote illustrates that the interviewee perceived TransCom to be more capable than other companies when it comes to building a traveling-related service, given the company's domain-specific expertise:

> "I think that TransCom could build a better service when talking about traveling, because of their expertise in the local market compared to TechCom." (i7)

As mentioned, the fifth dimension of enterprise-service-fit refers to a fit between available and required technological expertise. We observed two consequences of this fit dimension: *information quality* and *system quality*. Going further, we provide examples and brief explanations for each consequence. First, if participants felt that a company had a strong technological expertise, which is relevant for the specific digital service, they assumed that the company's skills regarding the processing and analysis of data could lead to a higher *information quality* of the service:

> "From a technological perspective, I think TechCom is more capable [to provide the introduced service …]. I believe they could offer it with more features, more possibilities for people who are really interested in these topics […] to inform themselves." (i29)

Second, a perceived fit in this dimension was also associated with a higher *system quality*, which has been linked to individuals' adoption decisions in prior research (Wixom and Todd 2005). Thereby, system quality has been conceptualized as a service's reliability, flexibility, integration, accessibility, and timeliness (Wixom and Todd 2005). Along these lines, a participant emphasized that he would rather choose the service of TechCom if the service required a high availability:

> "For me, TechCom represents availability [of their services]. Thus, I would rather use a service from TechCom, if I'd need to frequently access it […]. In contrast, I don't see that as an area of expertise of TransCom." (i13)

Overall, our data showed several salient relationships of enterprise-service-fit with constructs of existing adoption, use, and privacy theories. Table 12 provides an overview of all fit dimensions and their possible consequences.

6.4.3 Exploring Enterprise-Service-Fit and the Role of Context

During the identification of the fit dimensions and their possible consequences, we constantly compared our observations with the existing categories and data. Exploring our data this way made us aware that whether individuals incorporated a fit dimension in their evaluations of the service should depend on different contextual factors (i.e., different service and/or compa-

ny-related characteristics). In other words: considering different enterprise-service-constellations could result in the fact that the fit dimensions become more or less important for individuals' evaluations of the particular service in this context. Both IS research (Davison and Martinsons 2016) as well as literature on brand extensions (Völckner and Sattler 2007) emphasizes that elaborating on context is of significant importance. Therefore, we offer initial evidence on how the enterprise-service-fit dimensions' effects on users' evaluations of services might depend on context. This way, we provide future research with initial ideas how context might be relevant. Specifically, we point to potential moderators of the relationships between enterprise-service-fit and its consequences.

Table 13 offers an overview of the total number of participants who incorporated each fit dimension in their evaluations of the service in question. Note that this count only represents our particular enterprise-service constellation and the relative importance of each dimension is not generalizable across contexts. In fact, we argue below that these numbers are conditional on the specific context under investigation.

Fit Dimension	Number of Participants Who Incorporated the Dimension in Their Evaluation of the Service
Fit 1 (personal user data fit)	15
Fit 2 (non-customer data fit)	22
Fit 3 (service functionalities fit)	18
Fit 4 (domain-specific expertise fit)	9
Fit 5 (technological expertise fit)	14

Table 13. Importance of the Fit Dimensions

Table 13 shows that the importance of the fit dimensions substantially differs. Participants incorporate fit dimension 2 (i.e., non-customer data fit, in 22 cases) and 3 (i.e., service functionalities fit, in 18 cases) most often in their evaluations. Next, dimension 1 (i.e., personal user data fit) was referred to in 15 cases, whereas fit dimension 5 (i.e., technological expertise fit) was incorporated in 14 cases. Finally, fit dimension 4 (i.e., domain-specific expertise fit) was mentioned in 9 cases.

We believe that other services than our exemplary travel assistant service could substantially alter the importance of each fit dimension. In the case of our smart travel assistant service, we asked participants to disclose only little data (i.e., GPS data). Consequently, if we consider a service that requires more and also more critical user data (e.g., financial or health data), the importance of dimension 1 (i.e., personal user data fit) should increase. Similarly, our smart

travel assistant service included a rather broad set of features (i.e., providing information and recommendations regarding different places, cities, and countries, travel planning functionalities, and options for ticket purchasing). As a result, the importance of dimensions 2 (i.e., non-customer data fit) and 3 (i.e., service functionalities fit) might be rather high as a large feature set usually requires to integrate much data and functionalities. If we look at a digital service with a narrow feature set instead, the importance of these dimensions might decrease. Finally, the smart travel assistant service is not characterized by a high technological complexity. Therefore, the relevance of dimension 5 (i.e., technological expertise) shows a rather immediate level in our context. In contrast, if we regard a service that incorporates high technological complexity (e.g., predictions with advanced machine learning techniques), the relevance of dimension 5 (i.e., technological expertise) might increase.

In sum, these preliminary results can provide future research with ideas how contextual factors might influence the ways in which individuals' enterprise-service-fit perceptions affect different outcomes.

6.5 Discussion and Theoretical Integration

The objective of this study was to explore the nature of enterprise-service-fit in the context of digital services. In this section, we integrate the results of our grounded theory study with prior literature and highlight our contributions. We begin by discussing our findings in the light of existing research on individuals' evaluations of digital services and continue by relating them to the brand extension literature. Subsequently, we discuss practical implications of our study and complete this section by describing our limitations and avenues for future research.

6.5.1 Integration with Research on Individuals' Evaluations of Digital Services

Given prior literature on individuals' evaluations of digital services, we contribute by (1) conceptualizing a new construct (i.e., enterprise-service-fit) including the identification of its dimensions, and by (2) presenting an initial exploration of its possible consequences. Below, we describe these contributions in more detail. We start by discussing enterprise-service-fit on the construct level, before elaborating on its dimensions and their consequences.

Within the conceptualization of the enterprise-service-fit construct, we introduced the idea that individuals' evaluations of a digital service depend on the company behind it. Using a qualitative study, we investigated this notion and provided evidence that individuals indeed incorporate their perception of how well a company fits the service it offers when evaluating a

service. As our study's participants considered the concept of fit in the form of an alignment between a service's requirements and a company's resources, we defined enterprise-service-fit referring to this interplay. Given the frequent occurrence of individuals' enterprise-service-fit reflections in our data, our findings highlight the importance of a joint consideration of a company's resources and a service's requirements when accounting for individuals' evaluations of digital services. This perspective appears to be promising since existing IS adoption and use literature has neglected to consider the interplay between organizational and service characteristics to date. Accordingly, prior research has analyzed the influence of these characteristics merely separately so far (e.g., Gefen et al. 2003a; Gefen et al. 2003b; Pavlou 2003).

Referring to the five dimensions of enterprise-service-fit identified in this study, we describe below how they relate to existing constructs present in IS research. Besides, we also account for the dimensions' consequences and discuss how considering them in individuals' evaluations of digital services contributes to prior research concerned with this topic.

Fit dimension 1 (i.e., personal user data fit) relates to the amount of information that individuals need to provide to use a service. By emphasizing that a company's reuse of available customer data can change how many information individuals need to disclose, fit dimension 1 improves our understanding of how individuals' privacy concerns and their perceptions of the service's ease of use form. Specifically, prior research stated that individuals' privacy concerns depend on the amount of information they are requested to disclose (e.g., Malhotra et al. 2004; Smith et al. 1996; Stewart and Segars 2002). However, existing studies considered this amount of information solely based on the information required by the regarded service. Fit dimension 1 of our study refines this perspective by highlighting that we can better understand individuals' privacy concerns, if we additionally incorporate the information that already has been disclosed to a company, beyond the particular service. Indeed, already disclosed information should not further concern individuals when they have to provide them again. Besides, our findings show that individuals expect a service to be easier to use if they do not have to provide their already disclosed data again due to the company's reuse of it. Given this result, fit dimension 1 emphasizes the relevance of incorporating the benefits of reusing existing data, which come along with a fit between the service's requirements and the company's resources, when accounting for individuals' perceptions of a service's ease of use. This way, fit dimension 1 complements prior research that mainly focused on considering individuals' perceptions of a service's ease of use regarding its functionalities (e.g., Davis 1989; Davis et al. 1989; Venkatesh and Davis 2000).

Fit dimension 2 (i.e., non-customer data fit) refers to the benefits that can arise when companies are able to combine data across different products and services. By carving out that individuals consider these benefits when evaluating a digital service, fit dimension 2 offers a new perspective on why individuals might expect a service to provide high-quality information. Precisely, existing literature on big data and data analytics underlined the potential companies could tap in when linking large amounts of data to create improved products and services (e.g., Davenport 2006; Davenport et al. 2012). So far, previous studies discussing this thought solely covered the organizational perspective, neglecting a user-centric lens. Accordingly, research on individuals' adoption and use of digital services did not incorporate this idea. Extending prior research, fit dimension 2 of our study provides new insights into individuals' service evaluations by stressing that individuals consider a company's potential of utilizing its existing data in a new service when assessing the service's information quality. This way, we complement the organization-centric perspective present in the big data and data analytics literature (e.g., Davenport 2006; Davenport et al. 2012).

Fit dimension 3 (i.e., service functionalities fit) relates to the benefits that can occur when companies are able to reuse existing service functionalities. By stressing that individuals incorporate these benefits in their evaluations of digital services, fit dimension 3 provides a new perspective on why individuals might expect a service to be more useful. Specifically, existing studies on software and code reuse proposed that companies can develop digital services more efficiently by building on the functionalities already implemented in existing services (e.g., Frakes and Kang 2005; Sojer and Henkel 2010). By utilizing such a strategy, it should be possible to develop a better service in less time. However, while this idea has frequently been considered using an organization-centric perspective, individuals' perceptions of reusing service functionalities have not been regarded yet. Rather, existing adoption and use literature solely focused on considering the functionalities of the service in question, without respecting a company's existing functionalities. Extending prior research in this area, fit dimension 3 of our study reflects a new angle accounting for individuals' service evaluations by emphasizing that they take a company's potential of reusing functionalities into consideration when estimating a service's usefulness.

Fit dimension 4 (i.e., domain-specific expertise fit) and fit dimension 5 (i.e., technological expertise fit) refer to individuals' perceptions of a company's ability to provide the service in question. By highlighting that individuals incorporate the interplay between a company's expertise and a service's requirements when evaluating a service, fit dimensions 4 and 5 refine

our understanding of how they estimate its usefulness, information quality, and system quality. Precisely, prior IS adoption and use research frequently studied the concept of trust (e.g., Casey and Wilson-Evered 2012; Gefen et al. 2003a; Gefen et al. 2003b), suggesting that individuals' perceptions of a service provider's ability influence their trust in the provider. Following Mayer et al. (1995, p. 717), ability refers to the "group of skills, competencies, and characteristics that enable a party to have influence within some specific domain." In fact, our fit dimensions 4 and 5 well cover this definition. Still, they also extend our understanding of how individuals' perceptions of a company's ability influence their service evaluations. On the one hand, they suggest that individuals consider a company's ability in the context of a particular service and not just on a general level, which underlines the benefits of a fit between a company and a service. On the other hand, fit dimensions 4 and 5 detail what kinds of expertise individuals deem to be essential to provide digital services (i.e., domain-specific and technological expertise). By providing this differentiation, we also disentangle the consequences of the dimensions: Our results indicate that a domain-specific expertise fit directly influences a service's usefulness, while a technological expertise fit affects a service's information and system quality that, in turn, impact its usefulness (Wixom and Todd 2005). Consequently, a technological expertise fit asserts an indirect effect on a service's usefulness. Therefore, our findings refine prior research that usually focused on the relationship between trust (including the ability dimension) and a service's usefulness without considering its information and system quality (e.g., Gefen et al. 2003b).

6.5.2 Integration with Brand Extension Research

In this section, we relate our findings to literature on brand extensions. This way, we show that our results are well aligned with existing theory underpinning the validity of our emerged enterprise-service-fit concept. Further, we discuss how our findings extend prior brand extension research.

Studies on brand extensions frequently showed that individuals evaluate a new product or service based on their perception of fit between the offering and the brand providing it (e.g., Aaker and Keller 1990; Völckner and Sattler 2006; Völckner and Sattler 2007). In fact, fit has been regarded in different forms, such as a product-category-fit and a brand-level-fit (Czellar 2003). Remarkably, the results of our study thoroughly reflect the ideas expressed in these forms of fit, which we discuss with more details below:

The notion of a product-category-fit suggests that it is beneficial for a company if the category of existing offerings resembles a new product's or service's category. Developing a new

service in a familiar service category usually enables companies to reuse some of its resources. In the context of digital services, the possibilities to reuse resources in particular refer to given data, functionalities, and expertise. As our enterprise-service-fit accounts for utilizing existing resources in the form of data (i.e., customer and non-customer data fit), functionalities (i.e., service functionalities fit) and expertise (i.e., domain-specific and technological expertise fit), it well reflects the ideas included in a product-category-fit.

Besides, a brand-level-fit implies that a new product or service is more successful if its category represents a brand's image (Czellar 2003). While the scope of this perspective varies depending on what is regarded as a brand's image, our fit concept still covers different brand-level-fit constellations. For instance, some of our participants perceived TechCom to be a "data-driven company." Therefore, offering a new data-driven service should fit its brand image well. Being a data-driven organization usually implies that the company already possesses large amounts of data, implemented functionalities to use them, and has the corresponding technological expertise at its disposal. Against this background, our fit concept well reflects the ideas included in this particular brand-level-fit as harnessing existing data (i.e., customer and non-customer data fit), functionalities (i.e., service functionalities fit), and technological expertise (i.e., technological expertise fit) is of concern to our fit dimensions. Beyond this example, other brand-level-fit constellations can be similarly represented by our fit concept, for instance, if we regard brands that are perceived to be specialists in a particular domain (which relates to our domain-specific expertise fit).

Finally, we also contribute back to brand extension theory by offering new insights on the concept of fit in the signifying and so far barely studied context of digital services, which increasingly gains importance in marketing research (Keller 2016). In particular, we reveal which fit dimensions are relevant in this context. Compared to non-digital brand extensions, the possibilities to reuse existing data and already implemented functionalities directly refer to the peculiarities of digital services. Against this background, our findings can inform future research by pointing to service characteristics promising to study prospectively. Besides, the enterprise-service constellation considered in our study (i.e., an inherently non-digital company competes with a digital company) can help to improve our understanding of how companies, which substantially differ from each other regarding their digital experience, are perceived by potential customers.

6.5.3 Implications for Practice

From a practical perspective, our results support companies in better understanding how users assess digital services. More precisely, we provide managers with guidance regarding which fit dimensions are important from the users' perspective. Further, our findings might also help companies to understand possible consequences of (mis-)fit. In the following, we discuss implications for the development of new and the communication around existing services.

When companies have to decide which digital services they should develop in the future, our study emphasizes that they need to consider their own strengths and weaknesses with regard to the services in question (as well as those of their competitors). Against this background, the dimensions of enterprise-service-fit can help to identify these strengths and weaknesses. For instance, traditional automotive companies currently evaluate the potential of digital services based on the data produced by drivers every day. A service which builds on these data should leverage the fact that this resource is unavailable to purely digital companies. Accordingly, digital companies cannot achieve a personal user data fit in this regard. Similarly, our findings can support traditional banks in developing new digital payment services that have to compete with the solutions provided by companies like Apple or Google.

Our results can also support companies in improving users' fit perceptions of already existing services. Companies could try to influence users' perceptions of enterprise-service-fit using appropriate communication and marketing measures. For instance, a transportation company such as TransCom could try to improve individuals' perceptions of its technological expertise. In this regard, marketing efforts should be targeted at positioning the company as a competitor in the digital age. As our data showed, many participants did not associate this company with expertise in the area of digital services. The company could benefit from showcasing innovative examples of their capabilities regarding data analytics and digital services to its customers.

6.5.4 Limitations and Future Research

Our results should be viewed in the light of their limitations, which also point to possibilities for future research. First, our sample consisted of relatively young (mean age was 31.5 years) and rather educated smartphone users, which represent an important target group of digital services. Although our findings are well aligned with existing brand extension literature concerned with the idea of fit between a company and its offerings, it is possible that other populations could differ regarding their enterprise-service-fit perceptions. So far, we accounted for

possible differences by purposefully looking for variations in our participants' fit perceptions depending on their age, but could not detect any substantial deviations. However, future studies drawing on different samples could further validate and refine our results.

Second, future theory testing research could account more thoroughly for the consequences of our fit dimensions. While we provided preliminary insights on which constructs from prior adoption and use theory could be affected by our fit dimensions, we were not able to quantify the sizes of these effects yet. Accordingly, little is known about the dimensions' relative importance so far. Therefore, a quantitative study with appropriate measurements for enterprise-service-fit could greatly complement our findings by revealing the effect sizes and relative importance of the dimensions' consequences identified in this study.

Third, while we started to explore the role of context for individuals' fit perceptions, a good deal of work is necessary to examine which contextual factors (such as a service's data requirements, its feature set or technological complexity) indeed exert a significant influence. Consequently, future research could improve our understanding of the enterprise-service-fit construct by considering additional enterprise-service constellations reflecting different contextual factors. For instance, constellations interesting to examine can be found in the financial services industry that increasingly faces competition from digital companies or in the automotive industry which competes with companies like Google or Uber.

7 Contributions and Implications

The goal of this thesis was to improve the understanding of digital innovations. In particular, two stages of the digital innovation process have been addressed. First, the thesis relates to the role of digital technologies in the *discovery of innovations*, which is essential as many companies face difficulties to develop innovative ideas by thinking out-of-the-box (Parmar et al. 2014). In addition, existing theory barely considers the increasing openness of today's innovation processes that can involve a variety of employees (Edmondson and Harvey 2017; Rizy et al. 2011). Thus, two papers of this thesis aimed at enhancing the understanding of organizations' innovation discovery. They concentrated on the role of ESNs since the communication visibility of these systems can be particularly beneficial for creating innovative ideas according to CVT (Leonardi 2014; 2015). The first paper validated the newly developed CVT across different contexts and extended it by considering ESNs' short-term benefits and differences based on employees' managerial responsibility. Besides, the second paper investigated how a company's culture influences employees' information disclosure in ESNs, which is crucial for facilitating innovative ideas as outlined by CVT.

Second, this thesis refers to the *diffusion of digital innovations*. A solid understanding of how innovations diffuse is vital to counteract the risk that innovations might be declined by their target audience, which is often an issue (Forbes 2018). Furthermore, digital technologies affect the diffusion of innovations by blurring previous industry boundaries and fostering new competition (Seo 2017; Yoo et al. 2012; Yoo et al. 2010), which has scarcely been considered in existing theory so far. Thus, two papers of this thesis aimed at improving the knowledge of companies' innovation diffusion. They focused on data-driven business models as the growing competition across previous boundaries especially applies to this context, because both incumbent and inherently digital companies have a strong motivation to leverage their data in new ways (as argued in section 2.3.2). Against this backdrop, the third paper developed a taxonomy of data-driven business models, which illustrates which types of data-driven business models exist and indicates how they have diffused so far. Additionally, the fourth paper analyzed how individuals evaluate data-driven services in the case that they are offered by highly diverse companies, which is essential for the diffusion of the associated business models.

In the remainder of this section, theoretical contributions and practical implications of the papers are described in more detail.

7.1 Theoretical Contributions

The first part of this thesis (i.e., papers A and B) enhances the theoretical understanding of organizations' innovation discovery. *Paper A* validates and extends CVT, which accounts for the creation of innovative ideas owing to an increased meta-knowledge enabled by ESNs. Specifically, the paper contributes in three ways. First, while the literature has developed the theory in the context of a leadership group of a financial services institution (Leonardi 2014; 2015), the paper considers CVT across different contexts. As the paper's results support CVT's propositions, they confirm the theory's external validity. In this way, they also empirically underline ESNs' potential to foster organization-wide TMS, as suggested but not yet purposefully tested by previous research (Fulk and Yuan 2013; Trier and Richter 2015). The TMS literature is closely connected to CVT as meta-knowledge is one of its central elements (Griffith et al. 2003; Majchrzak et al. 2004).[7] Second, the paper shows that gaining meta-knowledge not only happens in the long-run, as indicated by Leonardi (2014), but also within a relatively short time. This result is essential as it informs the refinement of existing success measures for ESNs (e.g., Herzog et al. 2015; Herzog et al. 2013) and offers novel insights into the process of TMS development (e.g., Brandon and Hollingshead 2004; Lewis 2004). Third, the paper provides evidence that managers can develop more meta-knowledge in ESNs compared to non-managers. This result contrasts with prior literature's finding that managers are often particularly skeptical toward ESNs' benefits (Denyer et al. 2011; Han et al. 2015; Koch et al. 2012). Besides, it is important since managers' meta-knowledge has consequences that go beyond those of non-managers' meta-knowledge (Heavey and Simsek 2015; Rulke et al. 2000). Further, the result adds to TMS research as it points out that gains in meta-knowledge enabled by IS can vary among different employees.

Paper B contributes to theory in three ways. First, it transfers research on individuals' willingness to disclose information from the OSN (e.g., Krasnova et al. 2010; McKnight et al. 2011; Sun et al. 2015) to the ESN context and shows that the respective relationships with trusting and risk beliefs still hold. In this way, the paper complements the work of Mettler and Winter (2015) who focused on employees' privacy concerns when investigating their information disclosure. Employees' information disclosure in an ESN is needed to enable the de-

[7] In general, TMS research is concerned with how groups develop a "shared division of cognitive labor with respect to the encoding, storage, retrieval, and communication of information" (Hollingshead 2001, p. 1080).

velopment of meta-knowledge and innovative ideas according to CVT (Leonardi 2014). Second, the paper reveals that a company's culture substantially affects employees' trusting and risk beliefs. Specifically, it provides evidence for the hypothesis that cultures highlighting flexibility are particularly relevant for employees' behaviors in ESNs given that the nature of these systems is likewise flexible (McAfee 2009; Richter and Riemer 2013b). Therefore, the paper's results are consistent with prior literature that has emphasized the importance of organizational culture (e.g., Schein 1990; Schein 2004). Third, the paper shows the mechanisms of how a company's culture affects employees' trusting and risk beliefs, namely in the form of a direct effect of group and an indirect effect of development culture, with the latter being transmitted through error aversion culture.

The second part of this thesis (i.e., papers C and D) improves the knowledge of organizations' innovation diffusion in the context of data-driven business models. *Paper C* builds on the perceptions of business model experts to identify dimensions that meaningfully distinguish different data-driven business models. To that end, the paper refers to the "science of diversity" that emphasizes the importance of understanding similarities and differences when analyzing a population of objects (McKelvey 1978; McKelvey 1982). Accordingly, the paper's differentiation between different data-driven business models offers a foundation for future research to dig deeper into this new field. For instance, the paper's results can inform prospective design science efforts (see Gregor and Hevner 2013) aimed at fostering the development of data-driven business models or future research that aspires to concretize existing business models representations (e.g., Al-Debei and Avison 2010; Osterwalder et al. 2005). Along these lines, the paper underlines the significance of a joint consideration of the business model concept and the potential that comes with the increasing availability of (big) data (Buhl et al. 2013; Loebbecke and Picot 2015; Veit et al. 2014). Beyond that, the paper uses the identified dimensions to specify eight ideal-typical categories of data-driven business models, which provide a basic structure for examining the diffusion of these business models.

Paper D accounts for individuals' service evaluations in markets that are characterized by highly diverse companies providing similar services. In particular, the paper analyzed the example of a data-driven service offered by two different providers. Individuals' evaluations of data-driven services are important as they determine the diffusion of the associated business models. Based on a qualitative study, the paper found that individuals regularly consider how well a service fits its provider when making evaluations. According to this result, the paper introduced a new construct named "enterprise-service-fit" and defined it as an "individual's

perception of how well a service's requirements are aligned with the resources available to the company providing the service." As part of the construct conceptualization, the paper identified five dimensions of enterprise-service-fit, referring to 1) customer data, 2) non-customer data, 3) service functionalities, 4) domain-specific expertise, and 5) technological expertise. This novel perspective complements prior research on individuals' service evaluations that has regarded a service's and company's characteristics only separately so far (e.g., Gefen et al. 2003a; Gefen et al. 2003b; Pavlou 2003). Furthermore, the paper relates its findings to the brand extension literature, which has likewise been concerned with individuals' fit perceptions (e.g., Aaker and Keller 1990; Völckner and Sattler 2006; Völckner and Sattler 2007). Additionally, the paper offers a first exploration of the consequences of perceived enterprise-service-fit.

7.2 Practical Implications

Besides theoretical contributions, the papers result in several practical implications. The first part of this thesis (i.e., papers A and B) supports organizations in facilitating the discovery of innovations using ESNs.

Paper A implies that different companies can profit from ESNs in the form of an increase in employees' meta-knowledge, which fosters the recombination of existing into new ideas (Leonardi 2014). Therefore, organizations should revisit the possibility of an ESN introduction if they have not implemented such a system yet. Companies that already introduced an ESN should reconsider how they can facilitate its use, for instance through increasingly integrating the system with existing processes. As the paper also reveals short-term improvements in employees' meta-knowledge that complement ESNs' long-term effects, it provides an additional argument for companies to leverage ESNs. Based on this result, companies should consider the different ways of gaining meta-knowledge (i.e., in the short- vs. the long-run) when evaluating the systems. By revealing managers' particular benefits, the paper furthermore points to the potential that might unfold if companies can motivate their managers to participate in ESNs, which often has been difficult so far (Denyer et al. 2011; Han et al. 2015). Against this backdrop, the paper discusses different ways of how organizations might be successful, which particularly refer to handling preconceptions and sensitizing managers for meta-knowledge's inconspicuous nature.

Paper B is of practical importance since it shows when employees disclose information in ESNs, which is essential for creating meta-knowledge and innovative ideas as described by

CVT (Leonardi 2014). By revealing that an organization's group and development culture influence employees' trusting and risk beliefs and, in this way, their information disclosure, the paper offers two recommendations. First, organizations should purposefully consider employees' trusting and risk beliefs and try to compensate for potential drawbacks in this regard to facilitate their information disclosure in ESNs. Second, companies should deliberately account for their culture, especially if they are in the process of evaluating the potential of introducing an ESN. If their culture does not fit the flexible nature of ESNs, companies could try to foster values like belonging and commitment to enhance their group culture or to promote entrepreneurial activities to strengthen their development culture (Denison and Spreitzer 1991; Quinn and Rohrbaugh 1983). However, changing a company's culture will usually take time (Groysberg et al. 2018). Therefore, organizations might sometimes be well-advised to decide against an ESN introduction if massive cultural changes would be required to ensure employees' effective ESN use in the form of their information disclosure.

The second part of this thesis (i.e., papers C and D) enhances organizations' understanding of the diffusion of data-driven business models. *Paper C* offers an overview of the dimensions that meaningfully distinguish these business models using a taxonomy. As part of the taxonomy, eight ideal-typical business model categories are highlighted. In this way, the paper provides organizations with a basic understanding of data-driven business models. In particular, companies can utilize the taxonomy as inspiration and guidance to identify which kinds of business models they could newly develop. If companies have an idea of the kind of business model they want to create, they should not only be able to develop it more efficiently but also to identify common challenges associated with this type of business model. For instance, typical difficulties might occur if a data-driven business model involves the extensive handling of user data or high technological complexity. However, using the taxonomy, organizations can discover examples showing how others have dealt with these challenges. Beyond that, practitioners can consider the number of business models assigned to the ideal-typical categories to explore which business models have successfully diffused so far.

Paper D helps organizations to understand how individuals evaluate data-driven services that are simultaneously offered by highly diverse companies such as incumbent and inherently digital organizations. Specifically, the paper shows that individuals' perception of fit between a service and its provider affects their service evaluation, which, in turn, influences the diffusion of the associated business models. The paper points to five dimensions that individuals consider in this regard, which are related to an organization's 1) customer data, 2) non-

customer data, 3) service functionalities, 4) domain-specific expertise, and 5) technological expertise. Mainly, organizations can use this knowledge in two ways. First, if they plan to create new services, they can draw on the dimensions to estimate if individuals might evaluate a service positively after its development. Second, if they try to facilitate the success of an existing service, companies can build on the dimensions to develop new communication means aimed at improving individuals' fit perception. Beyond that, the paper illustrates the different consequences of a perception of fit, which helps companies to understand the advantages and disadvantages of offering a (barely) fitting service in more detail.

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Appendix

A1. Measurements (Paper A)

Awareness of Content of Coworkers' Messages (ACM) (based on Leonardi 2015)	
ACM1	I happen to notice the things colleagues communicate within the ESN.
ACM2	I notice the titles of the documents colleagues are posting within the ESN.
ACM3	I am aware of what colleagues speak about within the ESN.
Awareness of Coworkers' Connections (ACC) (based on Leonardi 2015)	
ACC1	I happen to notice the names of persons with whom colleagues communicate within the ESN.
ACC2	I notice the names of persons that are mentioned in colleagues' posts within the ESN.
ACC3	I am aware of with whom colleagues are interacting within the ESN.
Community Identification (CI) (based on Chiu et al. 2006)	
CI1	I feel a sense of belonging towards the company I work in.
CI2	I have the feeling of togetherness or closeness in the company I work in.
CI3	I have a strong positive feeling toward the company I work in.
CI4	I am proud to be a member of the company I work in.
ESN Use (USE) (Kügler and Smolnik 2014)	
USE1	I use the ESN to maintain social relationships with my colleagues.
USE2	I use the ESN to create social relations with my colleagues.
USE3	I use the ESN to get to know people in my organization.
Innovative Climate (IC) (based on Van der Vegt et al. 2005)	
IC1	In the department I work in, people are encouraged to come up with innovative solutions to work-related problems.
IC2	The department I work in has established a climate where employees can challenge traditional ways of doing things.
IC3	In my experience, the department I work in learns from the activities of other departments in the company.
IC4	In my experience, the department I work in learns from the activities of other companies.
Knowledge About "Who Knows What" (KWA) (based on Kanawattanachai and Yoo 2007)	
With regard to the colleagues whose posts are displayed to me within the ESN, …	
KWA1	… I have a good "map" of their talents and skills.
KWA2	… I know which task-related skills and knowledge they possess.
KWA3	… I know who of them have specialized skills and knowledge that is relevant to my work.
Knowledge About "Who Knows Whom" (KWO) (based on Kanawattanachai and Yoo 2007)	
With regard to the colleagues whose posts are displayed to me within the ESN, …	
KWO1	… I have a good "map" of their contacts to other colleagues.
KWO2	… I know which contacts they have to other colleagues.
KWO3	… I know with which other colleagues they are in contact.
Management Responsibility (MGM)	
MGM	Do you possess managerial responsibilities in your company?

A2. Measurement Quality (Paper A)

	ACM	ACC	MGM	KWA	KWO	USE	AGE	CI	ECU	EMP	EOI	EPS	ESU	EUI	EUP	IC	LOC	SEX	TEN
M	3.73	3.59	0.34	3.58	3.27	3.14	3.61	4.75	4.25	5.30	4.98	4.19	8.13	3.59	3.29	4.48	2.59	1.35	3.60
SD	1.42	1.48	0.48	1.41	1.53	1.64	1.04	1.47	1.54	1.22	1.66	2.01	2.27	1.91	1.74	1.32	0.55	0.48	1.30
CA	.857	.878	-	.896	.946	.908	-	.940	-	-	-	-	-	-	-	.850	-	-	-
CR	.913	.925	-	.935	.965	.942	-	.956	-	-	-	-	-	-	-	.896	-	-	-

(M = mean, SD = standard deviation, CA = Cronbach's alpha, CR = composite reliability, ACM = awareness of the content of coworkers' messages, ACC = awareness of coworkers' connections, MGM = managerial responsibility, KWA = knowledge about "who knows what", KWO = knowledge about "who knows whom", USE = ESN use, CI = community identification, ECU = coworkers' average ESN use, EMP = organization's number of employees, EOI = beginning of ESN introduction, EPS = beginning of personal ESN use, ESU = share of employees intended to use the ESN, EUI = interactions with ESN users beyond the system, EUP = number of ESN users working in close proximity, IC = innovative climate, LOC = organization's geographical distribution, TEN = job tenure)

A3. Construct Correlations (Paper A)

	ACM	ACC	MGM	KWA	KWO	USE	AGE	CI	ECU	EMP	EOI	EPS	ESU	EUI	EUP	IC	LOC	SEX	TEN
ACM	**.882**																		
ACC	.671	**.896**																	
MGM	.030	.085	**1.00**																
KWA	.470	.444	.186	**.910**															
KWO	.494	.561	.255	.607	**.950**														
USE	.506	.459	.138	.551	.542	**.919**													
AGE	.083	.080	.222	.102	.072	.051	**1.00**												
CI	.093	.139	-.017	.158	.109	.174	-.040	**.920**											
ECU	.149	.220	.080	.331	.285	.254	.081	.059	**1.00**										
EMP	.014	.088	-.045	-.026	-.010	-.032	-.010	.067	-.075	**1.00**									
EOI	-.074	-.023	.103	.046	-.004	-.038	.224	-.076	.251	.071	**1.00**								
EPS	.063	.101	.164	.156	.101	.107	.305	-.121	.330	.005	.780	**1.00**							
ESU	.032	-.027	-.191	.037	-.079	-.037	-.022	.029	.059	-.065	.115	.058	**1.00**						
EUI	.250	.146	.221	.461	.362	.341	-.023	.120	.239	-.193	-.022	.071	-.054	**1.00**					
EUP	.066	.111	.140	.316	.325	.193	-.067	.153	.213	-.150	-.072	-.038	.010	.446	**1.00**				
IC	.148	.142	-.039	.279	.130	.234	-.013	.597	.043	.028	-.076	-.119	.036	.173	.185	**.826**			
LOC	.037	.056	-.061	.072	-.001	.075	-.031	.121	-.069	.511	.139	.058	.028	-.040	-.128	.195	**1.00**		
SEX	.032	-.017	-.174	.002	-.044	.010	-.289	-.006	.094	-.070	-.038	-.099	.074	.007	.035	.003	-.061	**1.00**	
TEN	.081	.106	.170	.066	.056	.054	.571	-.061	.054	.106	.222	.412	-.073	-.017	-.052	-.094	-.019	-.294	**1.00**

(ACM = awareness of the content of coworkers' messages, ACC = awareness of coworkers' connections, MGM = managerial responsibility, KWA = knowledge about "who knows what", KWO = knowledge about "who knows whom", USE = ESN use, CI = community identification, ECU = coworkers' average ESN use, EMP = organization's number of employees, EOI = beginning of ESN introduction, EPS = beginning of personal ESN use, ESU = share of employees intended to use the ESN, EUI = interactions with ESN users beyond the system, EUP = number of ESN users working in close proximity, IC = innovative climate, LOC = organization's geographical distribution, TEN = job tenure)

A4. PLS Item Factor Loadings and Cross Loadings (Paper A)

	ACM	ACC	MGM	KWA	KWO	USE	AGE	CI	ECU	EMP	EPS	ESU	EOI	EUI	EUP	IC	LOC	SEX	TEN
ACM1	.858	.591	.042	.364	.390	.440	.115	.077	.039	.067	.054	.011	-.046	.151	-.028	.099	.110	-.001	.108
ACM2	.876	.555	.053	.435	.435	.418	.084	.073	.194	-.037	.103	.041	-.038	.280	.113	.154	.010	.021	.069
ACM3	.912	.630	-.011	.441	.479	.481	.027	.096	.154	.010	.013	.032	-.108	.226	.082	.136	-.012	.060	.043
ACC1	.591	.889	.035	.339	.482	.392	.052	.163	.115	.118	.060	-.029	-.027	.087	.093	.135	.090	.000	.091
ACC2	.609	.887	.081	.343	.467	.379	.085	.082	.238	.004	.121	.043	-.016	.095	.116	.122	.009	-.041	.096
ACC3	.606	.912	.108	.496	.553	.456	.078	.128	.235	.108	.091	-.077	-.018	.199	.090	.125	.050	-.007	.099
MGM	.030	.085	1.00	.186	.255	.138	.222	-.017	.080	-.045	.164	-.191	.103	.221	.140	-.039	-.061	-.174	.170
KWA1	.440	.430	.209	.897	.564	.529	.106	.135	.301	.024	.168	-.034	.086	.383	.298	.262	.092	-.079	.107
KWA2	.391	.377	.170	.921	.520	.459	.055	.153	.272	-.030	.079	.075	-.007	.411	.282	.202	.028	.070	.034
KWA3	.448	.401	.131	.911	.569	.511	.111	.143	.325	-.065	.172	.062	.043	.461	.281	.290	.072	.020	.037
KWO1	.488	.544	.209	.570	.933	.490	.077	.139	.276	.005	.126	-.091	.025	.338	.310	.136	.045	-.048	.041
KWO2	.468	.521	.264	.576	.960	.535	.055	.093	.262	.002	.069	-.079	-.042	.346	.291	.134	-.016	-.057	.046
KWO3	.453	.535	.254	.584	.957	.519	.073	.080	.274	-.034	.094	-.056	.004	.349	.324	.101	-.032	-.020	.072
USE1	.403	.378	.048	.497	.455	.896	-.016	.189	.246	-.059	.098	-.031	-.018	.329	.226	.197	.014	.032	.020
USE2	.498	.451	.140	.545	.514	.967	.052	.145	.241	-.041	.091	-.039	-.055	.342	.196	.223	.041	.006	.057
USE3	.489	.432	.186	.478	.523	.893	.097	.150	.215	.010	.106	-.032	-.029	.271	.114	.226	.147	-.007	.069
AGE	.083	.080	.222	.102	.072	.051	1.00	-.040	.081	-.010	.305	-.022	.224	-.023	-.067	-.013	-.031	-.289	.571
CI1	.103	.189	.017	.164	.134	.155	.032	.930	.077	.081	-.057	-.035	-.029	.075	.131	.527	.138	-.040	.047
CI2	.077	.107	.004	.117	.112	.184	-.040	.886	.031	.067	-.131	.001	-.093	.116	.123	.558	.125	-.010	-.102
CI3	.093	.085	-.030	.147	.080	.155	-.058	.939	.047	.030	-.154	.105	-.096	.163	.174	.594	.083	.039	-.128
CI4	.061	.101	-.074	.143	.057	.150	-.120	.922	.052	.060	-.130	.066	-.082	.104	.142	.529	.088	.005	-.090
ECU	.149	.220	.080	.331	.285	.254	.081	.059	1.00	-.075	.330	.059	.251	.239	.213	.043	-.069	.094	.054
EMP	.014	.088	-.045	-.026	-.010	-.032	-.010	.067	-.075	1.00	.005	-.065	.071	-.193	-.150	.028	.511	-.070	.106
EPS	.063	.101	.164	.156	.101	.107	.305	-.121	.330	.005	1.00	.058	.780	.071	-.038	-.119	.058	-.099	.412
ESU	.032	-.027	-.191	.037	-.079	-.037	-.022	.029	.059	-.065	.058	1.00	.115	-.054	.010	.036	.028	.074	-.073
EOI	-.074	-.023	.103	.046	-.004	-.038	.224	-.076	.251	.071	.780	.115	1.00	-.022	-.072	-.076	.139	-.038	.222
EUI	.250	.146	.221	.461	.362	.341	-.023	.120	.239	-.193	.071	-.054	-.022	1.00	.446	.173	-.040	.007	-.017
EUP	.066	.111	.140	.316	.325	.193	-.067	.153	.213	-.150	-.038	.010	-.072	.446	1.00	.185	-.128	.035	-.052
IC1	.128	.119	-.023	.221	.125	.155	-.057	.649	.078	.052	-.144	-.011	-.094	.119	.147	.824	.198	.027	-.099
IC2	.054	.021	-.083	.171	-.040	.113	.034	.560	.030	.056	-.143	.109	-.056	.035	.162	.767	.191	-.063	-.059
IC3	.163	.173	-.054	.274	.135	.205	-.030	.437	.065	.059	-.092	.041	-.045	.144	.191	.891	.187	.034	-.096
IC4	.103	.095	.010	.224	.132	.270	.042	.399	-.043	-.070	-.042	.019	-.058	.226	.114	.817	.081	-.033	-.043
LOC	.037	.056	-.061	.072	-.001	.075	-.031	.121	-.069	.511	.058	.028	.139	-.040	-.128	.195	1.00	-.061	-.019
SEX	.032	-.017	-.174	.002	-.044	.010	-.289	-.006	.094	-.070	-.099	.074	-.038	.007	.035	.003	-.061	1.00	-.294
TEN	.081	.106	.170	.066	.056	.054	.571	-.061	.054	.106	.412	-.073	.222	-.017	-.052	-.094	-.019	-.294	1.00

(ACM = awareness of the content of coworkers' messages, ACC = awareness of coworkers' connections, MGM = managerial responsibility, KWA = knowledge about "who knows what", KWO = knowledge about "who knows whom", USE = ESN use, CI = community identification, ECU = coworkers' average ESN use, EMP = organization's number of employees, EOI = beginning of ESN introduction, EPS = beginning of personal ESN use, ESU = share of employees intended to use the ESN, EUI = interactions with ESN users beyond the system, EUP = number of ESN users working in close proximity, IC = innovative climate, LOC = organization's geographical distribution, TEN = job tenure)

A5. Significant Control Variables (Paper A)

P#	Path	Coefficient	p-Value
1	Coworkers' average ESN use → Knowledge about "Who Knows What"	.130	.024
2	Interactions with ESN users beyond the system → Knowledge about "Who Knows What"	.203	.001
3	Number of ESN users working in close proximity → Knowledge about "Who Knows Whom"	.159	.035

A6. Measurements (Paper B)

Group Culture (GC) – Based on Iivari and Huisman (2007) (* Dropped Items)	
GC1	The company I work in is a very personal place. It is like an extended family and people seem to share a lot of themselves.
GC2	The glue that holds the company I work in together is loyalty and tradition. Commitment to company runs high.
GC3	The company I work in emphasizes human resources. High morale is important.
Development Culture (DC) – Based on Iivari and Huisman (2007)	
DC1	The company I work in is a very dynamic and entrepreneurial place. People are willing to stick their necks out and take risks.
DC2	The glue that holds the company I work in together is commitment to innovation and development. There is an emphasis on being first with products and services.
DC3	The company I work in emphasizes growth through acquiring new resources. Acquiring new products/services to meet new challenges is important.
Rational Culture (RC) – Based on Iivari and Huisman (2007)	
RC1	The company I work in is a very production-oriented place. People are concerned with getting the job done and are not very personally involved.
RC2	The glue that holds the company I work in together is an emphasis on tasks and goal accomplishment. A production and achievement orientation is commonly shared.
RC3	The company I work in emphasizes competitive actions, outcomes and achievement. Accomplishing measurable goals is important.
Hierarchical Culture (HC) – Based on Iivari and Huisman (2007)	
HC1	The company work in is a very formal and structured place. People pay attention to bureaucratic procedures to get things done.
HC2	The glue that holds the company I work in together is formal rules and policies. Following rules and maintaining a smoothrunning institution are important.
HC3	The company I work in emphasizes permanence and stability. Efficient, smooth operations are important.*
Error Aversion Culture (EA) – Based on Van Dyck et al. (2005)	
EA1	In general, people in this company feel embarrassed after making a mistake.*
EA2	People in this company are often afraid of making errors.
EA3	During their work, people are often concerned that errors might occur.
Trusting Beliefs (TR) – Based on Malhotra et al. (2004)	
TR1	My employer would be trustworthy in handling the information.
TR2	I trust that my employer would keep my best interests in mind when dealing with the information.
TR3	My employer is always honest with the employees when it comes to using the information that I would provide.
Risk Beliefs (RI) – Based on Malhotra et al. (2004)	
RI1	In general, it would be risky to give the information to my employer.
RI2	There would be high potential for loss associated with giving the information to my employer.
RI3	Providing my employer with the information would involve many unexpected problems.

Willingness to Disclose Information (WI) – Based on Malhotra et al. (2004) Given this scenario, specify the extent to which you would reveal the information to the ESN…					
WI1	… Unlikely / likely	WI2	… Not probable / probable	WI3	… Willing / unwilling

A7. List of considered companies (Paper C)

ID	Name	Crunchbase Profile
1	AddThis	http://www.crunchbase.com/organization/addthis
2	Unigo	http://www.crunchbase.com/organization/unigo
3	Skybox Imaging	http://www.crunchbase.com/organization/skybox-imaging
4	Kreditech	http://www.crunchbase.com/organization/kreditech
5	The Climate Corporation	http://www.crunchbase.com/organization/the-climate-corporation
6	Hopper	http://www.crunchbase.com/organization/hopper
7	App Annie	http://www.crunchbase.com/organization/app-annie
8	Chitika	http://www.crunchbase.com/organization/chitika
9	Yandex	http://www.crunchbase.com/organization/yandex
10	Statista	http://www.crunchbase.com/organization/statista
11	Zoominfo	http://www.crunchbase.com/organization/zoominfo
12	Unified	http://www.crunchbase.com/organization/unified
13	Trax Technologies	http://www.crunchbase.com/organization/trax-technologies
14	Klout	http://www.crunchbase.com/organization/klout
15	MarketWatch	http://www.crunchbase.com/organization/marketwatch
16	Pew Research Center	http://www.crunchbase.com/organization/pew-research-center
17	Compete	http://www.crunchbase.com/organization/compete
18	CB Insights	http://www.crunchbase.com/organization/cb-insights
19	ClearFit	http://www.crunchbase.com/organization/clearfit
20	Sense Networks	http://www.crunchbase.com/organization/sense-networks
21	SmartZip	http://www.crunchbase.com/organization/smartzip
22	Talentoday	http://www.crunchbase.com/organization/talentoday
23	FiscalNote	http://www.crunchbase.com/organization/fiscalnote
24	1-Page	http://www.crunchbase.com/organization/the-one-page-company
25	Profitero	http://www.crunchbase.com/organization/profitero
26	Statricks	http://www.crunchbase.com/organization/statricks
27	dMetrics	http://www.crunchbase.com/organization/dmetrics
28	Implisense	http://www.crunchbase.com/organization/implisense
29	MedWhat	http://www.crunchbase.com/organization/medwhat
30	Feelter	http://www.crunchbase.com/organization/feelter
31	ImportGenius	http://www.crunchbase.com/organization/importgenius
32	GymHit	http://www.crunchbase.com/organization/gymhit
33	DwellAware	http://www.crunchbase.com/organization/dwellaware
Please note: Meanwhile, some of the companies have been acquired or shut down.		

A8. Interview Protocol (Paper D)

1. Please provide us with some personal information (age, gender, and education).
2. Do you possess a smartphone? If yes, how often do you regularly use it? How often do you try new services?
3. How well do you know the following companies (i.e., TransCom, TechCom)? What comes to your mind when thinking about these companies?
4. [Introduction of the exemplary service concept]
5. Could you imagine using such a service? What are the reasons? Which functionalities do you particularly like about the service?
6. Do you have any concerns regarding the data, which needs to be disclosed when using the service? Why?
7. Which role does the particular organization offering this service play for making your assessment?
8. [Introduction of the possibility to choose between different providers for the described service]
9. Which advantages and disadvantages do you associate with having the different organizations as the provider of this service?
10. Which company would you prefer to provide you with the mentioned service? For which reasons?
11. How would this service need to be different to make you choose it from a different company than the one you just picked?