Ansätze zur verbesserten Nutzung von Big Data Analytics in B2C-Unternehmen

DISSERTATION
der Universität St. Gallen,
Hochschule für Wirtschafts-,
Rechts- und Sozialwissenschaften (HSG),
zur Erlangung der Würde eines
Doktors der Wirtschaftswissenschaften

Vorgelegt von

Alexander Wieneke

aus

Deutschland

Genehmigt auf Auftrag der Herren

Prof. Dr. Reinhard Jung

und

Prof. Dr. Rainer Alt

Dissertation Nr. 4805

Difo-Druck GmbH, Bamberg 2018

Die Universität St. Gallen, Hochschule für Wirtschafts-, Rechts- und Sozialwissenschaften sowie Internationale Beziehungen (HSG), gestattet hiermit die Drucklegung der vorliegenden Dissertation, ohne damit zu den darin ausgesprochenen Anschauungen Stellung zu nehmen.

St.Gallen, den 22. Mai 2018

Der Rektor:

Prof. Dr. Thomas Bieger

Vorwort

Diese kumulative Dissertation habe ich in der Zeit als wissenschaftlicher Mitarbeiter am „Competence Center Digital Service Innovation“ des Instituts für Wirtschaftsinformatik der Universität St.Gallen (HSG) verfasst. Was mit einer Masterarbeit als Gaststudent begann endet nun nach der Veröffentlichung verschiedener Fachbeiträge mit der Einreichung der Dissertation.

Das Doktorat und die Zeit am Institut möchte ich nicht missen. Es war sicherlich nicht immer eine entspannte Zeit, dafür habe ich aber viele lehrreiche, freudige und somit wertvolle Erfahrungen sammeln können. Ich habe am IWI, neben der Arbeitszeit, ganze Nächte und Wochenenden verbracht, dafür aber auch die Berge im Appenzell bestiegen, im grössten Freibad Europas – Zürich – gebaded und über den Dächern Singapurs getanzt. Ich möchte deshalb die Gelegenheit nutzen, mich bei meinen Wegbegleitern zu bedanken.

Ich danke meinem Referenten Prof. Dr. Reinhard Jung, der es mir zum einen ermöglicht hat, mein Ziel, die Doktorwürde an der HSG zu erlangen, zu verfolgen. Zum anderen hat Prof. Dr. Reinhard Jung eine Arbeitsumgebung geschaffen, in der ich nicht nur fachlich und menschlich reifen, sondern mit meinen Kollegen als Team wachsen konnte. Ich danke auch meinem Ko-Referenten Prof. Dr. Rainer Alt für die Betreuung der Dissertation.

Ich danke meinem Büronachbarn Tobias Mirsch. Durch Tobias wurde die Zeit im Büro weder langweilig noch zu ernst. Zudem konnte ich mich auch in den kuriosesten Situationen auf ihn als Freund verlassen. Mein Dank gilt auch meiner Projektleiterin Christiane Lehrer dafür, dass wir am IWI gemeinsam die Nacht zum Tag und dabei Unmögliches möglich gemacht haben. Zudem möchte ich mich bei Christian Grape bedanken, der sich als Leiter des EMBE auch den Doktoranden angenommen hat und uns in allen Lebenslagen unterstützt hat. Dies gilt gleichermaßen für sein Team Elisabeth, Natascha und natürlich ganz besonders für Bernadette - herzlichen Dank. Ausserdem danke ich meinen ehemaligen Kollegen Tobias Lehmkuhl und Torben Küpper für ein wunderbares erstes Jahr am Institut. Für eine sehr lehrreiche Zusammenarbeit danke ich auch meinen Co-Autoren Raphael Zeder, Ioanna Constantiou und Stefan Seidel. Ein ganz besonderer Dank gilt Jan vom Brocke für die Motivation sowie die Unterstützung bei der Organisation meines Aufenthalts an der National University of Singapore. In diesem Rahmen danke ich auch Bernard Tan, der mich dort als Gaststudent aufgenommen und unterstützt hat. Ausserdem danke ich meinem Mentor Peter Kraus für die vielen lehrreichen Hinweise, die Vorbereitung auf den Schritt in die Praxis und die sehr schönen Tage am Bodensee. Ich bin sehr stolz darauf, sagen zu können, dass aus den vielen beruflichen Beziehungen gute Freundschaften hervorgegangen sind.

Ich danke meinen Freunden, die nicht nur die Zeit in St.Gallen, Zürich und Singapur zu etwas ganz Besonderem gemacht haben, sondern auch von weit entfernt mit Rat und Tat zur Seite standen. Neben den St.Galler und Züricher „Kollegen“ Axel, Michaela, Andreas, Nicolas, Niki, Tuomo, Rene und meiner Mitbewohnerin Jennifer, die gemeinsam die Schweiz für mich zum Lebensmittelpunkt machten, danke ich auch Florian, Fabian, Daniel, Pris, Edward, Dimitry und Kasey für eine unvergessliche Zeit in Singapur. Ausserdem möchte ich meinen Freunden aus Hannover, Sven, Tessi und Peter, sowie aus Bayreuth, Tholli und David, danken, die mich trotz der Entfernung und meinen seltenen Besuchen niemals aus den Augen verloren haben. Ein ganz besonderer Dank gilt Sebastian, der mich motiviert hat, das Abenteuer Doktorat in St.Gallen zu wagen. Zu guter Letzt danke ich Stefan für sein stets sehr wachsames Auge.

Diese Arbeit widme ich meiner Schwester und meinen Eltern. Ich hatte das Glück, dass meine Familie mir ganz selbstverständlich die Voraussetzungen geschaffen hat, diesen Weg gehen zu können, und mich dabei immer begleitet hat. Meine Dankbarkeit hier in Worte zu fassen, ist leider unmöglich.

St.Gallen, 01.07.2018 Alexander Wieneke

Fachbeiträge

Fachbeitrag A1	Lehrer, C., Wieneke, A., vom Brocke, J., Jung, R.., & Seidel, S. (2018). How big data analytics enables service innovation: materiality, affordance, and the individualization of service. *Journal of Management Information Systems, 35*(2), 424-460.
Fachbeitrag A2	Wieneke, A. (2018). Approaches to the implementation of big data analytics.
Fachbeitrag B	Wieneke, A., & Lehrer, C. (2016). Generating and exploiting customer insights from social media data. *Electronic Markets, 26*(3), 245-268.
Fachbeitrag C	Wieneke, A., Lehrer, C., Zeder, R., & Jung, R. (2016). Privacy-related decision-making in the context of wearable use. In *Proceedings of the 20th Pacific Asia Conference on Information Systems (PACIS 2016)*, Taiwan, Chiayi.

Inhaltsverzeichnis

Abkürzungsverzeichnis

ACAP	Absorptive Capacity
API	Application Programming Interface
BDA	Big Data Analytics
BI	Business Intelligence
BI&A	Business Intelligence and Analytics
GPS	Global Positioning System
IoT	Internet of Things
RFID	Radio Frequency Identification
WLAN	Wireless Local Area Network

Abbildungsverzeichnis

Tabellenverzeichnis

Kurzfassung

Der Einsatz von Big Data Analytics (BDA) zur Analyse von Big Data, d. h. intern als auch extern gesammelter Daten mit den Charakteristika der „4Vs“ („Volume“, „Variety“, „Velocity“ und „Veracity“), ist aktuell in Unternehmen ein viel diskutiertes Thema. Die Erwartungen in BDA sind immens, wird es doch in der Fachliteratur als Haupttreiber für die Umsetzung von Innovationen und die Generierung von langfristigen Wettbewerbsvorteilen beschrieben. Jedoch gelingt es aktuell nur wenigen Unternehmen, die hohen Investitionen in BDA zu rechtfertigen. Auf die unterschiedlichen Herausforderungen, die sich Unternehmen bei der Nutzung von BDA stellen wie die Identifikation konkreter Nutzungspotentiale sowie die notwendigen technischen sowie nicht-technischen Anforderungen und Rahmenbedingungen für die Umsetzung von BDA bietet auch die wissenschaftliche Literatur noch keine hinreichenden Antworten bzw. Lösungen. Dies gilt auch für das tiefgreifende Verständnis des Entscheidungsprozesses von Kunden hinsichtlich der Weitergabe von persönlichen Daten.

Um die bestehende Forschungslücke zu schliessen und die unternehmerischen Herausforderungen zu adressieren, wird in dieser Dissertation über unterschiedliche empirische Studien untersucht, wie Unternehmen die Potentiale von BDA realisieren können. Dabei wird das übergeordnete Ziel verfolgt, Ansätze zur verbesserten Nutzung von BDA abzuleiten. Der Fokus der Untersuchungen liegt dabei auf Unternehmen im B2C-Sektor und der Anwendung von BDA im Kontext von Service Innovation. Für die Zielerreichung wurden drei untergeordnete Zielsetzungen mit entsprechenden Forschungsfragen formuliert, die die Identifikation von Nutzungsmöglichkeiten von BDA im Kontext von Service Innovation, die Identifikation von relevanten Prozessen und Ressourcen für die Generierung von „Customer Insights“ sowie die Analyse des Entscheidungsprozesses von Kunden in Bezug auf die Weitergabe persönlicher Daten an Unternehmen fokussieren.

Um die untergeordneten Forschungsziele sowie die dazugehörigen Forschungsfragen zu beantworten, wurden im Rahmen dieser Dissertation vier Forschungsbeiträge verfasst. Als Ergebnis beinhaltet der Forschungsbeitrag A1 ein theoretisches Modell, das den Beitrag von BDA für Serviceinnovation beschreibt, indem die relevanten technologischen Komponenten, die sich daraus bietenden Nutzungsmöglichkeiten („Functional Affordances) sowie der daraus resultierende Beitrag aufgezeigt werden. Ausserdem wird im Forschungsbeitrag A2 skizziert, wie durch BDA unterstützte servicerelevante Aktivitäten dargestellt und wie diese implementiert werden können. Der Forschungsbeitrag B beschreibt für die Generierung von „Customer Insights“ relevante Prozesse und Routinen („Dynamic Capabilities“) sowie die für deren Umsetzung benötigten Ressourcen („Contingent Factors“). In Forschungsbeitrag C werden die erwarteten Vorteile, die Kunden zur Weitergabe von Daten bewegen, sowie die Entscheidungsstrategien, auf die Kunden im Rahmen des Entscheidungsprozesses zurückgreifen, aufgezeigt.

Auf Grundlage der Ergebnisse und Implikationen der einzelnen Forschungsbeiträge wurden drei Ansätze abgeleitet, die Aussagen zur strategischen Ausrichtung, zur Umsetzung sowie zur Gewinnung von Kundendaten im Rahmen von BDA-Initiativen beinhalten. Die Ansätze verdeutlichen, dass (1) mit Hilfe von BDA neue Formen der Kundeninteraktion etabliert werden können, die es ermöglichen, Kunden individuell, in Echtzeit und proaktiv zu adressieren und somit neue Nutzenversprechen anzubieten. Des Weiteren wird gezeigt, dass (2) Unternehmen für einen zielgerechten Einsatz von BDA ihre Strukturen, Prozesse und Routinen anpassen bzw. transformieren müssen und dafür auf personeller, organisatorischer und technologischer Ebene neue Ressourcen benötigen. Abschliessend wird erläutert, dass (3) Unternehmen sich zur Motivation des Kunden bezüglich der Weitergabe persönlicher Daten auf die Darstellung relevanter, unter anderem hedonistischer Vorteile fokussieren und dabei auch die Relevanz intuitiver Entscheidungsstrategien berücksichtigen müssen.

Abstract

Companies widely discuss the use of big data analytics (BDA)—that is, analyses of internally and externally collected data characterized by the “4Vs” (volume, variety, velocity and veracity) - is much discussed by companies. The widespread use of BDA has raised high expectations. The literature names BDA as one of the main drivers in implementing innovations and generating long-term competitive advantage. However, most companies struggle to harness the full potential of BDA and have difficulty justifying high investments in BDA.

Although BDA is widely used and discussed in practice, information systems (IS) scholars have offered little information about how to solve the many challenges companies face when they use BDA, especially challenges related to the identification of promising use potential of BDA, the necessary technical and non-technical (i.e., organizational and cultural) requirements for the implementation of BDA and those related to customers’ decision-making process regarding the disclosure of personal data.

In order to close this research gap, the dissertation investigates how companies can best realize the potential of BDA. The overarching research goal is to define approaches to harnessing BDA’s potential, with a focus on BDA in the business-to-company (B2C) sector and the application of BDA in the context of service innovation. Three subordinate research objectives are to identify possible BDA-related actions in the context of service innovation, to identify processes and resources that are relevant to the generation of customer insights, and to describe the process of privacy-related decision-making.

Four articles address the three research objectives. The first article contains a theoretical model that describes BDA’s contribution to service innovation, reports possible BDA-related actions in the context of service innovation and the technological components that afford the possible uses. The second article illustrates how service-related activities that BDA can be used to realize, can be described and implemented. The third article describes the dynamic capabilities that are necessary for the generation of customer insights, as well as the contingent factors that are required for implementing these capabilities. The fourth article outlines customers’ expectations about the value of disclosing their data and the decision-making strategies that customers use in the process of privacy-related decision-making.

Three approaches derived from the four articles’ results and implications that contain statements on the strategic orientation of BDA, the requirements for implementing BDA, and the acquisition of customer data. The first approach shows how BDA affords new ways of interacting with customers—that is, it enables companies to address customers individually, proactively, and in real time so companies can offer their customers new value propositions. The second approach shows that companies must adapt their existing structures, processes, and routines to ensure efficient and effective use of BDA and must develop new personal, organizational, and technological resources. Finally, the third approach explains that companies can increase their customers’ willingness to share personal data by highlighting hedonistic benefits and motivating their customers to use intuitive decision-making strategies.

1. Einleitung

Die steigende Nutzung des Internets (z. B. Social Media Plattformen) sowie der vermehrte Einsatz digitalisierter Gegenstände (z. B. Wearables) ermöglichen Unternehmen die Sammlung und Analyse einer Vielzahl neuer, vom Kunden generierter Daten (Newell & Marabelli, 2015, S. 4). Diese als Big Data bezeichneten Daten, charakterisiert mit den „4Vs“: „Volume“, „Variety“, „Velocity“ und „Veracity“ (Goes, 2014, S. iv), stellen bisherige Verfahren im Bereich von Business Intelligence und Analytics (BI&A) vor neue Herausforderungen (Chen, Chiang, & Story, 2012, S. 1182). Mit Big Data Analytics (BDA) als evolutionäre Weiterentwicklung von BI&A bieten sich für Unternehmen Chancen, die für die Analysen bislang verwendeten strukturierten, vornehmlich operativen Transaktionsdaten um Big Data (Chen et al., 2012, S. 1166) und somit auch das Wissen über die Kunden durch tiefgreifende Erkenntnisse („Customer Insights“) ihrer Verhaltensweisen und Bedürfnisse zu erweitern (Chen et al., 2012, S. 1168). BDA wird vor allem im Wirtschaftsbereich eine wachsende Bedeutung zugemessen. Manyika et al. (2011) beschreiben den zielgerichteten Einsatz von BDA bereits als „[t]*he next frontier for innovation, competition and productivity*“ (S. 1). In Unternehmen spiegeln sich die Potentiale in den Möglichkeiten wider, durch BDA die strategische Entscheidungsfindung zu verbessern (Constantiou & Kallinikos, 2015, S. 44ff) wie auch Geschäftsmodellinnovation (Woerner & Wixom, 2015, S. 60ff) umzusetzen. Insbesondere die Umsetzung von Serviceinnovationen (Yoo, Boland, Lyytinen, & Majchrzak, 2012, S. 1400) ist aufgrund von Wettbewerbsdruck und veränderten Kundenbedürfnissen (z. B. der Wunsch nach individualisierten Dienstleistungen) sowohl in der Praxis als auch in der Wissenschaft ein viel diskutiertes Thema (Setia, Venkatesh, & Joglekar, 2013, S. 565ff). Daher wird im Rahmen dieser Dissertation der Fokus auf die Nutzung von BDA bei B2C-Unternehmen im Kontext von Service Innovation gelegt.

Trotz des Potentials von BDA gelingt es bisher allerdings nur wenigen Unternehmen, die hohen Erwartungen zu realisieren: „*Despite successful testimonials of ´big data first movers´, a recent industry survey indicates that a majority of companies have still not begun to engage in the practice of capitalizing on big data*“ (Chen, Preston, & Swink, 2015, S. 5). Gründe hierfür sind verschiedene Herausforderungen, denen Unternehmen bei der Nutzung von BDA begegnen und die sie aktuell nur selten bewältigen können. So fehlen einheitliche Aussagen über die Nutzungsmöglichkeiten von BDA sowie den Beitrag zur Erreichung strategischer Ziele (Chen et al., 2015, S. 5). Ebenso besteht Unklarheit über die zu etablierenden Prozesse und Routinen sowie die benötigten technischen sowie nicht-technischen Ressourcen, die eine anforderungsgerechte Kapitalisierung der externen Daten durch die Generierung und Anwendung von „Customer Insights“ ermöglichen (Choudhury & Harrigan, 2014, S. 151). Ausserdem sind die Gründe noch nicht hinreichend bekannt, die Kunden bewegen, trotz diskutierter Risiken für den Datenschutz und den Schutz der Privatsphäre ihre persönlichen Daten mit den Unternehmen zu teilen (Newell & Marabelli, 2015, S. 3).

Auch in der Wissenschaft gibt es zu diesen Herausforderungen noch keine konkreten Lösungen. Beiträge, die die Nutzungsmöglichkeiten von BDA analysieren, fokussieren entweder den Einsatz von BDA in anderen Fachbereichen, z. B. Supply Chain Management (Chen et al., 2015), sind konzeptionelle Arbeiten und liefern lediglich erste Ansätze (Constantiou & Kallinikos, 2015) oder entstammen praxisorientierten Fachzeitschriften (Davenport, 2013). Empirische Studien, die auf Basis empirischer Untersuchungen die Potentiale von BDA im Kontext von Service Innovationen beleuchten und sich hierbei vornehmlich auf die Nutzung von Kundendaten fokussieren, sind in der aktuellen wissenschaftlichen Literatur nicht zu finden. Zu den Anforderungen zur Generierung und Anwendung von „Customer Insights“ fokussieren bisherige Arbeiten insbesondere die erforderlichen technischen und methodischen Komponenten (Chatla & Shmueli, 2017; Chau & Xu, 2012; Lewis, Zamith, & Hermida, 2013; Li, Chen, Liou, & Lin, 2014; Yahav, Shmueli, & Mani, 2016) und vernachlässigen nicht-technische Voraussetzungen wie zum Beispiel die relevanten unternehmensinternen Prozesse. Auch wenn zum Thema der Datenweitergabe die Risiken für den Datenschutz und den Schutz der Privatsphäre in verschiedenen Arbeiten aufgegriffen werden (Belanger & Crossler, 2011; Kehr, Kowatsch, Wentzel, & Fleisch, 2015; Lowry, Dinev, & Willison, 2017; Menon & Sarkar, 2016; Smith, Dinev, & Xu, 2011), fehlen Forschungsbeiträge, die mit Blick auf den Kunden die erwarteten Vorteile einer Datenweitergabe identifizieren und den Prozess der Entscheidungsfindung im Detail analysieren.

Um diese Forschungslücken zu schliessen, verfolgt die Dissertation insgesamt drei Forschungsziele. Die für die Erreichung der Ziele gestellten Forschungsfragen werden über einzelne Forschungsbeiträge beantwortet. Das erste Forschungsziel fokussiert die Identifikation der Potentiale von BDA. Anhand der theoretischen Konzepte „Materiality“ (Lusch & Nambisan, 2015; Yoo et al., 2012) und „Functional Affordances“ (Markus & Silver, 2008, S. 622) wird im Forschungsbeitrag A1 der Beitrag von BDA zu Service Innovation analysiert. Es wird dargestellt, wie die Mitarbeiter eines Unternehmens die Nutzungsmöglichkeiten von BDA für Service Innovationen definieren resp. interpretieren. Darauf aufbauend wird im Forschungsbeitrag A2 skizziert, wie durch BDA unterstützte servicerelevante Aktivitäten dargestellt werden können. Das zweite Forschungsziel befasst sich mit den für die Realisierung der Potentiale relevanten Anforderungen von BDA. Unter Berücksichtigung der „Dynamic Capabilities Perspective“ (Eisenhardt & Martin, 2000) sowie des Konzepts der „Absorptive Capacity“ (ACAP) (Cohen & Levinthal, 1990) werden im Forschungsbeitrag B die erforderlichen Prozesse sowie die technischen und nicht-technischen Voraussetzungen identifiziert, um die relevanten Daten sammeln, analysieren und die generierten „Customer Insights“ kommunizieren sowie den Nutzungsmöglichkeiten entsprechend anwenden zu können. Das dritte Forschungsziel thematisiert die Bereitschaft des Kunden, persönliche Daten mit Unternehmen zu teilen. Im Forschungsbeitrag C wird am Beispiel von Wearables der entsprechende Entscheidungsprozess genauer analysiert. Es werden anhand des „Means-End Chain Approach“ (Reynolds & Gutman, 1988, S. 11ff) die für eine Datenweitergabe motivierenden Aspekte identifiziert. Anschliessend wird erläutert, dass die Kundenentscheidung nicht vorwiegend auf Basis einer rationalen Abwägung von Vor- und Nachteilen vorgenommen wird, sondern auch auf intuitive Entscheidungsstrategien (z. B. Heuristiken) zurückgegriffen wird.

Das Erreichen der drei Forschungsziele soll Wissen darüber generieren, wie Unternehmen die Potentiale von BDA ausschöpfen und die hohen Erwartungen an die Technologie erfüllen können. Als Gesamtziel dieser Dissertation sollen somit Ansätze aufgezeigt werden, die Unternehmen eine verbesserte Nutzung von BDA ermöglichen. Die Ansätze, die aus den Ergebnissen und Implikationen der Forschungsbeiträge abgeleitet werden, beziehen sich auf die strategische Ausrichtung von BDA-Initiativen, den Umsetzungsprozess von BDA-Initiativen sowie die Gewinnung von Kundendaten im Rahmen von BDA-Initiativen.

Die Dissertation leistet damit verschiedene Beiträge für die Wissenschaft. So wird beispielsweise durch die Darstellung der Nutzungsmöglichkeiten von BDA im Kontext von Service Innovation ein Beitrag zur aktuellen Diskussion um die Potentiale von BDA geleistet (Chen et al., 2015; Constantiou & Kallinikos, 2015). Des Weiteren wird durch die Berücksichtigung der relevanten Unternehmensprozesse und nicht-technischer Ressourcen bestehende Fachliteratur erweitert, die sich lediglich auf technische Aspekte fokussiert und organisationale Aspekte aussen vor lässt (Gandomi & Haider, 2015; Jagadish et al., 2014). Die Erkenntnisse zu den von Kunden erwarteten Vorteilen bei der Weitergabe persönlicher Daten erweitern die Fachliteratur, die vorwiegend die Auswirkungen von erwarteten Risiken auf die Bereitschaft, persönliche Daten zu teilen, thematisiert (Belanger & Crossler, 2011; Smith et al., 2011).

Für die Praxis bietet die Dissertation eine Hilfestellung, konkrete Einsatzszenarien resp. „Use Cases" von BDA im Kontext von Service Innovation zu entwickeln sowie ihren Maturitätsgrad bzgl. der Umsetzungsfähigkeit von BDA-Initiativen zu planen. Ausserdem können Unternehmen die Strategien und Massnahmen für die Gewinnung von Kundendaten anpassen.

Dieser Dachbeitrag dient als Zusammenfassung des Dissertationsprojekts. Es wird ein Überblick über den thematischen Kontext der Dissertation gegeben, die Forschungsziele und Forschungsfragen werden hergeleitet, das wissenschaftliche Vorgehen zur Zielerreichung wird skizziert und die Ergebnisse sowie der Beitrag der Arbeit zur Wissenschaft und Praxis werden in Kürze dargestellt. Im Sinne einer Übersicht und Einordnung der Dissertation werden deshalb nach der Einleitung, im Kapitel 2, die konzeptionellen Hintergründe des Dissertationsthemas dargestellt. Es wird auf die Generierung „digitaler Spuren" durch den Kunden eingegangen. Zudem werden die Begriffe Big Data und BDA eingeordnet und erläutert. Anschliessend werden positive Aspekte von BDA für Unternehmen sowie negative Aspekte resp. Risiken für die Kunden reflektiert. Vor diesem Hintergrund werden in Kapitel 3 die Forschungsziele motiviert und die Forschungsfragen abgeleitet. Das Vorgehen zur Beantwortung der Forschungsfragen und zur Erreichung der Forschungsziele wird über die Darstellung der einzelnen Forschungsbeiträge skizziert. Im Kapitel 4 werden die Ergebnisse hinsichtlich der übergeordneten Zielsetzung der Dissertation diskutiert und Ansätze für die verbesserte Nutzung von BDA abgeleitet. Ausserdem wird der Beitrag für die Wissenschaft sowie für die Praxis erläutert. Anschliessend finden sich in Kapitel 5 eine Zusammenfassung und eine kritische Würdigung der Dissertation sowie ein Ausblick auf weitere mögliche Forschungsvorhaben. Im Anhang dieser Arbeit sind die verfassten Forschungsbeiträge aufgelistet[1].

2. Konzeptionelle Hintergründe

2.1. Zur Generierung von „Digitalen Spuren"

Digitale Technologien prägen in einem wachsenden Maße die privaten, wirtschaftlichen und politischen Bereiche unseres Lebens (Lowry et al., 2017, S. 556; Newell & Marabelli, 2015, S. 6). Zum einen ermöglichen die nahezu allgegenwärtige Verfügbarkeit des Internets und die unter dem Terminus Web 2.0 zusammengefassten Nutzungsmöglichkeiten den Akteuren, das Internet nicht nur passiv, lesend, sondern aktiv zu nutzen, sich in der virtuellen Welt direkt miteinander zu vernetzen, an unterschiedlichen Geschehnissen zu partizipieren und Informationen sowohl individuell als auch kooperativ bzw. kollaborativ zu erstellen und zu modifizieren (Faase, Helms, & Spruit, 2011, S. 7ff). Solche im Web 2.0 mit großer Dynamik bereitgestellten Dienste sind v.a. soziale Netzwerke, Blogs, Kurznachrichtendienste, Wikis oder weitere fach- oder themenspezifische Internetplattformen (Chen et al., 2012, S. 1167; Faase et al., 2011, S. 6f). Daten dieser virtuellen Interaktionen (z. B. „User Generated Content") lassen sich in den Netzen im epischen Ausmaß speichern und verwalten und sind langfristig für verschiedene Stakeholder zugänglich (Baesens, Bapna, Marsden, Vanthienen, & Zhao, 2016, S. 807; Drummer, Feuerriegel, & Neumann, 2017, S. 225). In der Fachwelt werden entsprechende Dienste und Funktionen auch unter dem Begriff soziale Medien („Social Media") subsumiert: „*Social Media is a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user generated content*" (Kaplan & Haenlein, 2010, S. 61).

[1] An den Forschungsbeiträgen wurden keine Veränderungen zu der veröffentlichten resp. eingereichten Originalversion vorgenommen. Lediglich die Form wurde den für diese Dissertation geltenden Formatierungsvorgaben angepasst. Die Zitierweise sowie die Nummierung der Abbildungen und Tabellen wurden explizit im Sinne einer originalgetreuen Wiedergabe nicht geändert.

Neben diesem aktiven Nutzungs- resp. Interaktions-/Kommunikationsaspekt von „Social Media“ steigen Angebot und Einsatz von systemintegrierten, tragbaren, vernetzten Computersystemen bzw. -komponenten stetig an (Baesens et al., 2016, S. 808; Gholami, Watson, Hasan, Molla, & Bjorn-Andersen, 2016, S. 526). Die Einbettung von „Radio Frequency Identification“-Systemen (RFID), Chips, Sensoren und Aktoren, Datenspeichern und Internet-Schnittstellen (WLAN) in alltäglich genutzte Gegenstände ermöglicht die Vernetzung dieser digitalisierten Gegenstände über das Internet (Newell & Marabelli, 2015, S. 5; Trickler, 2013, S. 197ff). Es kommt zu einer Konvergenz von physikalischer und digitaler Welt – beschrieben als das „Internet of Things“ (IoT) (Atzori, Iera, & Morabito, 2010, S. 2ff). Im IoT ergeben sich somit völlig neue Möglichkeiten der Ermittlung und des Austauschs von Zustandsdaten und Bewegungsprofilen (Atzori, Iera, Morabito, & Nitti, 2012, S. 3594ff). Die Einsatzbereiche digitalisierter Gegenstände resp. des IoT sind vielfältig. Sie reichen von einem „Connected Car“, bei dem Daten zum Fahrverhalten, GPS-basierende Bewegungsprofile sowie technische Zustandsdaten gesammelt und an Versicherungsunternehmen übermittelt werden (Newell & Marabelli, 2015, S. 5), über vernetzte Haushaltsgeräte (Loebbecke & Picot, 2015, S. 149) zur Steuerung z. B. der Heiz-, Klima-, Sicherungs- und Beleuchtungstechnik („Smart Home“) bis hin zu sogenannten Wearables wie Smartwatches (um digitale Funktionen erweiterte Uhren) oder Fitnessarmbänder (Armbänder ausgestattet mit verschiedenen Sensoren) für das sogenannte „Self-Tracking“ (Sjöklint, Constantiou, & Trier, 2015, S. 1ff). Die Verbreitung entsprechender Techniken belegen Zahlen und Prognosen zur Entwicklung der digitalisierten Gegenstände (Statista, 2016).

Auch wenn in erster Linie die Nutzungsabsichten von „Social Media“ und digitalisierten Gegenständen unterschiedlich scheinen, haben diese Technologien mindestens eine Gemeinsamkeit: Die Nutzer resp. Kunden entsprechender Technologien generieren durch deren alltäglichen Einsatz Exabytes an Daten (The Economist 2010) und hinterlassen damit „digitale Spuren“ (Müller, Junglas, vom Brocke, & Debortoli, 2016, S. 289; Newell & Marabelli, 2015, S. 4). Die Datenmenge ist so gewaltig, dass McAfee und Brynjolfsson bereits 2012 schrieben: *„More data cross the Internet every second than were stored in the entire Internet just 20 years ago“ (S. 4).* Die Daten werden durch die Nutzer sowohl explizit wie implizit generiert. Eine explizite Datenbereitstellung erfolgt beispielsweise bei der Erstellung textbasierter Nachrichten auf sozialen Netzwerken oder der Veröffentlichung von Standortdaten und Bewegungsprofilen (z. B. mit Smartphone auf „Foursquare“) (Newell & Marabelli, 2014, S. 1). In diesen Fällen wird der Nutzer selbst aktiv. Die implizite Bereitstellung von Kundendaten vollzieht sich hingegen oft ohne Wissen oder aktives Handeln des Kunden (Newell & Marabelli, 2014, S. 1). So werden beispielsweise durch das ständige Mitführen des Smartphones implizit Bewegungsprofile generiert. Darüber hinaus werden z. B. das Surfverhalten im Internet, die Nutzung von Suchmaschinen oder Webseiten oder Kaufentscheidungen in Onlineportalen über sogenannte „Clickstreams“ implizit dokumentiert (Chen et al., 2012, S. 1167). Entsprechend dieser Vielzahl an Möglichkeiten, persönliche Daten zu teilen resp. zu sammeln, konstatieren McAfee und Brynjolfsson (2012): „*Each of us is now a walking data generator*“ (S. 5).

Die von Kunden generierten Daten können auf Grund des technologischen Fortschrittes im Bereich der Datenspeicherung, -verarbeitung und -analyse von unterschiedlichen Stakeholdern gesammelt und analysiert werden (Chatla & Shmueli, 2017, S. 340). Für die Prozesse der Datensammlung, -verarbeitung sowie -auswertung und -analyse haben sich in der Fachwelt die Begriffe wie Business Intelligence (BI), BI&A und BDA etabliert, auf die nachfolgend näher einzugehen ist.

2.2. Zur Entwicklung von Business Intelligence & Analytics hin zu Big Data Analytics

Der Begriff BI findet sich erstmals in einem Beitrag von Luhn aus dem Jahr 1958 und umschreibt die Aufgaben der Gewinnung und Aufbereitung von Unternehmensdaten. In den 90er Jahren etablieren sich Terminus und entsprechende Anwendungen in den Unternehmungen. Mit der Erweiterung des BI-Begriffs um „Analytics“ wurde in den nachfolgenden Jahren die über die klassische Bereitstellung und Visualisierung von Daten vollzogener Prozesse hinausgehende analytische Ausrichtung der Datenverarbeitung unterstrichen (Baesens et al., 2016, S. 808). Hierbei werden Daten nicht nur in aggregierter und leicht verständlicher Form dargestellt. „Analytics“ ermöglichen durch verschiedene Methoden, z. B. Simulationen oder maschinelles Lernen, sowohl prädiktive Aussagen zu treffen als auch kausale Zusammenhänge aufzuzeigen, um somit datengetriebene Entscheidungsfindung in Unternehmen zu verbessern (Baesens et al., 2016, S. 808). Dementsprechend beschreibt der Begriff BI&A „(…) *the techniques, technologies, systems, practices, methodologies and applications that analyse critical business data to help an enterprise better understand its business and market and make timely business decisions*“ (Chen et al., 2012, S. 1166).

In der letzten Dekade ist eine ständige Weiterentwicklung von BI&A zu beobachten, die wiederum auf die Herausforderungen bei der Verarbeitung und Analyse von Daten zurückzuführen ist, die die im Kapitel zuvor beschriebenen „digitalen Spuren“ mit sich bringen (Chen et al., 2012, S. 1165ff). Sowohl die über „Social Media“ als auch über digitalisierte Gegenstände generierten Datenmengen sind häufig zu gross, zu unterschiedlich, zu kurzlebig und mit einem schwer einzuschätzenden Wahrheitsgehalt behaftet, um sie mit konventionellen Datenbanksystemen und Analyseverfahren verarbeiten und auswerten zu können (Constantiou & Kallinikos, 2015, S. 49; Yoo, 2015, S. 63ff). Als Charakteristika dieser neu verfügbaren Daten werden die Dimensionen der „4Vs“: „Volume“, „Variety“, „Velocity“ und „Veracity“ hervorgehoben (Debortoli, Müller, & vom Brocke, 2014, S. 289). Verbunden mit diesen Charakteristika wird der Begriff Big Data: „*More specifically, researchers and practitioners use the term ‘Big Data’ to refer to the ongoing expansion of data in terms of volume, variety, velocity, and veracity*“ (Debortoli et al., 2014, S. 289). Jedoch gibt es in der Fachliteratur unterschiedliche Ansichten, welche Dimensionen entscheidend sind, um Datenmengen als Big Data zu bezeichnen, bzw. welche Dimensionen die Unterschiede von Big Data zu konventionellen Daten am besten verdeutlichen. Auf der einen Seite wird im Rahmen dieser Diskussion das Volumen der gesammelten Daten als entscheidend für das Potential von Big Data herausgestellt (Menon & Sarkar, 2016, S. 964). Autoren wie z. B. Clarke (2016, S. 964) konstatieren, dass die zuvor nicht dagewesene Datenmenge neue Vorgehensweisen bei der Datenanalyse und -auswertung erlaubt (z. B. der Einsatz von Algorithmen (Menon & Sarkar, 2016, S. 964)) und somit auf Grund der generierten Informationen neue Arbeitsweisen (King, 2013, S. 195) sowie eine neue Form der Entscheidungsfindung im Unternehmen ermöglicht (Kelly & Noonan, 2017, S. 873). Auf der anderen Seite vertreten weitere Autoren die Meinung, dass die Vielfalt („Variety“) der gesammelten Daten ausschlaggebend für die Einzigartigkeit von Big Data ist (Goes, 2014, S. iv; Yoo, 2015, S. 63). Zum einen ermöglicht die Kombination unterschiedlicher Daten in unterschiedlichen Formaten aus einer Vielzahl verschiedener, zuvor nicht zusammenhängender Datenquellen eine bessere Abbildung der Realität und somit das Erkennen neuer, vorher nicht abbildbarer Zusammenhänge und Muster (Belanger & Xu, 2015, S. 573). Zum anderen bietet die neue Möglichkeit der Nutzung unstrukturierter Daten ebenfalls eine Erweiterung der Datenbasis, da nun bislang nicht nutzbare Inhalte, z. B. „User-Generated Content“ aus sozialen Netzwerken, mit in Analysen einfliessen können (Müller et al., 2016, S. 289). Diese neue Vielfalt der Daten ermöglicht nicht nur bessere Analysen individuellen Kundenverhaltens, sondern darüber hinaus Aussagen zu gesellschaftlichen Trends (Goes, 2015, S. iv).

Zusammenfassend sei im Rahmen dieser Diskussion auf Goes (2014, S. iv) verwiesen, der betont, dass die Betrachtung von bzw. der Umgang mit Big Data nicht nur auf einzelne Dimensionen fokussiert werden sollte: „*The new paradigm comes by combining these dimensions. The hard core science disciplines have been working on volume and perhaps velocity, but it's the 4 V's together, the integration of the several data sources, different data types, making sure we work with valid data, that are what this paradigm is all about*" (Goes, 2014, S. vi).

Einen alternativen Ansatz zur Definition von Big Data bieten darüber hinaus z. B. Baesens et al. (2016) sowie George, Haas und Pentland (2014). Diese Autoren fokussieren sich insbesondere auf die Herkunft der Daten. Hierbei wird unterschieden, ob die Daten intern, z. B. im Rahmen von geschäftlichen Transaktionen, oder extern, z. B. auf „Social Media" Plattformen, oder via digitaler Gegenstände generiert werden (Baesens et al., 2016, S. 808). Letztendlich betonen die Autoren, dass Big Data nicht nur Daten aus externen Quellen, sondern auch aus internen Quellen (z. B. Tonspuren aus dem Call-Center) zugeordnet werden. Dementsprechend definieren George et al. (2014) Big Data wie folgt: „*Big data is generated from an increasing plurality of sources, including Internet clicks, mobile transactions, user-generated content, and social media as well as purposefully generated content through sensor networks or business transactions such as sales queries and purchase transactions*" *(S. 321).*

Wie bereits dargestellt, bietet die Nutzung von Big Data Unternehmen eine Vielzahl neuer Möglichkeiten zur Datenanalyse und somit der Generierung von bisher nicht dagewesenen „Insights". Jedoch ist die Generierung dieser „Insights" abhängig davon, inwiefern die zur Verfügung stehenden Technologien und Methoden zur Datensammlung, -speicherung, -verarbeitung und -analyse den Herausforderungen von Big Data nachkommen (Sivarajah, Kamal, Irani, & Weerakkody, 2017, S. 265). Um die Möglichkeiten von Big Data in Gänze ausschöpfen zu können, wurde BI&A, wie oben bereits erwähnt, in der letzten Dekade ständig weiterentwickelt. Der evolutionäre Entwicklungsprozess von BI&A lässt sich nach Chen et al. (2012, S. 1166ff) anhand von drei Entwicklungsstufen beschreiben. BI&A 1.0 umfasst die Nutzung konventioneller BI&A-Systeme, das sind vornehmlich relationale Datenbanksysteme und konventionelle „Datawarehouse" Lösungen, mit denen vor allem operative Unternehmensdaten gesammelt und nachgehend analysiert werden können (Chen et al., 2012, S. 1166f). Die zweite Evolutionsstufe (BI&A 2.0) beschreibt die Option des Einbezugs von Internet- und „Social Media" Daten als externe Datenquelle. Neue Technologien wie z. B. „Cookies", „Web-Crawler" oder „Text Analytics Tools" ermöglichen es, Onlineaktivitäten von Kunden (z. B. das Suchverhalten), individuelle „Social Media" Profile (z. B. Name, Alter, Wohnort) sowie von Kunden generierte Inhalte (z. B. Feedbacks, Meinungen zu kulturellen, politischen Ereignissen) zu sammeln und zu analysieren (Chen et al., 2012, S. 1167f). Die dritte Entwicklungsstufe (BI&A 3.0) beschreibt die Nutzung von „Mobile-" oder „Location-Aware" Methoden, die die Analyse der o.g. Daten digitalisierter Gegenstände ermöglichen (Chen et al., 2012, S. 1168). Beispiel für diese jüngste Entwicklungsstufe ist das von Versicherungsunternehmen unterbreitete Angebot von Datenrekordern für PKWs, die es erlauben, das Fahrverhalten des Kunden zu analysieren und die Prämien entsprechend anzupassen (Newell & Marabelli, 2015, S. 5).

Die Weiterentwicklung der konventionellen Datenbanksysteme und Analyseverfahren wird in der Fachliteratur auch unter dem Begriff BDA subsumiert (Kache & Seuring, 2017, S. 10). Beschrieben wird damit die Nutzung fortgeschrittener Technologien, um Big Data aus neuen Datenquellen zu sammeln (z. B. durch erweiterte API-Schnittstellen), die Menge an unstrukturierten und schnelllebigen Daten zu speichern und zu verarbeiten (z. B. „Data Lakes" und „Hadoop-Anwendungen") sowie neue Analysemethoden für die verbesserte Entscheidungsfindung ableiten zu können (Chen et al., 2012, S. 1176; Chen et al., 2015, S. 5; Porter & Heppelmann, 2015)[2]. Auch wenn der enorme Hype um BDA gelegentlich den Eindruck erweckt, die Technologien und Methoden zur Sammlung, Verarbeitung und Analyse von Big Data würden eine informationstechnische Revolution darstellen, so sind diese Technologien

[2] Für eine Auflistung von BDA-relevanten Technologien und Methoden sei auf den Fachbeitrag A verwiesen.

und Methoden doch, wie oben skizziert, als eine evolutionäre Weiterentwicklung von BI&A anzusehen (Loebbecke & Picot, 2015, S. 150): Zunächst strukturierte Daten können nun um massenhaft, mit hoher „Geschwindigkeit“ generierte, unstrukturierte Datentypen (v.a. Text-, Sprachnachrichten) erweitert werden (Debortoli et al., 2014, S. 289). Um den Begriff BDA genauer zu beschreiben, sei deshalb auf die Ausführungen von Chen et al. (2012) verwiesen: „*More recently big data and big data analytics have been used to describe the data sets and analytical techniques in applications that are so large (from terabytes to exabytes) and complex (from sensor to social media data) that they require advanced and unique data storage, management, analysis, and visualization technologies*“ (S. 1166).

2.3. Vor- und Nachteile von Big Data Analytics

2.3.1. Big Data Analytics als „Enabler“ für Service Innovation

Mithilfe von BDA können aus den zuvor genannten Quellen generierte Daten gesammelt, zusammengeführt, gespeichert und analysiert werden (Chen et al., 2012, S. 1166). Organisationen erweitern damit das Wissen über den Kunden resp. den Nutzer dieser Dienstleistungen tiefgreifend: Demografische Daten aus sozialen Netzwerken vermitteln Informationen zum Familienstand oder aktuellen Wohnort des Kunden (Woerner & Wixom, 2015, S. 61). Daten aus Foren übermitteln Informationen über persönliche Meinungen, Bedürfnisse und Verhaltensweisen (Chen et al., 2012, S. 1167). Wearables messen täglich oder situativ zurückgelegte Wegstrecken, die Geschwindigkeiten, die Pulsfrequenz oder den Schlafrhythmus. Über die Analyse der Daten können damit Rückschlüsse auf den Gesundheitszustand und die Leistungsfähigkeit ermöglicht werden (Buchwald, Letner, Urbach, & von Entress-Fuerstenbeck, 2015, S. 3; Sjöklint et al., 2015, S. 1ff).

Die Nutzung der zuvor nicht vorhandenen Daten durch BDA bietet somit in unterschiedlichen Anwendungsfeldern eine Vielzahl neuer Optionen: BDA kann Sicherheitsbehörden bei der Kriminalitätsaufklärung und –bekämpfung unterstützen (Chen et al., 2012, S. 1173). In der Gesundheitsbranche erlaubt die Analyse der Daten von implementierten Sensoren, Wearables sowie elektronischen Patientenakten eine optimierte Behandlung von Patienten (Strong et al., 2014, S. 68f). Im Politiksektor kann BDA für die Analyse von Wählermeinungen und zur politischen Kampagnensteuerung eingesetzt werden (Chen et al., 2012, S. 1173). Ein weiteres, intensiv diskutiertes Anwendungsfeld ist der Einsatz von BDA in B2C-Unternehmen. Die Möglichkeiten, Big Data in kürzester Zeit durch BDA zu analysieren, erlaubt es Unternehmen, bisher nicht dagewesenes Wissen über ihr unternehmerisches Handeln, ihren Kunden sowie ihr Wettbewerbsumfeld zu generieren (Constantiou & Kallinikos, 2015, S. 44ff). Das generierte Wissen soll jedoch nicht nur die Entscheidungsfindung in Unternehmen verbessern und den Unternehmenserfolg steigern. Unternehmen sehen in BDA den Treiber für die Etablierung neuer Arbeitsweisen, die Realisierung disruptiver Innovationen und als Chance, langfristige Wettbewerbsvorteile zu generieren (Baesens, Bapna, Marsden, Vanthienen, & Zhao, 2014, S. 629). BDA wird deshalb auch als „*Management Revolution*“ (McAfee & Brynjolfsson, 2012, S. 3) beschrieben, die sich auf sämtliche Teile des Unternehmens auswirkt (McAfee & Brynjolfsson, 2012, S. 7). Die Aussage von Peter Sondergaard von der Gartner Group verdeutlicht die Relevanz von Big Data und BDA für den Unternehmenserfolg: „*Information is the oil of the 21st century, and analytics is the combustion engine*” (Zitat nach Goes, 2014, S. iii). Auf Grund der hohen Erwartungen entwickelt sich BDA bei Unternehmen zu einem wesentlichen Bestandteil von IT-Strategien. Capgemini zeigt in einer Studie auf, dass 90% der Finanzinstitutionen in Nord-Amerika BDA zur Nutzung der neuen Datenquellen als entscheidenden Aspekt für die Generierung von Wettbewerbsvorteilen ansehen (Coumaros et al., 2014, S. 3). Darüber hinaus konstatieren Li, Lui, Belitski, Ghobadian und O’Regan (2016, S. 199), dass kleine und mittelständische Unternehmen, die erste Initiativen bei der Nutzung von Big Data pilotiert haben, einen 12% höheren Umsatz haben als die Konkurrenz. Um solche Erfolge zu realisieren und den hohen Erwartungen gerecht zu werden, bietet BDA in Unternehmen verschiedene Einsatzfelder. Die über BDA generierten Einblicke in produkt- und markenbezogene Assoziationen, Einstellungen und Motivationen, beschrieben als „Customer Insights", bieten zum Beispiel deutlich erweiterte Grundlagen für strategische Entscheidungen (Constantiou & Kallinikos, 2015, S. 44ff). Zudem werden Geschäftsmodellinnovationen ermöglicht, z. B. durch den Verkauf von Daten an andere Unternehmen (Woerner & Wixom, 2015, S. 60ff).

Mit den durch BDA generierten „Customer Insights" lassen sich überdies Service Innovationen umsetzen (Woerner & Wixom, 2015, S. 60). Service Innovation beschreibt sowohl inkrementelle als auch radikale Veränderungen der Nutzeroberfläche der Kundenschnittstelle sowie interner Prozesse zum Angebot von Serviceleistungen und die Entwicklung neuer Dienstleistungen (den Hertog, 2000, S. 491). Wie von den Hertog (2000) dargestellt, geht es darum, eine neue Form der Kundeninteraktion anzubieten: „*The way the service provider interacts with the client can itself be a source of innovation*" (S. 5). Übergeordnetes Ziel ist es, durch das Angebot neuer Nutzenversprechen neue Möglichkeiten für die Mehrwertgenerierung beim Kunden zu schaffen (Barrett, Davidson, Prabhu, & Vargo, 2015, S. 144; Yoo et al., 2012, S. 1400). Beispielhaft sei hier das Unternehmen Whirlpool aufgeführt, das seine Produkte mit Sensoren zur Analyse der Produktnutzung sowie des Produktzustandes ausstattet. Ergänzt um die Analyse der über „Social Media" zugänglichen Kundenmeinungen werden aktuelle Kundenbedürfnisse analysiert und verschiedene Dienstleistungen (z. B. Instandhaltungsmassnahmen) dem Kunden zielgenau angeboten (Woerner & Wixom, 2015, S. 60). BDA im Kontext von Service Innovation gewinnt in der Literatur sowie in der Praxis zusehends an Bedeutung (Yoo et al., 2012, S. 1400), bedingt durch sich wandelnde Kundenbedürfnisse und einen steigenden Wettbewerbsdruck (Setia et al., 2013, S. 565). Zum einen erwartet der Kunde von einem Unternehmen individuelle Betreuung, zum anderen können sich Unternehmen auf Grund der voranschreitenden „Commoditisierung" ihres Kerngeschäfts durch hohe Servicequalität sowie wertstiftende Dienstleistungen von den Wettbewerbern differenzieren (Setia et al., 2013, S. 565ff). Mit Verweis auf die Relevanz dieses Themas fokussiert diese Dissertation die Nutzung von BDA im Kontext von Service Innovationen in B2C-Unternehmen.

2.3.2. Big Data Analytics als Gefahr für den Schutz der Privatsphäre

Wie fast jede technologische Innovation hat auch BDA eine sogenannte Doppelwirkung („Dual Effects") (Markus, 2015, S. 58). Neben den vor allem aus Unternehmenssicht skizzierten positiven Effekten sind insbesondere die negativen Aspekte resp. Risiken für die Kunden hervorzuheben, die mit der Verwendung der aus den verschiedenen Quellen generierten Daten einhergehen.

Ein in der Wissenschafts- sowie der Fachliteratur viel diskutierter negativer Effekt für den Kunden betrifft die Gefahr der Verletzung des Datenschutzes resp. der Privatsphäre („Information Privacy") (Newell & Marabelli, 2015, S. 3ff). Nach Belanger und Crossler (2011) beschreibt Datenschutz resp. der Schutz der Privatsphäre das Recht sowie das Bedürfnis jedes Einzelnen, die Kontrolle über seine eigenen Daten zu behalten: „*Information privacy refers to the desire of individuals to control or have some influence over data about themselve*" (S. 1017). Wie von Belanger und Xu (2015, S. 573) dargestellt, nennt die amerikanische Regierung in einem Bericht aus 2014 den Schutz der Privatsphäre von Kunden als eine Herausforderung der Digitalisierung. Ähnlich thematisieren zusehends Pressemedien mit Aussagen wie „*privacy is dead*" den Verlust der Privatsphäre (Belanger & Xu, 2015, S. 573). Feststellungen zum Aussterben der Privatsphäre finden sich auch in einschlägigen Fachzeitschriften: „*Privacy as we have known it is ending, and we're only beginning to fathom the consequences*" (Enserink, & Chin, 2015, S. 491).

Dass die Besorgnis durchaus gerechtfertigt ist, zeigen die Risiken, die mit der Speicherung von persönlichen Daten einhergehen. Die Praxis etlicher Unternehmen, die Vielzahl an persönlichen Daten zu sammeln, zu speichern und zu analysieren, kollidiert oftmals mit dem Recht bzw. dem Bedürfnis des Kunden, Einfluss auf die Weiternutzung seiner persönlichen Daten zu behalten (Newell & Marabelli, 2015,

S. 4). Es ist ausserdem schwierig vorherzusagen, für welche Zwecke die gesammelten Daten genutzt werden (Galliers, Newell, Shanks, & Topi, 2017, S. 185). Auf Grund unterschiedlicher Rechtsprechung in verschiedenen Ländern ist es zudem kaum nachzuvollziehen, welchen rechtlichen Einschränkungen die jeweiligen Unternehmen bei der Verwendung der gesammelten Daten unterliegen. Darüber hinaus könnten Unternehmen die gewonnenen Daten an Drittunternehmen veräußern, die diese Daten für den Kunden gänzlich unbekannte oder unerwartete Zwecke weiterverwenden (Lowry et al., 2017, S. 556). Hinzu kommen die Gefahren des Datendiebstahls und missbräuchlicher Datennutzung. Sicherheitslücken bei Unternehmen haben in der Vergangenheit immer wieder Kriminellen unerlaubten Zugang zu persönlichen Kundendaten ermöglicht (Markus, 2015, S. 58; Markus & Topi, 2015, S. iv). Weitere Probleme können durch unbefristete Speicherungen der Daten, Änderungen gesetzlicher Speicherungs- und Nutzungsregelungen und den damit einhergehenden neuen Möglichkeiten zweckfremder Datenanalyse entstehen (Maddox, 2016). Neben dem Kontrollverlust des Kunden über die von ihm generierten Daten ergeben sich weitere mögliche Negativeffekte: Das umfangreich gesammelte Datenmaterial ermöglicht es Versicherungen, kundenbezogen potenzielle Unfall- oder Krankheitsrisiken zu berechnen mit der Konsequenz, gewünschte Versicherungspolicen abzulehnen oder höhere Risikoprämien anzusetzen (Markus, 2015; Newell & Marabelli, 2015, S. 5). Häufig problematisiert wird des Weiteren die Einschränkung der Autonomie bzw. der Entscheidungskompetenz des Kunden. So können Unternehmen das neu gewonnene Wissen über den Kunden nutzen, um ihm Informationen zur gezielten Beeinflussung von Kaufentscheidungen zuzuführen (Newell & Marabelli, 2015, S. 8). Darüber hinaus lassen sich beispielsweise Nachrichten oder Informationen im Internet den ermittelten grundlegenden Interessen anpassen, um das Meinungsbild sowie das Verhalten eines Kunden zu manipulieren. Entsprechende Prozesse verlaufen oft schleichend, ohne dass es vom Kunden wahrgenommen wird und er dem entgegenwirken kann (Newell & Marabelli, 2015, S. 8).

Diese mit BDA für den Kunden einhergehenden negativen Aspekte resp. Risiken können letztendlich auch zu einer möglichen Einschränkung der zuvor genannten Vorteile von BDA für die Unternehmen führen. Zum einen sind es gesetzliche Anpassungen zur Gewährleistung der Datenhoheit für den Kunden, die die Möglichkeiten zur Datenspeicherung und –analyse sowie der Verwendung der daraus entstehenden „Customer Insights“ zukünftig einschränken (Park, El Sawy, & Fiss, 2017, S. 649). Zum anderen kann das Risiko des Kontrollverlusts kundengenerierter Daten die Bereitschaft des Kunden reduzieren, seine Daten mit dem Unternehmen zu teilen und datengetriebene Services zu nutzen (Smith et al., 2011, S. 1000).

3. Zum Forschungskontext

3.1. Übersicht über das Forschungsvorhaben

Mit Verweis auf die einleitend dargestellten offenen Fragen zur Realisierung der Potentiale von BDA verfolgt die vorgelegte Dissertation das Ziel, einzelne unternehmerische Herausforderungen sowie wissenschaftliche Fragestellungen aufzunehmen und erste Lösungsansätze zu bieten, die sowohl die wissenschaftliche Literatur erweitern als auch Unternehmen bei der Nutzung von BDA unterstützen. Konkret soll durch die Erreichung verschiedener Forschungsziele Wissen darüber generiert werden, wie Unternehmen die Potentiale von BDA ausschöpfen und die hohen Erwartungen erfüllen können, um darauf aufbauend Ansätze zur verbesserten Nutzung von BDA abzuleiten. Zur Zielerreichung wurden auf Basis der unternehmerischen Herausforderungen sowie der wissenschaftlichen Fragestellungen unterschiedliche untergeordnete Forschungsziele abgeleitet. Für jedes der Forschungsziele wurde eine Forschungsfrage formuliert. Die Forschungsfragen dienen als weitere Strukturelemente und sollen dabei helfen, das zu erreichende Ergebnis sowie die für die Zielerreichung notwendigen Forschungsbeiträge weiter zu spezifizieren. Die Umsetzung der Forschungsziele erfolgt in voneinander abgegrenzten Teilprojekten. Die Ergebnisse der Teilprojekte wurden in einzelnen Forschungsbeiträgen zusammengefasst. Das Gesamtergebnis der Dissertation setzt sich aus den Ergebnissen und Implikationen der einzelnen Forschungsbeiträge zusammen. Abbildung 2 gibt einen Überblick über die für diese Dissertation relevanten Zielsetzungen und Fragestellungen.

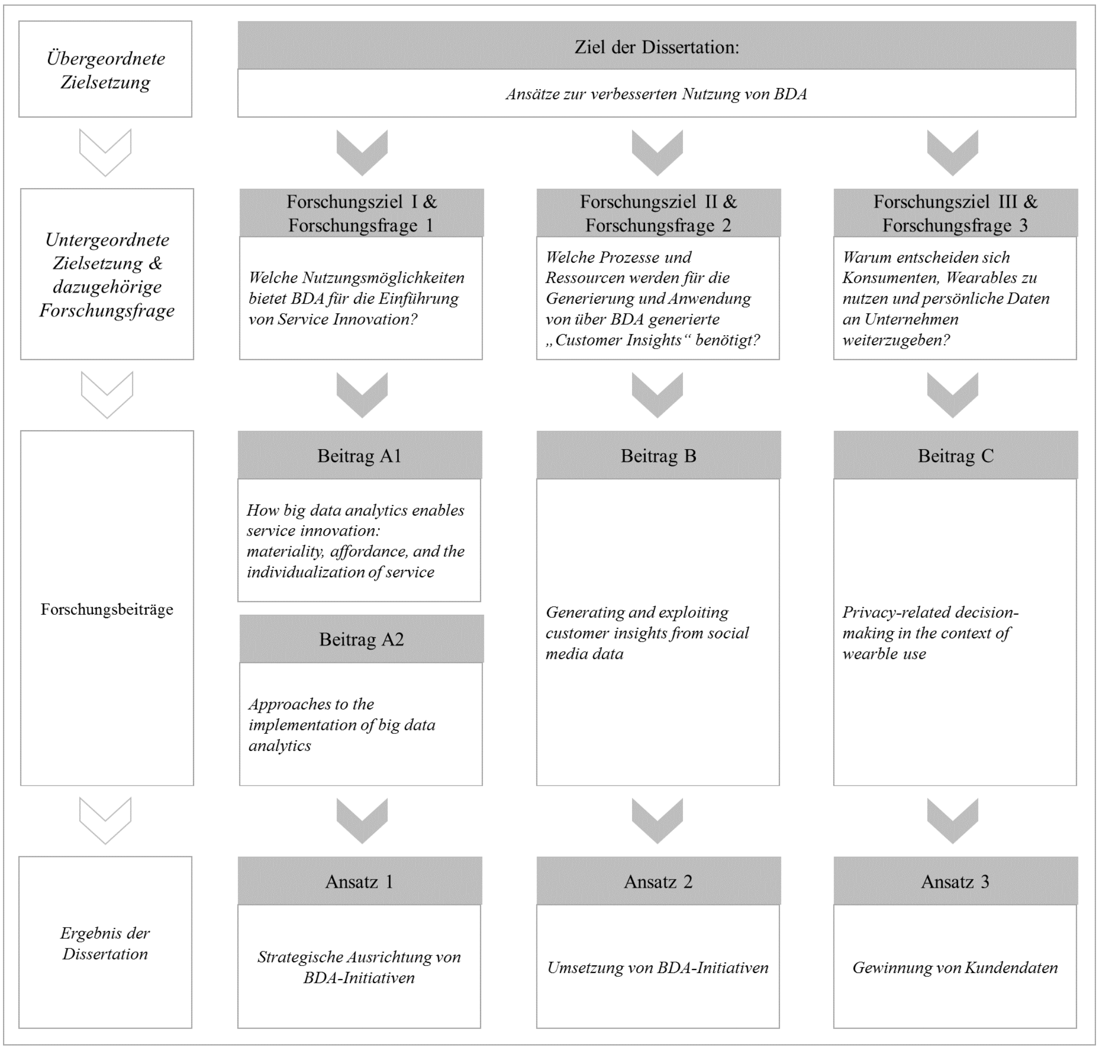

Abbildung 1: Übersicht Forschungsvorhaben

Die wissenschaftliche Relevanz der untergeordneten Forschungsziele ergibt sich aus den in der Literatur identifizierten Forschungslücken, auf die nachfolgend im Kapitel 3.2. noch näher eingegangen wird. Die praktische Relevanz der Forschungsziele wurde im Rahmen des Konsortialforschungsprogramms „Social CRM“[3] von vier Forschungspartnern (Axa Winterthur, Helsana, Swisscom, Zurich Versicherung) im Jahr 2015 bestätigt.

3.2. Untergeordnete Forschungsziele und Forschungsfragen

3.2.1. Forschungsziel I und Forschungsfrage 1

Praxisberichte, verfasst von verschiedenen Software- und Hardwareherstellern wie z. B. IBM (IBM, 2015) und SAS (SAS, 2015) zeigen beispielhaft erste, umgesetzte Szenarien auf, wie Unternehmen als „Pioniere“ BDA nutzen. In der Realität zeigt sich jedoch, dass etliche Unternehmen sich nicht hinreichend der Potentiale von BDA bewusst sind (Chen et al., 2015, S. 6). Es verwundert deshalb nicht, dass es viele Unternehmen überfordert, konkrete Einsatzszenarien zu definieren, die die Erreichung der strategischen Ziele unterstützen und somit die Investitionen rechtfertigen (Chen et al., 2015, S. 5). Wie von Chen et al. (2015, S. 5) und LaValle, Lesser, Shockley, Hopkins und Kruschwitz (2011, S. 23ff) dargestellt, ist für Unternehmen das Wissen essenziell, welche Potentiale BDA bietet und wie es zielgerichtet für die Erreichung strategischer Ziele eingesetzt werden kann: „*(…), the underlying mechanisms that lead to organizations' BDA usage, as well as the performance outcomes of such usage, deserve close investigation*“ (Chen et al., 2015, S. 5). Konkret stellt sich die Frage, welche Nutzungsmöglichkeiten BDA bietet, um die unternehmerischen strategischen Ziele zu erreichen: „*We need fundamental research on how big data and big data analytics are likely to impact management structures and processes, organizations (…)*“ (Baesens et al., 2014, S. 629).

Trotz des hohen Interesses ist die Forschung zu den Potentialen resp. den Nutzungsmöglichkeiten von BDA noch nicht sehr ausgeprägt (Markus, 2015, S. 59). Insbesondere zu den Auswirkungen von BDA auf Service Innovationen sind in der Fachliteratur keine detaillierten Aussagen zu finden. Lediglich in praxisnahen Beiträgen wird auf konzeptioneller Ebene konstatiert, dass durch den Einsatz von „Analytics“ servicerelevante Prozesse grundlegend verändert werden können (Davenport, 2013). Des Weiteren sind zu den Nutzungsmöglichkeiten von BDA aktuell vornehmlich konzeptionelle Arbeiten zum Einfluss von BDA auf verschiedene Unternehmensaktivitäten zu finden. Clarke (2016) zeigt sehr generische Einsatzszenarien von BDA auf. Constantiou und Kallinikos (2015) beschäftigen sich mit dem Einfluss von Big Data auf das strategische Management. Woerner und Wixom (2015) diskutieren die Möglichkeiten von BDA für die Entwicklung von Business Model Innovation. Chen et al. (2015) zeigen Einsatzoptionen von BDA im Kontext des Supply Chain Managements auf. Darüber hinaus, mit Bezug auf BI&A, demonstrieren Chen et al. (2012) erste Möglichkeiten des Einsatzes in verschiedenen Branchen. Von diversen Autoren wird die Rolle von BI&A in internen Entscheidungsprozessen von Unternehmen diskutiert (Popovic, Hackney, Coelho, & Jaklic, 2014; Shollo & Galliers, 2013). Zudem finden sich Studien, die die Nutzungsmöglichkeiten von „Social Media“ Analytics beschreiben, ohne hierbei auf einen spezifischen Kontext einzugehen (He, Zha, & Li, 2013; Kalampokis, Tambouris, & Tarabanis, 2013; Rao & Kumar, 2011).

Um die offensichtliche Forschungslücke zu schliessen sowie zu einem besseren Verständnis der Nutzungsmöglichkeiten von BDA beizutragen, soll aufgezeigt werden, welchen Beitrag BDA zur Umsetzung von Serviceinnovation leistet. Die Forschungsfrage für dieses Forschungsziel lautet wie folgt:

[3] Detaillierte Informationen finden sich auf https://dsi.iwi.unisg.ch/,

FF 1: Welche Nutzungsmöglichkeiten bietet BDA für die Einführung von Service Innovation?

Das Forschungsziel und die Forschungsfrage werden im Forschungsbeitrag A1, „How big data analytics enables service innovation: materiality, affordance, and the individualization of service“, aufgegriffen. Der Beitrag gibt unter anderem Auskunft über den Beitrag von BDA zu Service Innovation und zeigt verschiedene Nutzungsmöglichkeiten sowie die dafür notwendigen technologischen Komponenten auf. Im Forschungsbeitrag A2, „Approaches to the Implementation of Big Data Analytics“, wird neben der Klärung des Begriffs BDA dargestellt, wie die Nutzungsmöglichkeiten anhand von drei durch BDA ermöglichte servicerelevante Aktivitäten konkretisiert werden können. Anschliessend wird skizziert, auf welche Aspekte zu achten ist, um die Nutzungsmöglichkeiten von BDA zu implementieren.

3.2.2. Forschungsziel II und Forschungsfrage 2

Wie zuvor ausgeführt, können Unternehmen trotz der hohen Investition in IT die Potentiale von BDA nur selten realisieren. Ein Grund für dieses Defizit könnte eine zu starke Fokussierung auf die Einführung neuer IT-Lösungen sein (Kleindienst, Pfleger, & Schoch, 2015, S. 1ff; Trainor, Andzulis, Rapp, & Agnihotri, 2014, S. 1201). IT allein reicht nicht aus, um wertvolles Kundenwissen resp. die „Customer Insights“ zu generieren und einzusetzen (LaValle et al., 2011, S. 23; Trainor et al, 2014, S. 1201). Neben technischen werden nicht-technische Anforderungen an die Nutzung von BDA als entscheidende Voraussetzungen für die Realisierung der Potentiale von BDA betrachtet: „*The biggest challenges in adopting analytics are managerial and cultural*“ (LaValle et al., 2011, S. 21). Fokussieren Unternehmen lediglich IT-bezogene Fragestellungen zur Optimierung der Datenanalyse (z. B. durch Verringerung der Latenzzeiten), kann nicht sichergestellt werden, dass die benötigten Daten gesammelt und zielgerichtet, d. h. den Bedürfnissen verschiedener Stakeholder entsprechend, analysiert werden. Im Weiteren besteht die Gefahr, dass die generierten „Customer Insights“ nicht an die richtigen Stakeholder kommuniziert und für den richtigen Zweck eingesetzt werden (LaValle et al., 2011, S. 24). In diesem Fall besteht eine hohe Wahrscheinlichkeit, dass die über den Kunden gewonnenen Erkenntnisse für das Unternehmen wertlos sind und die Nutzungsmöglichkeiten von BDA nicht realisiert werden können. Um dieses Risiko zu minimieren, müssen deshalb angemessene Prozesse etabliert werden, die für die Sammlung und Analyse der extern generierten Daten, für die unternehmensweite Kommunikation der daraus resultierenden „Customer Insights“ sowie für die zielgerichtete Anwendung der gewonnenen Erkenntnisse benötigt werden (LaValle et al., 2011, S. 23ff). Zudem müssen die für die Umsetzung der Prozesse erforderlichen technischen, aber auch nicht-technischen Ressourcen identifiziert werden. Dies sind zum Beispiel interne Kommunikationsstrukturen oder menschliche Fähigkeiten (Chen et al., 2012, S. 1183; Trainor et al., 2014, S. 1202).

Auch in der Wissenschaft konzentrieren sich bisherige Beiträge vorwiegend auf die Identifikation technischer Anforderungen von BDA (Gandomi & Haider, 2015; Jagadish et al., 2014) und BI&A (Isik, Jones, & Sidorova, 2013; Zhang, Guo, & Yu, 2011). Weitere Studien fokussieren sich auf eine der zuvor dargestellten Datenquellen und untersuchen allgemeine Herausforderungen bei der Nutzung (Greenberg, 2010; Woodcock, Green, & Starkey, 2011) sowie konkrete Methoden zur optimalen Sammlung und Analyse von „Social Media“ Daten (Chau & Xu, 2012; Li et al., 2014). Schließlich beschäftigen sich weitere Arbeiten lediglich mit organisationalen strukturellen Fragestellungen, um generierte „Customer Insights“ optimal zu nutzen (Barwise & Meehan, 2011; Stone & Woodcock, 2014), sowie mit den konkreten technischen und analytischen Fähigkeiten, die Mitarbeiter benötigen (Chen et al., 2012). Empirische Studien, die sowohl technische und nicht-technische Aspekte betrachten als auch einen Überblick über Ansätze für das Management von BDA aufzeigen, waren in der wissenschaftlichen Literatur zum aktuellen Zeitpunkt noch nicht zu finden.

Um diese Forschungslücke zu schliessen, verfolgt die vorgelegte Dissertation das Ziel, die Anforderungen an die Generierung und Nutzung von „Customer Insights“ zu spezifizieren. Genauer gesagt soll aufgezeigt werden, welche Prozesse für die Generierung und Nutzung von „Customer Insights" etabliert werden müssen und welche Ressourcen für die Umsetzung der Prozesse notwendig sind. Dementsprechend lautet die dem Forschungsziel zu Grunde liegende Forschungsfrage wie folgt:

FF 2: Welche Prozesse und Ressourcen werden für die Generierung und Anwendung von über BDA generierte „Customer Insights" benötigt?

Die Forschungsfrage soll über den Forschungsbeitrag B, „Generating and exploiting customer insights from social media data", beantwortet werden. Der Beitrag untersucht, welche Prozesse Unternehmen als relevant erachten, um Daten zu sammeln und zu analysieren sowie um die daraus resultierenden „Customer Insights" zu kommunizieren und anschliessend anzuwenden. Für die Identifikation der dafür notwendigen Ressourcen wird zudem analysiert, inwiefern die Unternehmen neben technischen Ressourcen weitere Ressourcen, das heisst Fähigkeiten der Mitarbeiter und organisationale Strukturen, als notwendig erachten.

3.2.3. Forschungsziel III und Forschungsfrage 3

Neben den genannten Untersuchungen zur Realisierung der Nutzungspotentiale von BDA befasst sich die vorgelegte Dissertation auch mit den Risiken von BDA. Der Fokus wird dabei insbesondere auf den Umgang der Kunden mit dem Thema Datenschutz resp. Schutz der Privatsphäre gelegt. Im Zuge der in der Wissenschaft, aber auch in den Medien geführten Diskussion von Datenschutzaspekten steigt die Sorge der Kunden bezüglich der Weitergabe von Daten an Unternehmen. So äusserten zum Beispiel bei einer Befragung in den USA 45% der Weareable-Nutzer ihre Sorgen wegen möglicher Verletzung ihrer Privatsphäre (Mills, 2015). Ebenso sind Änderungen der Datenschutzrichtlinien bei sozialen Netzwerken wie Facebook stets mit Kritik der Nutzer und Datenschützer verbunden (Kühl, 2015). Die Bereitschaft des Kunden, seine Daten mit den Unternehmen zu teilen, ist jedoch ein essenzieller Aspekt für den Erfolg von BDA. Zum einen mindert es den Aufwand bei der Datenbeschaffung, zum anderen können auf Basis personalisierter Datensätze für den Kunden spezifische Angebote und Services generiert werden (Chen et al., 2012, S. 1173).

Paradoxerweise zeigen die Kunden trotz der Diskussion um den Datenschutz und den Schutz ihrer Privatsphäre weiterhin grosses Interesse, die problematisierten Technologien zu nutzen und persönliche Daten mit den Unternehmen zu teilen. Trotz aller Beschwerden über die Datenschutzrichtlinien sind die Nutzerzahlen von Facebook bislang nicht rückläufig, im Gegenteil, sie steigen weiterhin an (Roth, 2016). Die Nutzung von Wearables soll von 20 Mio. verkauften Exemplaren im Jahr 2014 auf mehr als 126 Mio. in 2019 ansteigen (IDC, 2015). Newell und Marabelli (2015) stellten bereits die These auf, dass die Kunden die Gefahr einer Verletzung der Privatsphäre akzeptiert haben und die Vorteile gegenüber den Risiken resp. Nachteilen überwiegen: „(…) *individuals seem to be likely to accept the 'dark side' of datification through digital traces (always there), and constant monitoring through sensors because they are persuaded that the benefits outweigh the cost.*" (S. 11). Aktuell gibt es in der Wissenschaft noch keine ausreichenden Belege zur Bestätigung bzw. Ablehnung dieser These. Baesens et al. (2014) verweisen auf die Notwendigkeit weiterer Forschung hinsichtlich des Datenschutzes resp. Schutzes der Privatsphäre im Kontext von BDA: „*From the individual perspective, issues include privacy and ethical use as compared to benefits from personalization*" (Baesens et al. 2014, S. 629). Arbeiten von Newell und Marabelli (2014; 2015) sowie Clarke (2016) skizzieren lediglich positive sowie negative Konsequenzen von BDA für die Gesellschaft. Weitere Forschung zum Entscheidungsprozess des Kunden findet sich vor allem im Forschungsfeld Datensicherheit bzw. Schutz der Privatsphäre. Ein Grossteil der Arbeiten konzentriert sich auf die Identifikation von Datenschutzrisiken sowie auf Ansätze ihrer Reduktionsmöglichkeiten (Smith et al., 2011; Xu, Teo, Tan, & Agarwal, 2009). Weitere Arbeiten befassen sich mit den Auswirkungen von Datenschutzrichtlinien und Datenschutzmassnahmen auf das Kundenverhalten (Sutanto, Palme, Tan, & Phang, 2013; Xu, Dinev, Smith, & Hart, 2011; Zhao, Lu, &

Gupta, 2012). Darüber hinaus untersuchen zum Beispiel Acquisti, John und Loewenstein (2012), Dinev, McConnell und Smith (2015) sowie Kehr et al. (2015), inwiefern situationsbedingte Entscheidungsmechanismen (z. B. Heuristiken) die Entscheidung der Individuen zum Teilen von Daten beeinflussen. Nur wenige Studien untersuchen die erwarteten Vorteile der Kunden mit der Weitergabe von Daten (Sun, Wanga, Shen, & Zhang, 2015). Die Frage, warum Kunden trotz bestehender Risiken bereit sind, Daten zu teilen, wurde hingegen noch nicht im Detail untersucht. Zudem befasst sich der überwiegende Anteil der Arbeiten mit der Datenweitergabe bei der Nutzung von E-Commerce Angeboten, sozialen Netzwerken oder mobilen Apps. Der Entscheidungsprozess des Kunden bei der Weitergabe von Daten im Rahmen der Nutzung von digitalisierten Gegenständen, wie z. B. Wearables, wurde noch nicht näher untersucht.

Um diese Forschungslücke zu schliessen, soll in einem weiteren Artikel der vorgelegten Dissertation aufgezeigt werden, warum Kunden bereit sind, Wearables zu nutzen und persönliche Daten an die Unternehmen weiterzugeben. Die Forschungsfrage lautet deshalb wie folgt:

FF 3: Warum entscheiden sich Kunden, Wearables zu nutzen und persönliche Daten an Unternehmen weiterzugeben?

Die Beantwortung der Forschungsfrage erfolgt über den Forschungsbeitrag C, „Privacy-related decision-making in the context of wearable use“. Der Beitrag fokussiert die Identifikation der für die Nutzung relevanten Vorteile und untersucht die Entscheidungsstrategien der Kunden.

3.3. Vorgehen, Methodik und Ergebnisse

3.3.1. Forschungsbeitrag A1: „How big data analytics enables service innovation: materiality, affordance, and the individualization of service“

Wie in Kapitel 3.1.1. beschrieben, wird über das Ergebnis dieses Beitrages das Forschungsziel I erreicht und die Forschungsfrage 1 beantwortet. Neben einer detaillierten Erklärung des Begriffs Service Innovation anhand der „Service-Dominant Logic“ (Lusch & Nambisan, 2015) werden deshalb für die Analyse die theoretischen Konzepte „Materiality“ (Lusch & Nambisan, 2015; Yoo et al., 2012) und „Functional Affordances“ (Strong et al., 2014) als theoretische Linse verwendet. Das Konzept „Materiality“ beschreibt spezifische technische Komponenten eines IT-Artefakts (z. B. Cloud Computing), die sich auch in unterschiedlichen Anwendungsszenarien nicht verändern (Leonardi, 2011, S. 152). Diese Eigenschaften können hardwarebezogene Komponenten (z. B. „In-Memory“-Technologie) wie auch softwarebezogene Komponenten (z. B. Softwareanwendungen wie „Python“ oder „R“) eines IT-Artefakts sein. Um zu beschreiben, inwiefern die technischen Komponenten genutzt werden können resp. welchen Beitrag sie leisten, um ein bestimmtes Ziel zu erreichen, kann das theoretische Konzept der „Functional Affordances“ genutzt werden. „Functional Affordances“ beschreiben die Interpretationen oder Wahrnehmung von Nutzungsmöglichkeiten durch ein Individuum oder eine Gruppe, die sich ergeben, wenn eine Technologie bzw. einzelne technische Komponenten einer Technologie angewendet werden (Leonardi, 2011, S. 153; Markus & Silver, 2008, S. 622; Volkoff & Strong, 2013, S. 822). Im Detail bedeutet dies, dass davon auszugehen ist, dass eine „Functional Affordance“ aus der Beziehung einer technischen Komponente und eines zielorientierten Nutzers resp. einer Nutzergruppe entsteht (Seidel, Recker, & vom Brocke, 2013, S. 1276). Strong et al. (2014) definieren eine „Functional Affordance“ als *„the potential for behaviors associated with achieving an immediate concrete outcome and arising from the relation between an artefact and a goal-oriented actor or actors*“ (S. 69). Darüber hinaus wird in dem Fachbeitrag dahingehend unterschieden, ob Nutzungsmöglichkeiten durch eine “human agency“ und „material agency“ umgesetzt werden. Gemäss Leonardi (2011, S. 147) spricht man von „human agency“, wenn die identifizierten Nutzungsmöglichkeiten durch die Fähigkeiten einer Person bzw. eines

Mitarbeiters umgesetzt werden. Von „material agency“ spricht man hingegen, wenn die Nutzungsmöglichkeiten ausschliesslich vom System, also automatisch, ausgeführt werden können.

Da bisher zu diesem Themenbereich nur wenige Studien vorliegen, wurde für die Datenerhebung ein explorativer qualitativer Forschungsansatz gewählt. Dementsprechend wurden multiple Fallstudien („multisite Case Study“) gemäss der Vorgaben von Eisenhardt (1989) und Paré (2004) durchgeführt. Insgesamt wurden vier Unternehmen aus vier verschiedenen Branchen (Versicherung, Banken, E-Commerce, Telekommunikation) betrachtet. Alle Unternehmen zeichnen sich dadurch aus, dass Service Innovationen als wichtige strategische Aspekte betrachtet werden. Zudem haben die Unternehmen erste Erfahrungen mit der Nutzung von BDA vorzuweisen. In jedem Unternehmen wurden Mitarbeiter aus IT- und kundenorientierten Funktionen befragt, um sicherzustellen, dass genügend Informationen über die verwendeten IT-Komponenten sowie deren Nutzung im Kontext von Service Innovation gesammelt werden können. Insgesamt wurden 30 Interviews geführt. Die primäre Datenerhebungsmethode erfolgte mittels halbstandardisierter Interviews (Paré, 2004, S. 247). Zunächst wurden die Daten jedes einzelnen Unternehmens unabhängig voneinander analysiert. Anschliessend wurden die Ergebnisse der einzelnen Unternehmen miteinander verglichen, um Unterschiede und Gemeinsamkeiten aufzuzeigen.

Das Ergebnis der Datenanalyse ist ein theoretisches Modell, das den Beitrag von BDA zu Service Innovation beschreibt. Das Modell zeigt auf, dass BDA die Ausführung kundenzentrierter Aktivitäten („customer-sensitive service practices“) ermöglicht. Konkret können Unternehmen „trigger-based“ als auch „customer-sensitive“ Serviceaktivitäten ausführen. Hinzu kommt, dass diese Aktivitäten durch die Nutzung von BDA nicht nur durch den Einsatz von Mitarbeitern, sondern nun auch vollautomatisiert ausgeführt werden können. Das Modell verdeutlicht ebenfalls, dass durch die technologischen Komponenten und daraus resultierenden Nutzungsmöglichkeiten Unternehmen eine stärkere Individualisierung von Serviceangeboten ermöglicht wird.

3.3.2. Forschungsbeitrag A2: „Approaches to the implementation of big data analytics“

Im Gegensatz zu den Forschungsbeiträgen A1, B und C dieser Dissertation zielt der Beitrag A2 in erster Linie darauf ab, Unternehmen bei der Implementierung von BDA zu unterstützen. Der Beitrag A2 bearbeitet die Forschungsfrage 1 somit nicht aus einer vorwiegend wissenschaftlichen, sondern vielmehr aus einer praktischen Sicht. Im Sinne des ausgesprochenen Praxisbezugs wird nicht auf theoretische Konzepte für die Datenanalyse zurückgegriffen. Als Grundlage des Beitrages wird auf praktische Problemenstellungen eingegangen. Genauer gesagt werden zunächst Herausforderungen aufgezeigt, mit denen Unternehmen bei der Implementierung von BDA konfrontiert werden. Neben dem in Kapitel 3.3.1. dargestellten fehlenden Verständnis für die Nutzungsmöglichkeiten von BDA wird ebenfalls auf fehlendes Wissen hinsichtlich der Bedeutung des Begriffs BDA sowie des relevanten Vorgehens für die Implementierung von BDA eingegangen.

Zudem liegt diesem Beitrag keine systematische Datenerhebung zu Grunde. Die Ergebnisse basieren zum Grossteil auf Gesprächen und Beobachtungen während der Zusammenarbeit mit unterschiedlichen Unternehmen. Zusätzlich werden die aus den Gesprächen und Beobachtungen resultierenden Erkenntnisse mit den Ergebnissen aus der wissenschaftlichen Literatur verglichen, um Gemeinsamkeiten und Unterschiede aufzuzeigen.

In dem Beitrag wird zunächst die Herausforderung des fehlenden Wissens hinsichtlich der Definition von BDA adressiert. Anhand der wissenschaftlichen Literatur werden verschiedene Ansätze zur Erklärung des Begriffs BDA dargestellt, die unter anderem Unternehmen dabei helfen sollen, BDA von konventionellen Analytics Lösungen abzugrenzen. Anschliessend wird im Detail aufgezeigt, wie Unternehmen BDA nutzen können, um Service Innovation zu realisieren. Hierfür wird zwischen den drei Nutzungsmöglichkeiten „behavior-based service“, „event-sensitive service“ und „emotion-sensitive service“ differenziert. Für jede dieser Nutzungsmöglichkeiten wird zudem der daraus resultierende Mehrwert für den Kunden und das Unternehmen aufgezeigt. Darüber hinaus wird in gegebener Kürze darauf eingegangen, wann die Unternehmen die Umsetzung der servicerelevanten Aktivitäten im Sinne der Generierung eines Mehrwerts als sinnvoll erachten. Es werden zudem die relevanten Dimensionen dargestellt, die von Unternehmen bei der Implementierung von BDA beachtet werden sollen. Neben dem sogenannten „Strategic Layer“, der relevant ist, um zu Anfang der Implementierung die Vision zu definieren und durch die Definition von konkreten Use Cases den möglichen Mehrwert für ein Unternehmen zu spezifizieren, müssen Unternehmen auch den „Organizational Layer“ und den „Technological Layer“ betrachten. Der „Organizational Layer“ ist vor allen Dingen wichtig, um die relevanten Prozesse und Strukturen zu definieren, die ein zielgerichtes Vorgehen bei der Sammlung und Analyse der Daten sowie die Kommunikation und Anwendung der daraus resultierenden „Insights“ sicherstellen sollen. Der „Technological Layer“ ist entscheidend, um anschliessend zu definieren, welche technischen Komponenten benötigt werden, um diese Prozesse umzusetzen und die für die Realisierung der vorab definierten Use Cases relevanten Insights zu liefern.

3.3.3. Forschungsbeitrag B: „Generating and exploiting customer insights from social media data“

Mit dem Forschungsbeitrag B wird das Forschungsziel II erfüllt und Forschungsfrage 2 beantwortet. Mit dieser Zielsetzung stützt sich der Beitrag auf die „Dynamic Capabilities Perspective“ und fokussiert in diesem Kontext das ACAP-Konzept (Zahra & George, 2002). Das Konzept beschreibt vier Aspekte, die für die Generierung und Anwendung von kundenbezogenem Wissen wichtig sind – die Akquisition und Assimilation von externen Daten für die Generierung von „Customer Insights“ sowie die Verbreitung und Anwendung der „Insights“ innerhalb der Unternehmung. Jede dieser Dimensionen ist nach Wang und Ahmend (2007, S. 35) von bedingenden Faktoren („Contingent Factors“) abhängig. Die „Contingent Factors“ können sowohl materielle als auch immaterielle Ressourcen wie z. B. Fähigkeiten von Mitarbeitern sein. Für die Identifizierung der relevanten „Contingent Factors“ wird als Orientierungsrahmen in diesem Fachbeitrag auf die Klassifikation von Barney (1991, S. 101) verwiesen, der die Ressourcen in drei unterschiedliche Dimensionen unterteilt, d. h. physische, menschliche und organisationale Ressourcen.

Auch wenn BDA, wie bereits dargestellt, nicht auf bestimmte Datenquellen beschränkt ist, fokussiert dieser Beitrag die Nutzung von Daten aus Social Media. Begründet wird dies mit dem Tatbestand, dass zu dem Zeitpunkt der Datenerhebung Unternehmen insbesondere die Nutzung von Social Media Daten thematisierten. Darüber hinaus lag das wissenschaftliche Interesse ebenfalls auf Fragestellungen zu „Social Media Analytics“. So fokussierte das „Special Issue“ der Fachzeitschrift „Electronic Markets“, für welches dieser Beitrag erstellt wurde, vorwiegend Beiträge, die sich mit Social Media spezifischen Fragestellungen beschäftigten. Insoweit wurden in dem Beitrag weitere Datenquellen ausser Acht gelassen.

Um die für die Umsetzung der ACAP-Dimensionen erforderlichen Prozesse und Ressourcen zu identifizieren, wurde ein multipler Fallstudienansatz („multisite Case Study") angewendet und im Sinne generalisierbarer Aussagen ein positivistisches Forschungsparadigma („positivistic research“) gewählt. Zur Verbesserung der Aussagekraft der Ergebnisse wurde vor der eigentlichen Datenerhebung eine Literaturrecherche nach vom Brocke et al. (2009) durchgeführt, um erste technische und nicht-technische Anforderungen aus der Literatur abzuleiten, die als empirische Grundlage für das weitere Vorgehen dienen sollen. Die Fallstudien wurden in mittleren und grossen Unternehmen aus dem B2C-Bereich durchgeführt. Zum Zweck einer höheren Repräsentativität der Aussagen wurden Unternehmen verschiedener Branchen (Telekommunikation, Krankenversicherung, Versicherung, Luftfahrt, Eisenbahn, E-Commerce, Automobil) ausgewählt. Die Unternehmen kommen aus Deutschland und der Schweiz. Die primäre Datenerhebungsmethode erfolgte mittels halbstandardisierter Interviews (Paré, 2004, S. 247). Es wurden 19 Interviews geführt, die in die Datenbasis dieses Beitrags einfliessen. Die Interviews der einzelnen Fallstudien wurden gemäss der Beschreibung von Bhattacherjee (2012) kodiert und die Ergebnisse der einzelnen Fallstudien miteinander verglichen, um generalisierbare Aussagen über die Anforderungen an die Generierung und Anwendung von „Customer Insights“ zu treffen.

Auf Basis der Datenanalyse kann in dem Beitrag zum einen aufgezeigt werden, wie die Unternehmen die vier Aspekte der ACAP umsetzen können. Als wesentlich kristallisierte sich heraus, vorab die relevanten Daten und Datenquellen zu definieren, um den Prozess der Datenakquise zu vereinfachen. Zudem müssen klare Anforderungen für die Analyse der gesammelten Daten spezifiziert werden, um sicherzustellen, dass die Bedürfnisse der Anwender der „Customer Insights“ bei der Assimilation der Daten berücksichtigt werden. Um das generierte Wissen schnell anwenden zu können, sind zudem schlanke und unbürokratische Kommunikationsstrukturen zu etablieren. Darüber hinaus sind Anwendungsfelder zu identifizieren, bei denen die Nutzung von „Customer Insights“ tatsächlich einen Mehrwert generieren kann. Im Weiteren kann festgestellt werden, dass für eine erfolgreiche Generierung und Anwendung von „Customer Insights“ das Etablieren eines iterativen Vorgehens notwendig ist. Damit wird gewährleistet, dass die Ausgestaltung der vorab beschriebenen Prozesse und Ressourcen regelmässig hinterfragt wird. Fehler können so frühzeitig erkannt und behoben und die Generierung und Anwendung der „Customer Insights“ optimiert werden. Abschliessend kann aufgezeigt werden, welche besonderen Anforderungen an die IT und die Fähigkeiten und Denkweisen der Mitarbeiter sowie der Governance gestellt werden.

3.3.4. Forschungsbeitrag C: „Privacy-related decision-making in the context of wearable use“

Mit dem Forschungsbeitrag C wird das Forschungsziel III erfüllt und Forschungsfrage 3 beantwortet. Als theoretische Grundlage wird in dem Beitrag das „Privacy Calculus“ Model genutzt. Dieses Modell betrachtet die Entscheidung zur Weitergabe von Daten als eine Kalkulation des Kunden, bei der die zu erwartenden Vorteile gegen die Risiken resp. die erwarteten Nachteile abgewogen werden (Dinev & Hart, 2006, S. 61ff; Smith et al., 2011, S. 1001). Mit der steigenden Nutzung des Internets und dem Angebot von Diensten, die auf der Weitergabe persönlicher Daten beruhen, hat sich die gesellschaftliche Einstellung zum Thema Datenschutz resp. zum Schutz der Privatsphäre geändert. Wurde Datenschutz bzw. Schutz der Privatsphäre in der Vergangenheit noch als ein Recht betrachtet, wird er heutzutage vielmehr als eine Währung resp. Handelsware im Austausch gegen verschiedene Vorteile bewertet (Smith et al., 2011, S. 993). Insoweit basiert die Entscheidung der Datenweitergabe auf einem rationalen Vorgehen. Gleichwohl haben Dinev et al. (2015) sowie Kehr et al. (2015) in ihren Arbeiten aufzeigen können, dass Kunden der Entscheidung nicht immer einen objektiven und rationalen Prozess zu Grunde legen. Vielmehr würden Kunden nicht alle Informationen verarbeiten und stattdessen auf intuitiv und subjektiv geprägte Entscheidungsstrategien zurückgreifen.

Unter Berücksichtigung dieser wissenschaftlichen Hintergründe wird der Entscheidungsprozess der Kunden durch einen qualitativen Forschungsansatz analysiert. Insgesamt wurden 22 Tiefeninterviews mit Wearables Nutzern aus der Schweiz geführt. Dieser Ansatz erlaubt es, die erwarteten Vor- und Nachteile resp. Risiken sowie die verwendeten Entscheidungsstrategien zu identifizieren. Bei den Tiefeninterviews wurde auf zwei unterschiedliche Interviewtechniken zurückgegriffen. Für die Identifikation der erwarteten Vorteile wird der sogenannte „Means-End Chain Analysis“ Ansatz verfolgt und die sogenannte „Laddering“ Interviewtechnik angewendet (Reynolds & Gutman, 1988, S. 11ff). Dieser Ansatz ermöglicht es, die für die Kunden relevanten technischen Attribute von Wearables und die erwarteten Vorteile zu identifizieren. Des Weiteren wurde auf die halbstandardisierte Interviewtechnik (Paré, 2004, S. 247) zurückgegriffen, um zu erfahren, welche Risiken bzw. Nachteile vom Kunden erwartet werden und warum die Vorteile überwiegen. Die erhobenen Daten wurden anschliessend gemäss den Ausführungen von Bhattacherjee (2012) sowie von Reynolds und Gutman (1988) ausgewertet.

Durch die Anwendung des „Means-End Chain Approach“ und der „Laddering Methode“ konnten für die Nutzer acht relevante Vorteile identifiziert werden. Diese sind: „Soziale Zugehörigkeit“ („social belonging“), „soziale Akzeptanz“ („social acceptance“), „Genugtuung“ („contentment“), „Erkundung“ („exploration“), „Erfolg“ („success“), „Gesundheit“ („health“), „Selbstoptimierung“ („self-optimisation“) und „Lebensqualität“ („quality of life“). Bei genauer Betrachtung der Vorteile wird deutlich, dass die Kunden „Vergnügen“ („enjoyment“), „Glück“ („happiness“) und „Freude“ („pleasure“) von der Nutzung von Wearables erwarten. Darüber hinaus konnte aufgezeigt werden, dass die Kunden ihre Entscheidung nicht zwingend auf Basis einer rationalen Abwägung von Vor- und Nachteilen treffen. Es konnte festgestellt werden, dass die befragten Probanden die Entscheidungen intuitiv getroffen haben. Das heisst, die Probanden greifen auf Entscheidungsstrategien zurück, die in erster Linie den Entscheidungsprozess verkürzen und eine rationale Betrachtung umgehen. Letztendlich konnten die folgenden vier Entscheidungsstrategien identifiziert werden: Affektheuristik („affective heuristic“), Verfügbarkeitsheuristik („availability heuristic“), Repräsentativitätsheuristik („representativeness heuristics“) sowie das Vertrauen auf prominente Dimensionen („reliance on prominent dimensions“).

4. Diskussion der Ergebnisse

Unter der übergeordneten Zielsetzung der Dissertation, Ansätze für die Realisierung der Potentiale von BDA abzuleiten, wurden einzelne Forschungsbeiträge erstellt. Auf Basis der Ergebnisse und Implikationen der Beiträge konnten Ansätze für die verbesserte Nutzung von BDA abgeleitet werden. Die Ansätze bieten Aussagen zu der strategischen Ausrichtung von BDA-Initiativen mit dem Fokus auf Service Innovation, zu den Umsetzungsanforderungen von BDA-Initiativen sowie zum Vorgehen bei der Gewinnung von Kundendaten für BDA-Initiativen.

Im Folgenden sollen die drei Ansätze und die dazugehörigen Aussagen kurz diskutiert und dabei auch der Beitrag dieser Ergebnisse für Wissenschaft und Praxis erläutert werden.

1) Ansatz zur strategischen Ausrichtung von BDA-Initiativen

Zusammenfassung

Insbesondere die Ergebnisse und Implikationen aus Forschungsbeitrag A1 sowie Teile der Resultate von Forschungsbeitrag A2 zeigen auf, wie BDA in Unternehmen einen konkreten Beitrag zum Unternehmenserfolg leisten kann. Somit kann die Dissertation Auskunft über mögliche strategische Stossrichtungen bei der praktischen Umsetzung von BDA geben. Es lassen sich hierzu drei Aussagen ableiten:

(1) BDA ermöglicht über die Generierung neuer „Insights“ die Verbesserung bestehender sowie die Einführung neuer Arbeitsprozesse bzw. neuer Mechanismen für die Umsetzung von Aufgaben. Im Kontext von Service Innovation beziehen sich diese Veränderungen vornehmlich auf Aktivitäten im Rahmen der Kundeninteraktion. Unternehmen können mit Hilfe von BDA jeden ihrer Kunden individuell, in Echtzeit und proaktiv ansprechen.

(2) Für Unternehmen bieten sich Optionen, die für die Kundeninteraktion relevanten Prozesse durch den Einsatz von BDA auch automatisiert umzusetzen. Unternehmen können nun entschei-

den, ob weiterhin eine menschliche Komponente resp. ein Mitarbeiter z. B. für die Kundenansprache eingesetzt werden soll oder ob dieser durch eine selbständig agierende Anwendung ersetzt werden kann.

(3) Es ist notwendig, den vorzufindenden Rahmenbedingungen entsprechend eine klare strategische Zielsetzung für die BDA-Initiative zu formulieren. Die erwarteten Nutzungsmöglichkeiten und die dazugehörigen technologischen Komponenten variieren bei Unternehmen mit unterschiedlichen Zielen und Rahmenbedingungen.

Zusammenfassend bleibt festzuhalten, dass durch den Einsatz von BDA neue Formen der Kundeninteraktion möglich sind, durch die Serviceangebote weiter individualisiert werden können. Die Nutzungsmöglichkeiten erlauben eine Neugestaltung der „Customer Journeys“ als auch neuer Serviceangebote und ermöglichen somit das Angebot neuer Nutzenversprechen.

Beitrag für die Wissenschaft

Mit den herausgearbeiteten Aussagen bzgl. der Nutzungsmöglichkeiten von BDA im Forschungsbeitrag A1 erweitert die Dissertation jene wissenschaftliche Literatur, die sich mit dem Beitrag von BDA zum Unternehmenserfolg auseinandersetzt (Chen et al., 2015; Constantiou & Kallinikos, 2015). Mit den aufgezeigten Möglichkeiten zur Kundeninteraktion und dem daraus resultierenden Potential zur proaktiven Kundenansprache sowie zur Individualisierung von Dienstleistungen wird zudem ein Beitrag zur Literatur zu den Themen „Customer Experience Managament“ (Homburg, Jozić, & Kuehnl, 2017) und „Omnichannel Management“ (Hansen & Sia, 2015) als auch zur Diskussion bzgl. der zunehmenden Personalisierung von Dienstleistungen durch Informationssysteme (Ho, Bodoff, & Tam, 2011; Thirumalai & Sinha, 2013) geleistet. Mit dem Aufzeigen von Möglichkeiten, durch den Einsatz von Technologien dem Kunden neue Nutzenversprechen anbieten zu können, erweitert die Dissertation des Weiteren die Diskussion zur „Service-Dominant Logic“ resp. der kundenzentrierten Ausrichtung von Unternehmen (Lusch & Nambisan, 2015). Die Ausführungen zu den Optionen, durch BDA Prozesse und servicebezogene Aktivitäten voll automatisiert durchzuführen und damit die menschliche Komponente zu ersetzen, leisten einen Beitrag zur Literatur, die das Zusammenspiel von menschlichen und technischen Komponenten für die Zielerreichung fokussiert (Fayard & Weeks, 2014; Hultin & Mähring, 2014).

Beitrag für die Praxis

Für Praktiker bieten die Ergebnisse zu den Nutzungsmöglichkeiten eine Grundlage einer zielgerichteten Planung von BDA-Initiativen. Praktiker können entsprechend der jeweiligen Zielsetzung zwischen den unterschiedlichen Ansätzen zur Neugestaltung der Kundeninteraktion wählen und den Automatisierungsgrad von Serviceaktivitäten prüfen und ggf. erweitern. Unternehmen können aufbauend auf die im Forschungsbeitrag A2 genannten servicerelevanten Aktivitäten konkrete „Use Cases“ für den Einsatz von BDA im Kontext von Service Innovation definieren und somit neue Formen der Kundeninteraktion etablieren. Ausserdem wird aufgezeigt, wie bei der Implementierung von BDA vorzugehen ist. Um sicherzustellen, dass die „Use Cases“ nicht nur für das Unternehmen, sondern auch für den Kunden einen Mehrwert schaffen, sollten Unternehmen auf kundenzentrierte, agile Entwicklungsmethoden wie z. B. „Design Thinking“ zurückgreifen.

2) Ansatz zur Umsetzung von BDA-Initiativen

Zusammenfassung

Insbesondere die Ergebnisse und Implikationen aus Forschungsbeitrag B bieten verschiedene Ansätze für die Umsetzung von BDA-Initiativen und zeigen auf, welche Prozesse und Ressourcen Unternehmen für die Generierung und Nutzung von „Customer Insights" benötigen. Konkret lassen sich drei Aussagen ableiten:

(1) Die Generierung und Nutzung von „Customer Insights" sollte nicht nur von der IT-Abteilung eines Unternehmens gesteuert werden, sondern als unternehmensweite Aufgabe unter Einbezug verschiedener Unternehmensbereiche angesehen werden. Es sind organisationale und strukturelle Veränderungen erforderlich, um eine intensive, abteilungsübergreifende Kommunikation und Kooperation zum Beispiel zwischen Mitarbeitern aus der IT-Abteilung und denen aus den Bereichen der Kundenschnittstelle zu gewährleisten.

(2) Wesentlich für Generierung und Nutzung von „Customer Insights" ist zudem die Anwendung iterativer und agiler Entwicklungsmethoden, um die „Insights" zeitnah und möglichst bedürfnisorientiert zu generieren.

(3) Unternehmen sollten sich nicht nur auf Investitionen in Technologien konzentrieren, sondern auch die Weiterbildung von Mitarbeitern fokussieren und zudem eine unternehmensweite datengetriebene Denkweise schaffen.

Die effektive und effiziente Generierung sowie Nutzung von „Customer Insights" benötigen somit nicht nur grundlegende Veränderungen von bestehenden Strukturen, sondern auch von etablierten Prozessabläufen und Routinen der Mitarbeiter. Deshalb kann die Umsetzung von entsprechenden Initiativen auch als unternehmensweiter Transformationsprozess beschrieben werden, bei dem durch die Etablierung neuer Prozesse und Erweiterung der Ressourcen neue Fähigkeiten bzw. „Dynamic Capabilities" für die Generierung und Nutzung von „Customer Insights" aufgebaut werden.

Beitrag für die Wissenschaft

Mit Verweis auf die zuvor dargestellten Aussagen zur Umsetzung von BDA-Initiativen erweitert die Dissertation die bestehende Fachliteratur, die sich hauptsächlich auf technische Aspekte fokussiert und organisationale Aspekte aussen vor lässt (Gandomi & Haider, 2015; Jagadish et al., 2014). Die detaillierte Darstellung von relevanten Prozessen und benötigten Ressourcen für die Generierung von „Customer Insights", insbesondere die Notwendigkeit der Einführung iterativer und agiler Prozesse, erweitert das Wissen bezüglich der „Absorptive Capacity" resp. der Gewinnung und Nutzung externer Informationen und somit die bestehende Literatur zu diesem Thema (Zahra & George, 2002). Mit der Darstellung der Besonderheiten von „Social Media" Daten wird zudem die Fachliteratur, die sich mit den Besonderheiten von Big Data auseinandersetzt, erweitert (Chen et al., 2012; Dinter & Lorenz, 2012).

Beitrag für die Praxis

Die ganzheitliche Betrachtung der relevanten Aspekte für die Umsetzung von BDA-Initiativen ermöglicht Praktikern eine verbesserte Planung von Umsetzungsinitiativen bzw. Transformationsprojekten zur Generierung und Nutzung von „Customer Insights". Zum einen können Praktiker auf Basis der Ergebnisse eine Bewertung des Maturitätsgrades der aktuellen Massnahmen zur Generierung und Nutzung von „Customer Insights" durchführen, zum anderen kann die Auflistung der relevanten Prozesse und Ressourcen genutzt werden, um KPIs für die Erfolgsbewertung und eine bessere Steuerung von Umsetzungsinitiativen zu gewährleisten.

3) Ansätze zur Gewinnung von Kundendaten

Zusammenfassung

Insbesondere die Ergebnisse und Implikationen aus Forschungsbeitrag C geben Auskunft über die Entscheidungsprozesse eines Kunden, persönliche Daten mit Unternehmen zu teilen. Somit kann die Dissertation Informationen zur Gewinnung von Kundendaten geben. Es lassen sich drei Aussagen ableiten:

(1) Bei den Entscheidungsprozessen eines Kunden zur Weitergabe der generierten Daten kommt der Wertorientierung beim Kundenverhalten eine prägende Bedeutung zu. Soweit die angebotenen Vorteile der Datenweitergabe für den Kunden von Relevanz sind, tendieren sie dazu, Risiken außer Acht zu lassen.

(2) Kunden scheinen sich bzgl. der Datenweitergabe nicht nur von utilitaristischen, sondern auch von hedonistischen Vorteilen überzeugen zu lassen.

(3) Bei Erwartung relevanter Vorteile durch die Datenweitergabe tendieren Kunden durchaus dazu, intuitive Entscheidungsstrategien anzuwenden. Die Bereitschaft zu einer rationalen Abwägung von Vorteilen und Risiken scheint sich zu verringern.

Das bedeutet, dass Unternehmen zur Gewinnung von Daten im Rahmen der Kundeninteraktion nicht vorwiegend die Risiken bzw. Massnahmen zum Datenschutz resp. Schutz der Privatsphäre adressieren sollten. Vielmehr sollten die Kunden von den Vorteilen eines Serviceangebotes begeistert werden, um ihre Bereitschaft zur Datenweitergabe zu motivieren. Durch die Bereitstellung spezifischer Informationen kann der Kunde angeleitet werden, auf spezifische Entscheidungsstrategien wie z. B. die „availablity heuristic“ zurückzugreifen und somit die mit der Datenweitergabe einhergehenden Risiken nicht weiter zu beleuchten.

Beitrag für die Wissenschaft

Mit den Ergebnissen des Forschungsbeitrag C wird ein Beitrag zum Themenfeld Datenschutz resp. Schutz der Privatsphäre geliefert. Die Erkenntnisse zur hedonistisch geprägten Motivation von Kunden zur Datenweitergabe erweitern die Darstellungen der Fachliteratur, die vorwiegend davon ausgeht, dass sich Kunden durch utilitaristische Vorteile (z. B. finanzielle Vorteile) beeinflussen lassen (Smith et al., 2011). Zudem zeigen die Ergebnisse auf, dass das Wissen der Kunden bzgl. der weitergehenden Nutzungsmöglichkeiten der Daten durch die Unternehmen durchaus limitiert ist. Diese Erkenntnis ist insbesondere für jene Forschungsaktivitäten von Relevanz, die sich mit ethischen Fragestellungen bzgl. BDA beschäftigen (Newell & Marabelli, 2015). Ausserdem erweitern die identifizierten intuitiven Entscheidungsstrategien die Fachliteratur, die die Annahmen des „Privacy Calculus“ hinterfragt (Dinev et al., 2015; Kehr et al., 2015).

Beitrag für die Praxis

Für die Praxis bieten die Ergebnisse wichtige Erkenntnisse darüber, wie Unternehmen den Kunden motivieren können, persönliche Daten zu teilen. Damit verknüpfen sich Auswirkungen auf die Gestaltung der Dienstleistungen, die auf die Freigabe persönlicher Daten angewiesen sind. Unternehmen können die Ergebnisse nutzen, um die relevanten Vorteile einer Datenüberlassung zu identifizieren und erfolgversprechende Nutzenversprechen zu formulieren. Zudem helfen die Ergebnisse Unternehmen dabei, die Kommunikation rund um das Thema Datensammlung anzupassen und Strategien oder Ansätze zu entwickeln, den Kunden zur Datenüberlassung positiv zu beeinflussen.

5. Zusammenfassung, kritische Würdigung und Ausblick

Ziel dieser Dissertation ist die Erweiterung des Wissens, wie Unternehmen die Potentiale von BDA nutzen können. Auf Basis der Untersuchungsergebnisse werden Ansätze beschrieben, die Unternehmen eine verbesserte Nutzung von BDA ermöglichen. Der Fokus liegt dabei auf Unternehmen im B2C-Sektor und der Anwendung von BDA im Kontext von Service Innovation. Es werden unternehmerische Herausforderungen sowie wissenschaftliche Forschungslücken im Bereich BDA adressiert, um bestehende wissenschaftliche Literatur zu erweitern und Unternehmen bei der Nutzung von BDA zu unterstützen. Um das übergeordnete Forschungsziel zu erreichen, wurden drei untergeordnete Forschungsziele mit jeweils einer dazugehörigen spezifischen Forschungsfrage entwickelt, die mit den erarbeiteten Antworten in den separaten Forschungsbeiträgen erreicht bzw. beantwortet wurden. Forschungsbeitrag A1 fokussiert die Identifikation von Nutzungsmöglichkeiten von BDA im Kontext von Service Innovation. Das Ergebnis ist ein theoretisches Modell, das den Beitrag von BDA zu Service Innovation beschreibt. Ausserdem wird im Forschungsbeitrag A2 skizziert, wie durch BDA innovative unterstützte servicerelevante Aktivitäten ermöglicht werden und wie diese implementiert werden können. Forschungsbeitrag B fokussiert die relevanten Faktoren für eine effektive und effiziente Generierung von „Customer Insights". Die Ergebnisse beschreiben diesbezüglich relevante „Dynamic Capabilities" bzw. Prozesse und Routinen sowie notwendige „Contingent Factors" bzw. technische als auch nicht-technische Ressourcen. Forschungsbeitrag C untersucht den Entscheidungsprozess des Kunden in Bezug auf die Weitergabe von persönlichen Daten an die Unternehmen. Das Ergebnis zeigt verschiedene Vorteile, die Kunden zur Datenweitergabe motivieren, und verweist auf die Relevanz von intuitiven Entscheidungsstrategien, die der Kunde im Rahmen des Entscheidungsprozesses anwendet.

Auf Basis des über die Forschungsbeiträge generierten Wissens konnten drei Ansätze zur verbesserten Nutzung von BDA abgeleitet werden. Der erste Ansatz bietet Informationen zur strategischen Ausrichtung von BDA-Initiativen und verdeutlicht den Beitrag, den BDA zur Umsetzung von Service Innovation leisten kann. So ermöglichen verschiedene technologische Komponenten die Einführung neuer bzw. die Verbesserung bestehender Arbeitsweisen, die wiederum neue Formen der Kundeninteraktion und somit Individualisierung von Serviceangeboten erlauben. Der zweite Ansatz bietet Unterstützung bei der Umsetzung von BDA-Initiativen und verdeutlicht, dass die Realisierung der Potentiale nicht nur von der Gewinnung der richtigen Daten und der Investition in die richtigen Technologien abhängt, sondern eine intelligente Vernetzung sämtlicher Unternehmensbereiche sowie die Einführung iterativer und agiler Entwicklungsprozesse ebenfalls entscheidende Erfolgsfaktoren für die Generierung von „Customer Insights" sind. Der dritte Ansatz gibt Empfehlungen zur Gewinnung von Kundendaten. Die Untersuchungsergebnisse zeigen bei der Entscheidungsfindung die Bedeutung der Wertorientierung und intuitiver Entscheidungsstrategien. Zur Motivation des Kunden sind also stärker hedonistische, emotionale Aspekte in den Vordergrund zu stellen als die Verweise auf Vermeidung möglicher Datenschutzrisiken.

Die Ergebnisse dieser Dissertation unterliegen gewissen Limitierungen. Im Wesentlichen ist auf die fehlende Generalisierbarkeit der Ergebnisse zu verweisen, die unter anderem auf die Wahl qualitativer Forschungsmethoden, der begrenzten Auswahl an Industriebranchen und Unternehmen sowie auf die Fokussierung spezifischer IT-Artefakte als Analyseobjekte zurückzuführen ist (z. B. Fokus auf „Social Media" Daten in Forschungsbeitrag B, Fokus auf Datenweitergabe im Rahmen der Nutzung von Wearables in Forschungsbeitrag C). Des Weiteren ist die thematische Fokussierung zu betonen, so dass sich sämtliche als Untersuchungsergebnis getroffene Aussagen in erster Linie auf eine verbesserte Nutzung von BDA in B2C-Unternehmen sowie im Kontext von Service Innovation beziehen. Eine detaillierte Darstellung der Limitierungen ist in den jeweiligen Forschungsbeiträgen zu finden.

Die Dissertation bietet diverse Ansätze für weitere Forschungsvorhaben. Neben den in den einzelnen Forschungsbeiträgen erwähnten Ansätzen sollen nachfolgend Forschungsvorhaben kurz skizziert werden, die auf Ergebnisse der Dissertation aufsetzen könnten.

Wie das theoretische Konzept der „Functional Affordances“ beschreibt, werden Technologien von Menschen konzipiert, die dabei oft einen bestimmten Zweck verfolgen bzw. explizite Nutzungsmöglichkeit mit der Technologie assoziieren. Nicht selten weicht aber die tatsächliche praktische Nutzung durchaus von den Erwartungen der Entwickler ab. Dieses von Leonardi (2011, S. 148ff) dargestellte Phänomen könnte auch im Kontext von BDA Anwendung finden. Mitarbeiter einschlägiger Softwarefirmen (z. B. SAP oder IBM) könnten deshalb zu den Nutzungsmöglichkeiten von BDA befragt werden, die sie mit den jeweiligen technologischen Komponenten verbinden. Anschliessend könnten die Aussagen mit den bereits vorhandenen Ergebnissen abgeglichen werden, um so Unterschiede und Gemeinsamkeiten herauszufinden. Soweit Abweichungen identifiziert werden, wären die Gründe zu analysieren, um somit relevante Faktoren zu identifizieren, die die Interpretation der Nutzungsmöglichkeiten von Technologie resp. von BDA beeinflussen.

Von Relevanz wären des Weiteren Untersuchungen zu den Verwendungsmöglichkeiten von künstlicher Intelligenz, die auf BDA aufbauen, insbesondere mit Blick auf weitere Ausgestaltungsmöglichkeiten der Kundeninteraktion. Einen besonderen Wertbeitrag könnten dabei Untersuchungen zu weiteren Automatisierungsmöglichkeiten der Kundeninteraktion leisten, die im B2C-Umfeld Substitutionsmöglichkeiten der menschlichen Komponente durch den Einsatz von künstlicher Intelligenz aufzeigen. Darüber hinaus könnte untersucht werden, nach welchen Kriterien Unternehmen entscheiden, ob die menschliche Komponente durch ein vollautomatisch agierendes System ersetzt wird.

Aufbauend auf Forschungsbeitrag C könnte tiefgreifender analysiert werden, ob die Entscheidung von Kunden zur Weitergabe persönlicher Daten von Kontextfaktoren beeinflusst wird. Konkret kann untersucht werden, ob bestimmte Charakteristika eines Unternehmens sowie dessen mit der Datensammlung verbundenen Nutzungsabsichten den Kunden bei der Entscheidungsfindung beeinflussen. Unter Berücksichtigung der erarbeiteten Untersuchungsergebnisse, die die Relevanz einer rational begründeten Entscheidungsstrategie auf Seiten der Kunden relativieren, wäre die Fragestellung interessant, ob sich das Kundenverhalten bzgl. der Datenweitergabe ändert, wenn dem Kunden Verfahren wie die Datenweitergabe an Dritte oder unerwartete Arten der Datennutzung bekannt werden. Diese Fragestellung ist von besonderer Relevanz, da die Thematisierung der Datenweitergabe an weitere Unternehmen oder der Veräusserung der gesammelten Datenbestände an Brisanz gewinnt.

Literaturverzeichnis

Acquisti, A., John, L., & Loewenstein, G. (2012). The impact of relative standards on the propensity to disclose. *Journal of Marketing Research, 49*(2), 160-174.

Atzori, L., Iera, A., & Morabito, G. (2010). The internet of things: a survey. *Computer networks, 54*(15), 2787-2805.

Atzori, L., Iera, A., Morabito, G., & Nitti, M. (2012). The social internet of things (SIOT) – when social networks meet the internet of things: concept, architecture and network characterization. *Computer Networks, 56*(16), 3594-3608.

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., & Zhao, J. L. (2014). Transformational issues of big bata and analytics in networked business. *MIS Quarterly, 38*(2), 629-631.

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., & Zhao, J. L. (2016). Transformational issues of big data and analytics in networked business. *MIS Quarterly, 40*(4), 807-818.

Barney, J. (1991). Firm resource and sustained competitive advantage. *Journal of Management, 17*(1), 99-120.

Barrett, M., Davidson, E., Prabhu, J., & Vargo, S. L. (2015). Service innovation in the digital age: key contributions and future directions. *MIS Quarterly, 39*(1), 135-154.

Barwise, P., & Meehan, S. (2011). Customer insights that matter. *Journal of Advertising Research, 51*(2), 342-344.

Belanger, F., & Crossler, R. E. (2011). Privacy in the digital age: a review of information privacy research in information systems. *MIS Quarterly, 35*(4), 1017-1041.

Belanger, F., & Xu, H. (2015). The role of information systems research in shaping the future of information privacy. *Information Systems Journal, 25*(6), 573-578.

Bhattacherjee, A. (2012). *Social science research: principles, methods, and practices*. Florida.

Buchwald, A., Letner, A., Urbach, N., & von Entress-Fuerstenbeck, M. (2015). Towards explaining the use of self-tracking devices: conceptual development of a continuance and discontinuance model. In *Proceedings of the Thirty Six International Conference on Information Systems* (ICIS 2015), Association for Information Systems, USA, Forth Worth.

Chatla, S. B., & Smueli, G. (2017). An extensive examination of regression models with a binary outcome variable. *Journal of the Association for Information Systems, 18*(4), 340-371.

Chau, M., & Xu, J. (2012). Business intelligence in blogs: understanding consumer interactions and communities. *MIS Quarterly, 36*(4), 1189-1216.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly, 36*(4), 1165-1188.

Chen, D. Q., Preston D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems, 32*(4), 4-39.

Choudhury, M. M., & Harrigan, P. (2014). CRM to social CRM: the integration of new technologies into customer relationship management. *Journal of Strategic Marketing, 22*(2), 149-176.

Clarke, R. (2016). Big data, big risks. *Information Systems Journal, 26*(1), 77-90.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128-152.

Constantiou, I. D., & Kallinikos, J. (2015). New games, new rules: big data and the changing context of strategy. *Journal of Information Technology*, *30*(1), 44-57.

Coumaros, J., Buvat, J., Auliard, O., Roys, S., KVJ, S., Chretien, L. et al. (2014). *Big data alchemy: how can banks maximize the value of their customer data?* Verfügbar unter https://www.capgemini-consulting.com/resource-file-access/resource/pdf/bigdatainbanking_2705_v5_0.pdf. Aufgerufen am 26. November 2016.

Davenport, T. (2013). Analytics 3.0: in the new era, big data will power consumer products and services. *Harvard Business Review*, *Dezember*, 2-9.

Debortoli, S., Müller, O., & vom Brocke, J. (2014). Comparing business intelligence and big data skills. *Business & Information Systems Engineering, 6*(5), 289-300.

Den Hertog, P. (2000). Knowledge-intensive business services as co-producers of innovation. *International Journal of Innovation Management, 4*(4), 491-528.

Dinev, T., Bellotto, M., Hart, P., Russo, V., Serra, I., & Colautti, C. (2006). Privacy calculus model in e-commerce – a study of Italy and the United States. *European Journal of Information Systems, 15*(4), 389-402.

Dinev, T., & Hart. P. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research, 17*(1), 61-80.

Dinev, T., McConnell, A. R., & Smith, H. J. (2015). Informing privacy research through infor-mation systems, psychology, and behavioral economics: thinking outside the "APCO" box. *Information Systems Research, 26*(4), 639-655.

Dinter, B., & Lorenz A. *(2012).* Social business intelligence: a literature review and research agenda. In *Proceedings of Thirty Third International Conference on Information System*s (ICIS 2012), Association for Information Systems, United States, Orlando.

Drummer, D., Feuerriegel, S., & Neumann, D. (2017). Crossing the next frontier: the role of ICT in driving the financialization of credit. *Journal of Information Technology*, *32*(3), 218–233.

Eisenhardt, K. M. (1989). Building theories from case study research. *The Academy of Management Review, 14*(4), 532-550.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: what are they? *Strategic Management Journal, 21*(10-11), 1105-1121.

Enserink, M., & Chin, G. (2015). The end of privacy. *Science*, 347, 490-491.

Faase, R., Helms, R., & Spruit, S. (2011). Web 2.0 in the CRM domain, defining social CRM. *International Journal of Electronic Customer Relationship Management, 5*(1), 1-22.

Fayard, A. L., & Weeks, J. (2014). Affordances for practice. *Information and Organization, 24*(4), 236-249.

Galliers, R. D., Newell, S., Shanks, G., & Topi, H. (2017). Datification and its human, organizational and societal effects: the strategic opportunities and challenges of algorithmic decision-making. *The Journal of Strategic Information Systems, 26*(3), 185-190.

Gandomi, A., & Haider, M. (2015). Beyond the hype: big data concepts, methods, and analytics. *International Journal of Information Managemen*t, *35*(2), 137-144.

George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. *Academy of Management Journal*, *57*(2), 321-326.

Gholami, R., Watson R. T., Hasan, H., Molla, A., & Bjorn-Andersen, N. (2016). Information systems solutions environment sustainability: how can we do more? *Journal of Association for Information Systems, 17*(8), 521-536.

Goes, P. G. (2014). Big data and IS research. *MIS Quarterly*, 38(3), iii-viii.

Goes, P. G. (2015). Inflection point: looking back or looking forward? *MIS Quarterly*, 37(3), iii-viii.

Greenberg, P. (2010). The impact of CRM 2.0 on customer insight. *Journal of Business & Industrial Marketing, 25*(6), 410-419.

Hansen, R., & Sia, S. K. (2015). Hummel's digital transformation toward omnichannel retailing: key lessons learned. *MIS Quarterly Executive*, *14*(2), 51-66.

He, W., Zha, S., & Li, L. (2013). Social media competitive analysis and text mining: a case study in the pizza industry. *International Journal of Information Management, 33*(3), 464-472.

Ho, S. Y., Bodoff, D., & Tam, K. Y. (2011). Timing of adaptive web personalization and its effects on online consumer behavior. *Information Systems Research, 22*(3), 660-679.

Homburg, C., Jozić, D., & Kuehnl, C. (2017). Customer experience management: toward implementing an evolving marketing concept. *Journal of the Academy of Marketing Science, 45*(3), 377-401.

Hultin, L., & Mähring, M. (2014). Visualizing institutional logics in sociomaterial practices. *Information and Organization, 24*(3), 129-155.

IBM (2015). *IBM big insights for apache hadoop*. Verfügbar unter http://www-01.ibm.com/common/ssi/cgi-bin/ssialias?sutype=SP&infotype=PM&htmlfid=IMD14496USEN&attachment=IMD14496USEN.PDF. Aufgerufen am 21. Juni 2016.

IDC (2015). *Worldwide wearables market forecast to reach 45.7 million units shipped in 2015 and 126.1 Million Units in 2019*. Verfügbar unter http://www.idc.com/getdoc.jsp?containerId=prUS25519615. Aufgerufen am 3. Januar 2016.

Isik, Ö., Jones, M. C., & Sidorova, A. (2013). Business intelligence success: the role of BI capabilities and decision environments. *Information & Management, 50*, 13-23.

Jagadish, H. V., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J. M., Ramakrishnan, R. et al. (2014). Big data and its technical challenges. C*ommunications of the ACM, 57*(7), 86-94.

Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of big data analytics and supply chain management. *International Journal of Operations & Production Management*, 37(1), 10-36.

Kalampokis, E., Tambouris, E., & Tarabanis, K. (2013). Understanding the predictive power of social media. *Internet Research, 23*(5), 544-559.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenge and opportunities of social media. *Business Horizons, 53*, 59-68.

Kehr, F., Kowatsch, T., Wentzel, D., & Fleisch, E. (2015). Blissfully ignorant: the effects of general privacy concerns, general institutional trust, and affect in the privacy calculus. *Information Systems Journal, 25*(6), 607-635.

Kelly, S., & Noonan, C. (2017). The doing of datafication (and what this doing does): practices of edification and the enactment of new forms of sociality in the Indian public health service. *Journal of the Association for Information Systems, 18*(12), 872-899.

King, J. L. (2013). Balance of trade in the marketplace of ideas. *Journal of the Association for Information Systems, 14*(4), 192-197.

Kleindienst, D., Pfleger, R., & Schoch, M. (2015). The business alignment of social media analytics. In *Proceedings of the 23th European Conference on Information Systems (ECIS 2015)*, Münster, Germany.

Kühl, E. (2015). *Was ändert sich bei Facebook?* Verfügbar unter http://www.zeit.de/digital/datenschutz/2015-01/facebook-agb-aenderung-datenschutz-fragen. Aufgerufen am 15. Juni 2016.

LaValle, S., Lesser, E., Shockley, R., Hopkins M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21-31.

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly, 35*(1), 147-167.

Lewis, S. C., Zamith, R., & Hermida, A. (2013). Content analysis in an era of big data: a hybrid approach to computational and manual methods. *Journal of Broadcasting & Electronic Media, 57*(1), 34-52.

Li, Y. M., Chen, H. M., Liou, J. H., & Lin, L. F. A. (2014). Creating social intelligence for product portfolio design. *Decision Support Systems, 66*(6), 123-134.

Li, W., Lui, K., Belitski, M., Ghobadian, A., & O'Regan, N. (2016). E-Leadership through strategic alignment: an empirical study of small- and medium sized enterprises in the digital age. *Journal of Information Technology*, *31*(2), 185-206.

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: a research agenda. *Journal of Strategic Information Systems, 24*(3), 149-157.

Lowry, B., Dinev, T., & Willison, R. (2017). Why security and privacy research lies at the centre of the information systems (IS) artefact: proposing a bold research agenda. *European Journal of Information Systems, 26*(6), 546-563.

Luhn, H. P. (1958). A business intelligence system. *IBM Journal of Research and Development, 2*(4), 314-319.

Lusch, R. F., & Nambisan, S. (2015). Service innovation: a service-dominant logic perspective. *MIS Quarterly*, *39*(1), 155-176.

Maddox, T. (2016). *The dark side of wearables: how they're secretly jeopardizing your security and privacy*. Verfügbar unter http://www.techrepublic.com/article/the-dark-side-of-wearables-how-theyre-secretly-jeopardizing-your-security-and-privacy/. Aufgerufen am 3. Januar 2016.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C. et al. (2011). *Big data: the next frontier for innovation, competition, and productivity*. Verfügbar unter https://bigdatawg.nist.gov/pdf/MGI_big_data_full_report.pdf. Aufgerufen am 23. Januar 2018.

Markus, M. L. (2015). New games, new rules, new scoreboards: The potential consequences of big data. *Journal of Information Technology, 30*(1), 58-59.

Markus, M. L., & Silver, M. S. (2008). A foundation for the study of IT effects: a new look at DeSanctis and Poole's concepts of structural features and spirit. *Journal of the Association for Information Systems*, *9*(10/11), 609-632.

Markus, M. L., & Topi, H. (2015). *Big Data, big decisions for science, society, and business*. Verfügbar unter https://www.bentley.edu/files/2015/10/08/BigDataWorkshopFinalReport.pdf. Aufgerufen am 3. Januar 2016.

McAfee, A., & Brynjolfsson, E. (2012). Big data: the management revolution. *Harvard Business Review*, *Oktober*.

Menon, S., & Sarkar, S. (2016). Privacy and big data: scalable approaches to sanitize large transactional databases for sharing. *MIS Quarterly, 40*(4), 963-981.

Mills, D. (2015). *Consumers like wearable technology but worry about data security*. Verfügbar unter http://www.healthline.com/health-news/consumers-concerned-about-privacy-personal-health-data-wearables-mobile-apps-072815#1. Aufgerufen am 3. Januar 2016.

Müller, O., Junglas, I., vom Brocke, J., & Debortoli, S. (2016). Utilizing big data analytics for information systems research: challenges, promises and guidelines. *European Journal of Information Systems*, *25*(3), 289-302.

Newell, S., & Marabelli, M. (2014). The crowd and sensors era: opportunities and challenges for individuals, organizations, society, and researchers. In *Proceedings of Thirty Fifth International Conference on Information System*s (ICIS 2014), Association for Information Systems, New Zealand, Auckland.

Newell, S., & Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: a call for action on the long-term societal effects of 'datification'. *Journal of Strategic Information Systems, 24*(1), 3-14.

Paré, G. (2004). Investigating information systems with positivist case research. *Communications of the Association for Information Systems, 13*(1), 233-264.

Park, Y. K., El Sawy, O. A., & Fiss, P. C. (2017). The role of business intelligence and communication technologies in organizational agility: a configurational approach. *Journal of the Association for Information Systems, 18*(9), 648-686.

Popovic, A., Hackney, R., Coelho, P. S., & Jaklic, J. (2014). How information-sharing values influence the use of information systems: an investigation in the business intelligence systems context. J*ournal of Strategic Information Systems, 23*(4), 270-283.

Porter, M. E., & Heppelmann, J. E. (2015). How smart, connected products are transforming companies. *Harvard Business Review, October*.

Rao, G. K., & Kumar, R. (2011). Framework to integrate business intelligence and knowledge management in banking industry. *Review of Business and Technology Research, 4*(1), 1-14.

Reynolds, T. J., & Gutman, J. (1988). Laddering theory, method, analysis, and interpretation. *Journal of Advertising Research – February/March*, 11-24.

Roth, P. (2016). *Die ersten offiziellen Facebook-Nutzerzahlen für das Jahr 2016*. Verfügbar unter http://allfacebook.de/toll/facebook-nutzerzahlen-2016. Aufgerufen am 16. Juni 2016.

SAS (2015). *Customer intelligence in the era of data-driven marketing*. Verfügbar unter http://www.sas.com/content/dam/SAS/es_es/doc/ebook/customer-intelligence-in-the-era-of-data-driven-marketing-english-ebook.pdf. Aufgerufen am 21. Juni 2016.

Seidel, S., Recker, J. C., & Vom Brocke, J. (2013). Sensemaking and sustainable practicing: functional affordances of information systems in green transformations. *MIS Quarterly, 37*(4), 1275-1299.

Setia, P., Venkatesh, V., & Joglekar, S. (2013). Leveraging digital technologies: how information quality leads to localized capabilities and customer service performance. *MIS Quarterly, 37*(2), 565-590.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of big data challenges and analytical methods. *Journal of Business Research*, 70, 263-286.

Shollo, A., & Galliers, R. (2013). Towards and understanding of the role of business intelligence systems in organizational knowing. In *Proceedings of the 23th European Conference on Information Systems* (ECIS 2013), European Research Centre for Information Systems, Netherlands, Utrecht.

Sjöklint, M., Constantiou, I., & Trier, M. (2015). The complexities of self-tracking - an inquiry into user reactions and goal attainment. In *Proceedings of the European Conference on Information Systems*, European Research Centre for Information Systems, Germany, Münster.

Smith, H. J., Dinev, T., & Xu, H. (2011). Information privacy research: an interdisciplinary review. *MIS Quarterly, 35*(4), 989-1015.

Statista (2016). *Prognose zur Anzahl der vernetzten Geräte im Internet der Dinge (IoT) weltweit in den Jahren 2014 bis 2020 (in Millionen Einheiten)*. Verfügbar unter https://de.statista.com/statistik/daten/studie/537093/umfrage/anzahl-der-vernetzten-geraete-im-internet-der-dinge-iot-weltweit/. Aufgerufen am 15. Juni 2016.

Stone, M. D., & Woodcock, N. D. (2014). Interactive, direct and digital marketing: a future that depends on better use of business intelligence. *Journal of Research in Interactive Marketing, 8*(1), 4-17.

Strong, D. M., Johnson, S. A., Tulu, B., Trudel, J., Volkoff, O., Pelletier, L. R. et al. (2014). A theory of organization-EHR affordance actualization. *Journal of the Association for Information Systems*, *15*(2), 53-85.

Sun, Y., Wanga, N., Shen X., & Zhang, J. X. (2015). Location information disclosure in location-based social network services: Privacy calculus, benefit structure, and gender differences. *Computers in Human Behavior, 5*2, 278-292.

Sutanto, J., Palme, E., Tan, C. H., & Phang, C.W. (2013). Addressing the personalization-privacy paradox: an empirical assessment from a field experiment on smartphone users. *MIS Quarterly, 37*(4), 114-1164.

The Economist (2010). *The data deluge*. Verfügbar unter http://www.economist.com/node/15579717. Aufgerufen am 19. Juni 2016.

Thirumalai, S., & Sinha, K. K. (2013). To personalize or not to personalize online purchase interactions: implications of self-selecting by retailers. *Information Systems Research, 24*(3), 683-708.

Trainor, K. J., Andzulis, J. M., Rapp, R., & Agnihotri, R. (2014). Social media technology usage and customer relationship performance: a capabilities-based examination of social CRM. *Journal of Business Research, 67*(6), 1201-1208.

Trickler, C. (2013). An overview of self-monitoring systems. In *Proceedings of the Nineteenth Annual 16th Southern Association for Information Systems Conference* (SAIS 2013), Southern Association for Information Systems, USA, Georgia.

Volkoff, O., & Strong, D. M. (2013). Critical realism and affordances: theorizing IT-associated organizational change processes. *MIS Quarterly*, *37*(3), 819-834.

Vom Brocke, J. M., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., & Cleven, A. (2009). Reconstructing the giant: on the importance of rigour in documenting the literature search process. In *Proceedings of the 17th European Conference on Information Systems (ECIS 2009)*, Verona, Italy.

Wang, C. L., & Ahmed, P. K. (2007). Dynamic capabilities: a review and research agenda. *International Journal of Management Reviews, 9*(1), 31-51.

Woerner, S. L., & Wixom, B. H. (2015). Big data: extending the business strategy toolbox. *Journal of Information Technology,* 30(1), 60-62.

Woodcock, N., Green, A., & Starkey, M. (2011). Social CRM as a business strategy. *Journal of Database Marketing & Customer Strategy Management, 18*(1), 50-64.

Xu, H., Teo, H. H, Tan, B. C., & Agarwal, R. (2009). The role of push–pull technology in privacy calculus: the case of location-based services. *Journal of Management Information Systems, 26*(3), 135-173.

Xu, H., Dinev, T., Smith, J., & Hart, P. (2011). Information privacy concerns: linking individual perceptions with institutional privacy assurances. *Journal of the Associations for Information Systems, 12*(12), 798-824.

Yahav, I., Shmueli, G., & Mani, D. (2016). A tree-based approach for addressing self-selection in impact studies with big data. *MIS Quarterly, 40*(4), 819-848.

Yoo, Y., Boland Jr., R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science, 23*(5), 1398-1408.

Yoo, Y. (2015). It is not about size: a further thought on big data. J*ournal of Information Technology, 30*(1), 63-65.

Zahra, S. A., & George, G. (2002). Absorptive capacity: a review, reconceptualization, and extension. *Academy of Management Review, 27*(2), 185-203.

Zhao, L., Lu, Y., & Gupta, S. (2012). Disclosure intention of location-related information in location-based social network services. *International Journal of Electronic Commerce, 16*(4), 53-90.

Zhang, D., Guo, B., & Yu, Z. (2011). The emergence of social and community intelligence. *Computer 44*(7), 21-28.

Anhang

Anhang 1	Fachbeitrag A1
Anhang 2	Fachbeitrag A2
Anhang 3	Fachbeitrag B
Anhang 4	Fachbeitrag C

Anhang 1: Fachbeitrag A1 – „How big data analytics enables service innovation: materiality, affordance, and the individualization of service“

Tabelle A1: Fakten zum Fachbeitrag A1

Informationstyp	Beschreibung
Titel	How big data analytics enables service innovation: materiality, affordance, and the individualization of service
Autor(en)	Christiane Lehrer, Universität St.Gallen, Schweiz Alexander Wieneke, Universität St.Gallen, Schweiz Jan vom Brocke, Universität Liechtenstein, Liechtenstein Reinhard Jung, Universität St.Gallen, Schweiz Stefan Seidel, Universität Liechtenstein, Liechtenstein
Publikationsorgan	Journal of Management Information Systems (JMIS)
Publication type	Fachjournal
Jahr der Veröffentlichung	2018
Ranking	A (VHS Jourqual 3.0 Ranking); FT50 Journal List; AIS - Bascet of Eights
Status der Publikation	Veröffentlicht
Referenz	Lehrer, C., Wieneke, A., vom Brocke, J., Jung, R., & Seidel, S. (2018). How big data analytics enables service innovation: materiality, affordance, and the individualization of service. *Journal of Management Information Systems, 35*(2), 424-460.[4]
Zugriff	https://www.tandfonline.com/doi/pdf/10.1080/07421222.2018.1451953

[4] Wie von der Prüfungsordnung der Universität St.Gallen (HSG) vorgeschrieben, findet sich im Folgenden eine Kopie sämtlicher Inhalte des erstellten Fachbeitrages. Als Quellenangabe ist die in Tabelle A1 angegebene Referenz zu verwenden. Diese verweist auf die veröffentlichte Originalversion des Fachbeitrages, welcher als “Open Access” zur Verfügung steht.

How big data analytics enables service innovation: materiality, affordance, and the individualization of service

Christiane Lehrer, University of St. Gallen, Switzerland
Alexander Wieneke, University of St. Gallen, Switzerland
Jan vom Brocke, University of Liechtenstein, Liechtenstein
Reinhard Jung, University of St. Gallen, Switzerland
Stefan Seidel, University of Liechtenstein, Liechtenstein

Christiane Lehrer (christiane.lehrer@unisg.ch; corresponding author) is an assistant professor of information systems at the University of St. Gallen, Switzerland. She received her doctoral degree from the LMU Munich, Germany. Her main research interests include IT-enabled organizational innovation, information privacy, and human-centered design of information systems. Her work has appeared, among others, in European Journal of Information Systems, Electronic Markets, and Business & Information Systems Engineering.

Alexander Wieneke (alexander.wieneke@unisg.ch) is a Ph.D. candidate at the Institute of Information Management at the University of St. Gallen, Switzerland. He received a master's degree in business administration from the University of Bayreuth, Germany. His research interests comprise big data analytics and information privacy. His work has been published in Electronic Markets.

Jan vom Brocke (jan.vom.brocke@uni.li) is Professor of Information Systems, the Hilti Chair of Business Process Management, Director of the Institute of Information Systems, and Vice President Research and Innovation at the University of Liechtenstein. His research focuses on business process management and related aspects of digital innovation and transformation. He has published, among others, in MIS Quarterly, Journal of Management Information Systems, Journal of Information Technology, European Journal of Information Systems, Information Systems Journal, Communications of the ACM, and MIT Sloan Management Review. He has held various editorial roles and leadership positions in Information Systems research and education.

Reinhard Jung (reinhard.jung@unisg.ch) is a professor of business engineering at the University of St. Gallen, Switzerland, Director of the Institute of Information Management, and Academic Director of the Executive MBA HSG in Business Engineering. His research interests focus on business engineering, digital transformation, and customer relationship management. He has published in such journals as Electronic Markets, Business & Information Systems Engineering, and Information Systems Frontiers.

Stefan Seidel (stefan.seidel@uni.li) is Professor and Chair of Information Systems and Innovation at the Institute of Information Systems at the University of Liechtenstein. His research explores the role of digital technologies in creating organizational, societal, and environmental innovation and change. Moreover, he is interested in philosophical and methodological questions about building theory and conducting impactful research. Stefan's work has been published or is forthcoming in prestigious journals, including MIS Quarterly, Information Systems Research, European Journal of Information Systems, Journal of Information Technology, Journal of the Association for Information Systems, and several others. He is an Associate Editor to Information Systems Journal, Past Chair of the AIS Special

Interest Group on Green Information Systems (SIGGreen), and Vice President for research of the Liechtenstein Chapter of the AIS

Abstract

The article reports on an exploratory, multisite case study of four organizations from the insurance, banking, telecommunications, and e-commerce industries that implemented big data analytics (BDA) technologies to provide individualized service to their customers. Grounded in our analysis of these four cases, a theoretical model is developed that explains how the flexible and reprogrammable nature of BDA technologies provides features of sourcing, storage, event recognition and prediction, behavior recognition and prediction, rule-based actions, and visualization that afford (1) service automation and (2) BDA-enabled humanmaterial service practices. The model highlights how material agency (in the case of service automation) and the interplay of human and material agencies (in the case of human-material service practices) enable service individualization, as organizations draw on a service-dominant logic. The article contributes to the literature on digitally enabled service innovation by highlighting how BDA technologies are generative digital technologies that provide a key organizational resource for service innovation. We discuss implications for research and practice.

Key words and Phrases: *affordances, agency, big data analytics, digital innovation, materiality, service-dominant logic, service innovation, services.*

The increasing commoditization of products and the rising customer demand for individualized experiences and interactions is causing chief executives to shift their focus from product innovation to service innovation [1]. Service innovation offers customers new and unique value propositions that allow companies to differentiate themselves from their competitors and to create strategic value [45]. Companies are thus seeking opportunities to capitalize on the flexible and malleable nature of digital technologies to innovate their service (e.g., [1, 24, 57]),[1] and service innovation is now an important area in the broader field of digital innovation [57].

The ever increasing abundance of digital trace data, coupled with advances in big data analytics (BDA), in particular, offer new possibilities for service innovation [1, 58]. BDA provides powerful methods and tools for gathering, processing, and analyzing large amounts of trace data, enabling organizations to generate valuable insights by compiling their customers' "*digital footprints into a comprehensive picture of an individual's daily life*" [60, p. 21]. These insights have the potential to create competitive advantage [6, 14, 32], and BDA is expected to support customer-oriented service innovation in a number of ways [34, 58].

Analyzing data gathered from sensors in cars, for instance, allows insurance firms to create offerings that are sensitive to their customers' driving behavior [32]. Whirlpool, the home-appliances manufacturer, uses sensors in their products to track how customers use their products, combine these data with user-generated content from social media platforms, and generate insights into their customers' preferences and behaviors [54]. While these examples suggest that BDA provides ample opportunity for service innovation across industries, we lack an empirically grounded theoretical understanding that attends to the materiality of BDA and how this materiality enables service innovation. Such a theoretical account will have to consider the role of both human and material agencies, as service, which has traditionally been a human enterprise, is now increasingly shaped by the use of digital technologies. Material agency describes a technology's capacity to act on its own, apart fromhuman intervention, while human agency refers to humans' capacity to form and realize their goals [21]. Developing such an empirically grounded theoretical model will complement and contribute to previous scholarly work on digitally enabled service innovation, which has highlighted how the generative nature of digital technologies enables service innovation [24, 58]. In addition, organizations that seek to innovate their service can benefit from such a model in their efforts to identify and implement appropriate BDA technologies. Moreover, developing theory on the impact of BDA on service innovation can contribute to the development of more general theories of digitally enabled service innovation. Therefore, our research question is:[2]

How do the material features of big data analytics technologies enable service innovation?

Our study has three primary objectives: (1) to develop an empirical description of how BDA has been used to develop service innovation, (2) to identify the pertinent material features of BDA that facilitate the implementation of service innovation, and (3) to integrate these findings into an empirically grounded theoretical model of BDA-enabled service innovation. To this end, we conducted four exploratory, theory-building case studies [9, 35] with private-sector business-to-customer (B2C) firms, which allowed us to gain an in-depth understanding of how BDA permitted these organizations to identify opportunities for new BDA-enabled service processes and their implementation. To develop an understanding of the more specific role of BDA, we draw on recent research on the role of materiality in IT-enabled change and innovation (e.g., [21, 22, 47]), as we are interested in what matters about BDA technologies in developing service innovation. Specifically, we use the concepts of materiality and affordances as analytical devices because they are predominant lenses through which to theorize about how digital technologies are involved in organizational change and innovation (e.g., [11, 12, 19, 21, 25, 26, 42]).

Our analysis suggests two main types of BDA-enabled service innovation. First, organizations use key material features of BDA technologies to automate service processes in order to provide (a) trigger-based service actions and (b) preferencebased service actions to customers. Second, organizations identify new ways for IT-enabled service processes where human service actors interact with BDA technologies (i.e., human-material service practices) to engage in trigger-based interactions and preference-based interactions with customers. In both cases, service innovation is based on the generativity and reprogrammability of BDA technologies as digital technologies [58].

The present research makes three primary contributions to theory and practice. First, it contributes to the literature on service innovation by providing an empirically grounded theoretical model of how the material features of BDA technologies enable service innovation, as organizations interpret BDA technologies as generalpurpose technologies in light of new action goals associated with a service-dominant logic [24]. Second, we contribute to the literature on digital innovation [30, 57, 58] in more general terms by highlighting how digital technologies afford two fundamentally different types of digital innovation: automation, which relies on material agency, and human-material practices, which relies on the interaction between human and material agencies. Third, our research yields practical insights for the design of BDA infrastructures that support service innovation. The proposed conceptualization provides the guidance for assessing current infrastructures and for making decisions about the implementation of new technologies.

Theoretical Background

Service innovation

Service innovation provides businesses with opportunities to create customer value and generate competitive advantage. The view of service innovation has shifted from a focus on firms' output (i.e., in terms of new or improved products and services) to a focus on new ways of creating customer value through service processes, so the shift has been from a goods-dominant (G-D) logic to a service-dominant (S-D) logic. From the G-D perspective, service innovation is the production of outputs in the form of innovative service products with new features and attributes [2], so service products are comparable to tangible products [1]. The S-D logic, in contrast, focuses on the processes of serving, rather than on output in the form of a product offering [24]. Here, the value of an innovation is not delivered to the customer as a product but can offer a promise of value creation—that is, value propositions. Customers approve these propositions by engaging with the firm's service process, thereby cocreating value with the firm [45]. Service innovation, then, is the creation of value propositions, which are generated when firms deliver resources (e.g., information, knowledge, skills) to improve the customer's own value creation. Organizations therefore renew their service-delivery processes to provide new value propositions to their customers [45], and this renewal becomes the essential source of service innovation.

Service innovation can range from incremental to radical [33, 45] and can be described along dimensions of innovation (i.e., provision of new service), changes in the client interface (e.g., intuitive design ofweb pages), the service delivery system (e.g., processes of service workers), and technology (e.g., new digital platforms for innovation) [7]. Changes along these dimensions involve information technologies, and studying service innovation in contemporary organizations requires that we attend to the specific role of materiality. The relationship between materiality and humans is increasingly dynamic, requiring an emphasis on relationality, materiality, and performativity [34]. The use of information technology reconfigures how humans enact practices, and entirely new practices emerge: "*Material-discursive practices redraw boundaries, changing inclusions/exclusions, and making a difference in who participates, how, and with what consequences*" [34, p. 214]. Practices are clusters of recurrent human activities that are informed by social and contextual relations [39, 40]. In addition to new humandiscursive practices, digital technologies can allow for service automation, for instance, through recommender systems [55].

Notably, IT-enabled service innovations are grounded in the flexible, reprogrammable nature of digital technologies [58].

Against this background, we seek to examine how BDA technologies enable service processes that create value propositions for customers. In doing so, we focus on the roles of materiality as well as human actors. Next, we turn to the class of digital technologies on which we focus: BDA.

Big data and big data analytics

Technological advancements in the tools and methods of business analytics provide unprecedented access to vast amounts of data beyond the firms' business transactions— big data [4, 28]. "Big data" describes data that are "*generated from an increasing plurality of sources, including Internet clicks, mobile transactions, user-generated content, and social media as well as purposefully generated content through sensor networks or business transactions such as sales queries and purchase transactions*" [14, p. 321]. Scalable techniques (e.g., text analytics, web analytics) enable firms to process and analyze such trace data—digital records of activities and events that involve information technologies [18]—from, for instance, websites and social media, including users' online activities (e.g., browsing and purchasing patterns) and online conversations (e.g., opinions, feedback, and sentiment regarding a product or firm). Firms also use data trails from digitized objects like sensor-equipped mobile phones and other devices. Web-based and sensor data are generated in high volumes (large-scale data), at high velocity (high-speed data), in wide variety (e.g., text-based data and numerical data), and with a high level of veracity [28]. Table 1 provides an overview of key BDA technologies.

The huge amount of information about customers from sources that reside inside and outside the firm provides a critical source for innovation in general and a variety of opportunities for service innovation in particular [38, 49].

Table 1: Key BDA technologies

BDA technologies	Description
API	Provides access to data sources like sensor data, clickstream data, and social media data [3]
Data lake	Stores data in its native format until it is needed; used in combination with, for example, a Hadoop framework, this technology allows firms to analyze large and/or unstructured data much faster than relational data warehouse systems do [37]
Stream analytics	Analyzes streaming data in real time in order to identify patterns and trends and/or to detect current and/or future deviations from normality [53]
Web analytics	Analyzes clickstream data logs to provide insights on customers' online activities and reveal their browsing and purchasing patterns [3]
Mobile analytics	Analyzes clickstream data logs and sensor data (e.g., location data) generated by mobile devices to provide insights on customers' mobile activities and movement patterns [3]
Social media analytics	Analyzes social media data (e.g., user posts) to provide insights on customers' activities, sentiment, opinions, and preferences [3]
Predictive analytics	Uses statistical techniques to analyze current and historical facts to make predictions about future events and/or behaviors [3]
Rule-based system	Applies pre-defined sets of rules to initiate actions based on the interaction between input and the rules [53]
Visualization application	Transforms the results of data analytics into visually comprehensible and customizable dashboards [3]

Insurance firms, for instance, offer customers electronic data recorders (EDR) for use in their cars to collect detailed information on how they operate their vehicles (e.g., average speed, use of brakes) and to provide the lowest rates to the safest drivers [31]. To capitalize on these opportunities for innovation, executives must understand BDA technologies and their transformational impact in order to choose the appropriate applications and analytical models that address their specific business needs. But what is the potential of BDA technologies in specific contexts of use with specific objectives, such as service innovation with the aim to create customer value? Next, we discuss the concepts of materiality and affordances, which provide a lexicon with which to theorize about how the material features of digital technologies are complicit in accomplishing change [21].

Materiality and affordances

Materiality refers to those properties and features of information technology artifacts (e.g., IT infrastructures, software systems, specific algorithms) that have some stability across contexts and across time [22], and that are also described as "continuants" [10]. Therefore, we identify the materiality of BDA technologies in terms of hardware, that is, physical materiality, and software, that is, digital materiality [24, 58]. Examples include in-memory technologies, data lakes, and software packages like Python and R that allow for predictive analytics.

Just how do the material features of digital technologies allow for innovation? The concept of affordance has become the predominant way to theorize about the action possibilities provided by the material features of information technology (e.g., [12, 25, 26, 21, 42, 59]). Affordances are potentials for actions that arise from the relationship between technical objects (e.g., the materiality of BDA technologies) and goal-oriented users or groups of users [26], such as organizations that seek to innovate their service. Users and user groups interpret technical objects in light of their objectives, which are influenced by the organizational context, including strategies, customers, competitive environment, values, and regulations [23, 42]. As affordances describe the potentials for action, they must be enacted or actualized to result in observable outcomes like service innovations [12, 21, 47].

The concept of affordances has been used in a variety of individual and organizational contexts. The material features of business process management tools and dashboards, for instance, afford the visualization of entire work processes [59]; features of knowledge sharing, acquisition, maintenance, and retrieval afford virtual collaboration [59]; interaction and information access features afford organizational sensemaking [42], and structured data-entry forms and common databases afford the capture and archiving of digital data about patients in health care [47].

In this study, we ask what BDA technologies afford if they are interpreted by organizations that seek to generate new value propositions for their customers as they draw on an S-D logic. It is against this background that we conducted our qualitative case studies, where the concepts of materiality and affordances served as analytical lenses through which to investigate how the material features of BDA technologies afforded service innovation in the case organizations as they interpreted BDA in light of an S-D logic.

Research Method

Because empirical evidence on the impact of BDA on service innovation is scarce, we employed an exploratory, multisite case study approach to develop a model that is firmly grounded in the analysis of data. The phenomenon of interest is an emergent phenomenon that has previously not been subject to in-depth empirical investigation, so we sought revelatory cases [8]. Despite the growing literature on BDA, there is currently no empirically based theoretical model that explains how BDA enables service innovation. In conducting our multiple case studies, we followed established guidelines for case study research (e.g., [9]). While our research process was exploratory, we were sensitized by the concepts of materiality and affordances to analyze what material features of BDA afforded the case organizations' service innovations. While we used this abstract framework, we remained open to the emergence of other concepts and relationships. For example, through this process we found that BDA technologies afforded service innovation in two ways: service automation and IT-supported service delivery by human service actors (i.e., human-material service practices); that is, the technology afforded human service actors new actions that led to fundamentally revamped practices.

We took several measures to corroborate our findings and ensure credibility, transferability, dependability, and confirmability, which are important measures of the trustworthiness of findings from qualitative research [52]. First, in order to ensure credibility, we triangulated across sources, methods, and researchers, and we debriefed with peers and participants. Second, to ensure transferability (i.e., the extent to which the interpretation can also be employed in other contexts), we triangulated across sites through purposive sampling, looking for the occurrence of phenomena across case sites, as well as for differences. Third, to ensure dependability (i.e., the consistency of the interpretation over time), we met with respondents over time, and we aimed to explain change. Finally, to ensure confirmability (i.e., the researchers' objectivity in interpreting findings), we triangulated across researchers by involving two researchers in conducting interviews with key respondents to avoid subjectivity and preconceptions. Moreover, data were analyzed by the first and second author independently. The results from this analysis and the coding decisions were discussed with coauthors, who contributed to the conceptualization of findings in terms of a coherent, integrated theoretical scheme. This approach led us to go back and forth between data analysis and theory development, and thus firmly ground our theory development in empirical data.

Site selection

We applied literal replication logic to purposefully select case organizations that we expected to yield similar results [35]. The cases have a number of common characteristics with regard to ownership, relevance of BDA to service innovation, and cultural proximity. They are all B2C firms that operate in industries with considerable experience and expertise in the collection and analysis of large amounts of customer data: insurance, banking, telecommunications, and e-commerce. All of the case organizations consider service innovation to be strategically important, as competitive pressure and changing customer behavior have led them to recognize the need to improve how they serve their customers through new value-creation opportunities and competitive differentiation. The case organizations see significant potential in BDA for service innovation and have performed concrete projects. To limit cultural differences, we sampled cases from Austria, Germany, and Switzerland, countries that have significant cultural commonalities.

Aside from these commonalities, we sought to obtain a sample of firms that are diverse in terms of industry, size, and BDA maturity. The use of BDA technologies in these firms ranged from full-blown BDA solutions that use, for instance, data lakes and in-memory technology (in the cases of the insurance and the bank firms), to limited solutions that use, for instance, web and predictive analytics (in the cases of the telecommunications and e-commerce firms).

Table 2: Overview of case organizations

	Company A	**Company B**	**Company C**	**Company D**
Country	Switzerland	Switzerland	Austria	Germany
Industry sector	Insurance	Banking	Telecommunications	E-commerce
Number of employees	4,000	20,000	8,600	1,700
Turnover in 2015	US$11.0 billion	US$28.0 billion	US$2.8 billion	US$1.0 billion
Big data vision	Increase customer centricity and the firm's position as a digital leader	Provide efficient but high-quality personal advice	Enhance core business by offering excellent individual service at all contact points	Tailor customer interactions and extend the service value chain
BDA technologies	Full-blown BDA infrastructure with data lake and in-memory technology	Full-blown BDA infrastructure with data lake and in-memory technology	High-performance data warehouse; predictive analytics	High-performance data warehouse; web and mobile analytics

Choosing cases from four industries allowed us to compare the cases for commonalities and differences, and to identify BDA-enabled service innovations that are not industry- or firm-specific. This approach enhances the analytical generalizability of our findings [35]. Table 2 presents an overview of the four cases.

Data collection

We used semistructured interviews as our primary data source—an approach that is appropriate for gathering rich, empirical data, particularly when the phenomenon under examination is episodic and infrequent. From each case firm, we sampled six to eight participants, whom we selected through purposeful sampling; that is, we chose respondents whom we expected would provide information that was relevant to our theory development [35].

For each case site, we first established a relationship with a C-level manager in the firm as the main point of contact. We briefed this person about the research project through a written project summary and a telephone call. Suitable respondents in each firm were then selected jointly by the manager and the first and second authors of this study. The principal criterion for selecting respondents was their knowledge about BDA use at the case firm and its application in the firms' service innovation. We chose experts from several functional areas, as the use of BDA for service innovation involves multiple business units. We conducted 30 interviews with both market (e.g., marketing, sales) and technical experts from a variety of functional areas and hierarchical levels to learn about the relationship between the material features of BDA and what they allowed for in terms of service innovation (Table 3).

The interviews were based on a set of open-ended questions that allowed us to follow up on interesting and unexpected responses and that left the participants free to elaborate on their perceptions, experiences, and reflections [35]. Prior to asking the questions, we introduced the goals of our study and the goals of the interview. The questions were guided primarily by three key issues: (1) the participants' understanding of big data and BDA in order to ensure a common understanding of the concepts under discussion, (2) the relevance of customer orientation and service innovation at the case organization, and (3) how BDA contributes to service innovation and improvement in the firm. Participants with technical backgrounds were asked additional detailed questions about current IT infrastructures and the role of BDA technologies in their organizations. The interview protocol is shown in the Appendix. The interviews lasted between 45 and 90 minutes and were recorded and transcribed verbatim so we could analyze the resulting data in a rigorous and transparent manner. Interviews and transcriptions were done in German, the participants' native language, and native German speakers conducted all data analyses. The resulting coding and quotations were translated into English for presentation purposes.

Table 3: Interview partners

Firm	Interview number	Participant's position	Interview number	Participant's position
A	1	Head of Digital Business	5	Head of Data Analytics
	2	Head of Sales Applications	6	Big Data Architect
	3	Head of Community Management	7	Project Manager
	4	Head of Digital Innovation	8	Transformation Manager
B	1	Head of Strategic Marketing	5	Solution Architect
	2	Head of Digital Innovation	6	Senior Manager Big Data
	3	Head of Customer Management	7	Head of IT Architecture
	4	Head of Online Communication	8	Head of Big Data
C	1	Chairman of the Board	4	Head of B2B Service
	2	CEO	5	CTO
	3	Head of Sales and Marketing	6	Head of Analytics
D	1	Senior Manager Business Strategy	5	Senior Manager of CRM
	2	Manager Business Strategy	6	Head of Business Intelligence
	3	Head of Business Operations	7	IT Project Manager
	4	Head of CRM	8	CTO

Additional data in the form of publicly available company information (e.g., annual reports, press releases) and internal presentations provided background information on the BDA infrastructures, data strategies, and current practices that were related to service innovation. These documents helped us further clarify the information gathered during the interviews and provided valuable ancillary information about the organizational context—that is, the firms' strategic objectives, customers, competitive environments, and regulations.

Data analysis and theory building

The data analysis process broadly followed the recommendations of Eisenhardt [9], Paré [35], and Yin [56] for within- and cross-case analyses. First, we analyzed each case as a separate study so we could focus on the collected case data and understand each case's unique patterns. In a second step, we aggregated the findings of the within-case analyses in order to determine whether they made sense beyond each individual case [9, 35]. The within-case analysis and cross-case analysis, as well as the coding and analysis we applied, were conducted in a manner that allowed us to move back and forth between the analysis of empirical data and theorizing, so the steps we describe here are not strictly sequential phases.

Within-case analysis

In the initial step of the data analysis process, we read the interview transcripts and noted our first impressions in interview and case reflection memos [29]. Memo writing continued throughout the entire data analysis process so we could keep track of our reflections, comments, questions, and ideas as they occurred and store them for further investigation and refinement. We then coded the case data (i.e., interview transcripts, and documents) using the qualitative data analysis tool ATLAS.ti, which enabled us to store all our data in a central location, analyze it, and maintain traceability of the coding. Each case was treated as a separate study, and each step was conducted independently by the first and second author, with regular discussions to avoid subjective interpretations and enhance validity.

In coding the case data, we first used open coding [46] in order to identify concepts that were related to the use of BDA for service innovation that were salient in the data,[3] while remaining as open and unconstrained by prior theory as possible. During this stage, we frequently compared the interviewees' responses in an effort to group answers that pertained to common codes and to analyze different perspectives on emerging codes. The process of open coding generated an initial list of more than 300 descriptive codes (e.g., goals like "identifying changes in the state of customer's house," "identifying customer's wedding") that were further grouped and integrated in order to derive more abstract categories (e.g., the open codes "identifying changes in the state of customer's house" and "identifying changes in the state of customer's car" were objectives that were grouped under the more abstract category of "identifying changes in the state of relevant objects.")

When no new concepts emerged, we conducted a coding stage similar to axial coding [46], where we organized the categories identified using the analytical framework of materiality and affordances; that is, we looked for the use context in terms of organizational goals and the service innovations that were afforded by the material features of BDA technologies. The concepts of materiality and affordances were appropriate theoretical lenses, as we saw that, indeed, BDA technologies afforded service innovation as material features of BDA were interpreted in light of new action goals related to creating improved service delivered through both human agency and material agency. By considering material features as well as what these features allowed for when they were interpreted under an S-D logic, we were able to establish links between the material features and specific service innovations. We compared the coders' results, discussed differences and commonalities, and merged the results.

Cross-case analysis

After analyzing the data in each case, we used cross-case analysis to identify crosscase patterns and determine whether the findings of the within-case analyses were applicable across the cases [9, 35]. We analyzed the cases' similarities and differences regarding the material features and what they afforded to identify patterns across the cases. We discussed the differences, focusing on the reasons that these differences occurred, and learned to what extent the cases were comparable. Then we compared the patterns for consistency and aggregation, discussed our conclusions, and refined the patterns, which helped us move toward the integrated theoretical scheme that was emerging from our analysis.

Next, we describe our analysis of the four cases using our lexicon of materiality, affordance, and human and material agencies, and then present a theoretical model of BDA-enabled service innovation.

Case Analysis

Company A: Insurance

Case organization A is the Swiss subsidiary of a multinational insurance firm that offers private individuals and corporate customers a broad range of personal, property, liability, and motor vehicle insurance. A decade ago the company was focused on the core insurance business of selling insurance policies and paying bills on time, but now it aims to increase its customer orientation and to change its role from "payer" to "player" by taking a more proactive stance in engaging with its customers. These strategic objectives translated into how the firm innovated its service processes, as it envisioned increasing its customer centricity so customers would feel they were in good hands before and in the event of damage, and improving its customer interaction beyond handling insurance claims. Accordingly, the firm sought to provide support to customers by meeting their needs at the right moment.

As part of the firm's overall strategy to become more customer-centric, the firm implemented advanced BDA technologies, including in-memory technology and a data lake with a Hadoop framework that allowed it to store data in a central location and analyze data from a variety of sources with reduced latency. Trace data were gathered from internal sources (e.g., the firm's website, mobile apps) and external sources (e.g., social media, price comparison portals, digitized objects like sensorequipped homes and cars). The company used several analytical applications, including stream analytics for analyzing sensor-based data streams in order to recognize insurance-related events (i.e., deviations from a normal state) and to initiate appropriate actions in real time using rule-based systems. The firm also applied web and social media analytics and predictive analytics in order to recognize and anticipate insurance-related changes in the customer's life at an early stage.

As the company pursued its goal of providing customer support at the right moment, the material features of BDA enabled the implementation of two types of service innovation: automation of certain customer service-related processes in a way that facilitated the individualized interaction with customers in real time, and opportunities for employees to engage in new service-provision practices like proactive advice. Thus, the material features of BDA in response to new strategic action goals afforded automation and new human-material service practices. Consider two examples.

First, stream analytics facilitated the automated, real-time recognition of insurancerelated events in, for instance, the customer's home (e.g., open window, burglary) or car (e.g., accident). These material features afforded automated trigger-based service actions on the customer's behalf. For example, the detection of a forced entry into the customer's home automatically triggered predefined actions in real time, such as starting an alarm or calling the police, potentially preventing loss:

> *We are trying to expand our business and think innovatively. . . . As people are increasingly building connected objects into their homes, we are thinking about how to offer a service in terms of security. . . . If you build such a connected protective shield around the house, then it must work reliably in real time.* (Respondent 2, Company A)

The automation of customer-related processes enabled the company to provide an entirely new kind of service—damage prevention and support. While the insurance firm previously got involved only after the damage had occurred, this service innovation improved customers' sense of well-being and security.

In the second example, the insurance agents were afforded entirely new ways of engaging with customers such that they proactively approached them with individualized information, products, or service at the right time. The material features of BDA, particularly web and social media analytics, as well as predictive analytics, facilitated the recognition and prediction of major lifetime events (e.g., marriage, property purchase, starting a family) that indicated changed insurance needs. For instance, the firm gathered and analyzed clickstream data from related third-party websites, price-comparison portals, and the social-media data of customers who were connected to their insurance agents through social networking sites. Visualization applications (i.e., dashboards) gave the insurance agents information about identified or predicted triggers so they could approach their customers with appropriate service offerings in a timely way:

> *We recognize a customer's lifetime event and, after a while, the customer receives information [related to that event]. What we want to achieve is [using] an event . . . in order to react immediately to the customer's current situation.* (Respondent 3, Company A)

This support was in the form of new human-material service practices. In these cases, insurance agents still had to make their own decisions about how to address the specific events; that is, the employees' skill sets, experiences, and customer contact strategies interacted with the material features of BDA to create new practices. This fundamentally revamped how service was delivered. Previously, insurance agents had no (or only limited) access to information about customers' lifetime events (e.g., through their personal social networks), so service provision was primarily reactive to customers' requests:

> *It used to be the decentralized insurance agents who went through life with open eyes and who saw that, for instance, a woman was expecting a child. It was the human sensor that brought the information. As the business and its services become more digitized and the customer increasingly communicates with us via digital channels, we have more information to find these magic moments digitally.* (Respondent 1, Company A)

The new, innovative practices served the individual customer at the critical moment, thereby increasing the relevance of product and service offerings and creating a sense of convenience.

To summarize, the insurance company used several BDA technologies in two ways. First, BDA allowed for service automation, taking action on the customer's behalf based on triggers (material agency). Second, BDA technologies afford human service actors to serve the customer based on lifetime events and adapting the customer contact strategy accordingly (human and material agencies). This approach changed how the firm served its customers by facilitating its ability to provide proactive service (either automatically or via human interaction) tailored to the individual customer's needs. Table 4 provides an overview of how the company's organizational goals translated into the provision of automated and human-material service, afforded by the material features of BDA technologies.

Table 4: BDA-enabled service innovation at Company A

Organizational goals	Material features of BDA	BDA-enabled service innovation
Provide tailored service to customers at the right moment	• Sensor data • Data lake • Stream analytics • Rule-based systems	Automatically taking action on the customer's behalf in response to triggers (material agency)
	• Clickstream and social media data • Data lake • Web and social media analytics, predictive analytics • Visualization applications	Approaching the customer in response to triggers (i.e., lifetime events) through a human service actor who adapts the contact strategy to the customer's individual needs (human and material agencies)

Company B: Banking

Case organization B is a leading global financial services firm and one of the largest full-service banks in Switzerland. The firm has a strong position in retail banking for private customers and wealth management for high-net-worth individuals. One of the firm's key strategic objectives was to further improve its provision of first-class financial advice and solutions. The use of digital technologies, including BDA, was an important pillar in implementing the bank's strategy of improving service provision and offering a unique customer experience. Against this background, the firm had implemented an omni-channel strategy in retail and wealth management, integrating its offline (i.e., branches, personal bank advisers) and online channels (i.e., online and mobile banking) and allowing customers to choose their preferred interaction channels, which were customized to their needs and habits. The online channels were not intended to substitute for the offline channels but to support personal advice, which the firm's customers expected because of the nature of the financial products. Accordingly, the firm sought to provide a convenient and highly individualized customer experience and a consistent and seamless customer journey across all channels.

In an effort to realize these objectives, Company B made significant investments in an advanced BDA infrastructure that included in-memory technology and a data lake, combined with a semantic knowledge base using open-source software. This infrastructure made it possible to complement traditional data sources (e.g., transaction and customer relationship management [CRM] data) with previously unavailable data sources, including new internal data sources like the firm's website, its online and mobile banking portal, and unstructured data generated from business-related interactions between customers and the firm (e.g., e-mail, letters). Various analytical applications facilitated the identification of patterns in the data, including web and text analytics. Moreover, based on a data discovery workbench, data scientists developed algorithms and statistical models for analyzing the variety of data stored in the data lake.

As the company followed its new goals in terms of providing a convenient and individualized customer experience, and offering a consistent and seamless customer journey, the material features of BDA allowed it to implement service innovation in two ways. First, BDA technologies allowed it to automate the customization of content that was provided through digital channels. Second, BDA technologies provided employees opportunities for engaging in new service practices in terms of highly individualized and consistent customer support. Consider two examples.

First, the newly available material features of BDA, particularly web analytics, allowed for the real-time recognition of business-related events on digital channels. For instance, the detection of a certain user behavior on the e-banking portal based on clickstream data, combined with insights from historical customer data, automatically resulted in the display of an appropriate message that addressed the customer's anticipated needs:

> *In e-banking, they [the campaigns] are quite specific because we measure the customer's behavior. We analyze the logs and compare them with the history. For example, a young man suddenly uses our mortgage calculator. We see this, of course, and then say: this is a young man who has never clicked on this before and now he has been doing it for three, four weeks or even two months. He is probably interested in a house. This might be a good moment to approach him and say: "Come in and talk with us. If you are interested in a mortgage, we can advise you in this way." This is much more individualized than the approach where the customer is 40 to 50 years old, or these are all students; let's offer them a credit card.* (Respondent 8, Company B)

The firm used BDA technologies in a way that enabled them to customize user interfaces (e.g., provide tailored content) automatically. Compared to their previous process, the new process did not base content on general customer segmentation criteria but adapted the content to observed customer activities combined with historical data. Therefore, it was highly individualized.

As for the second example, personal bank advisers and service employees were afforded new individualized ways of interacting with customers considering their customers' preferences. The material features of BDA allowed for collecting customer data from multiple new and traditional data sources, storing it in the data lake, and compiling a rich and up-to-date customer profile. Visualization applications (i.e., dashboards) provided insights for the advisers and service employees, allowing them to cater to their customers' individual preferences when they interacted with them:

> *It is about gaining a holistic view of the customers. . . . The great driving force and the keyword that drives us to know more about the customer is precisely this multichannel idea: we want to know what the customer is doing outside [the business relationship]. While once this view was never consistent and we did not know it, now we start to learn more about the customer, including her activities and behavior outside [the business relationship]. We also consider how this information is delivered to the personal adviser or call center agent and what we do with this data—how we use it to interact with the customer. It is very important that we record and understand the data in a way that allows us to improve how we speak with the customer.* (Respondent 5, Company B)

The customer profile informed employees about a customer's prior interactions with the bank, allowing for a seamless customer journey such that, if the customer initiated a process in one channel (e.g., on the e-banking portal), it could be taken up by another channel (e.g., a personal consultation conversation with the adviser). Employees were also given concrete recommendations for action based on the customer's preferences. For instance, they were instructed on topics that should be addressed during consultation or were informed about the customer's preferred interaction channel. In these cases, the customer profile provided additional support for employees in their efforts to interact with the customer in a customer-centric manner.

Table 5: BDA-enabled service innovation at Company B

Organizational goals	Material features of BDA	BDA-enabled service innovation
Provide individualized and consistent service at all touchpoints	• Clickstream data, historical customer data • Data lake • Web analytics, predictive analytics • Rule-based systems	Automatically customizing user interfaces (e.g., providing tailored content) in response to triggers (material agency)
	• Digital trace data from various sources compiled in the customer profile • Data lake • Predictive analytics • Visualization applications	Interacting with the customer in accordance with her preferences, as derived from previous interactions and behavior (human and material agencies)

Employees still had to make their own decisions on how they used the information and how they adapted their behavior, so the customer's profile and the employee's skill set and experience worked together.

To summarize, Company B used several BDA technologies in two ways. First, BDA allowed for service automation, for instance, customizing user interfaces based on triggers (material agency). Second, BDA technologies provided employees with comprehensive information on a customer's profile and history so employees could adapt the customer interaction to the customer's preferences (human and material agencies). Company B was enabled to provide highly individualized customer support and a consistent customer journey along all touchpoints. Table 5 provides an overview of how the bank's organizational goals translated into service innovation.

Company C: Telecommunications

Case organization C provides private and corporate clients with telecommunication services. The company operates its own mobile network and distributes products in the areas of fixed net, mobile voice, Internet, and TV. As a full-service provider, it also offers corporate clients cloud and machine-to-machine service. An infrastructure provider, the firm sees itself as an enabler of digitalization by offering high-quality networks in terms of availability, performance, and security. In the B2C sector, the company operates in a mature market, so it sought new ways to increase revenues and profits. While competition in the telecommunications sector had for a long time been driven by price and product, customer experience became the key brand differentiator. Therefore, in order to enhance their core business, the firm wanted to offer excellent individual service at all contact points to retain and create loyal customers. Accordingly, Company C sought to provide the product offering or problem solution that was most relevant to each customer.

The firm operates a modern and flexible analytics infrastructure that draws on an enterprise data warehouse that centrally stores large amounts of customer data (e.g., how and where subscribers use their phones) and data from network equipment and server logs. The analysis of customer data (e.g., demographic data, use patterns, browsing behavior from clickstream logs, and call center contacts) allowed the firm to generate a detailed profile of each customer and her needs.

We found evidence of one type of BDA-enabled service innovation in this firm. BDA technologies provided affordances to employees for engaging in new service practices, particularly preference-based support. In contrast to Case A and Case B, we found no evidence of automation. New human-material service practices emerged in response to strategic action goals offered by the material features of BDA. Consider the following example.

Sales and service employees (i.e., shop assistants and call center agents) were afforded entirely new ways of engaging with customers. They could convey the right message, make the right offer, and choose the right level of service during every customer engagement so every customer had an individual customer experience. The material features of BDA allowed for the recognition and anticipation of customer behavior by applying statistical models (e.g., predictive analytics) to the past interactions, usage, and purchase behavior that were compiled in individual customer profiles. The analyses resulted in concise, clear, and timely metrics on, for example, calling patterns, data consumption, and customer satisfaction. Moreover, recommendations for the next best actions (e.g., the most suitable offer, problem solution, or interaction channel) were derived and provided to the frontline employees through a uniform visualization application. Thus, employees were equipped with timely, actionable insights about the customer's history and anticipated behaviors and given decision support at the point of customer interaction. As a result, they were able to cater to the customer's individual preferences while engaging with that customer:

> *It's about anticipating . . . from the data—the human-like, the empathic. This is exactly what makes the difference to the customer, whether it is genuine or artificial. Empathy, in the case of a firm,*

means that it can put itself into the customer's shoes, know what she wants next. I think that is what differentiation must be all about because the rest is more of the same. (Respondent 3, Company C)

Guided in their decisions and customer interactions, sales and service employees applied their personal skill sets or experiences to incorporate the available information into their service practices. The new practice fundamentally changed the firm's service delivery, as previously frontline employees had limited visibility of their customers and could react to customer requests only on the spot, mainly based on the company's guidelines and their intuition.

Table 6: BDA-enabled service innovation at Company C

Organizational goals	Material features of BDA	BDA-enabled service innovation
Provide the product offering or problem solution that is most relevant to each customer	• Digital trace data from various sources that is compiled to a customer profile • Data warehouse • Predictive analytics • Visualization applications	Interacting with the customer in accordance with her preferences derived from previous interactions and behavior (human and material agencies)

BDA technologies enabled the agents to optimize their service practices by providing them with the contextual information they needed to engage with their customers in a way that was sensitive to their customers' preferences.

To summarize, BDA technologies at Company C provided employees with comprehensive information about a customer's profile and history, enabling them to adapt their interactions to the individual customer's preferences (human and material agencies). Table 6 provides an overview of how the telecommunications company's organizational goals translated into human-material service practices that were enabled by the material features of BDA technologies.

Company D: E-Commerce

Case organization D is a leading online provider in the German travel sector. It operates several websites that cover the entire travel-booking cycle, from weather forecasts to flight and hotel portals to rental car bookings. In line with the websites' transaction-based business model, the firm sought to increase growth through four key levers: traffic, conversion, cross-selling and up-selling, and retention. In addition, Company D sought to increase the efficiency of its communication activities by decreasing wasted coverage. It operates in a highly competitive market with a large number of competitors that offer similar or even the same products with a high level of price transparency. In order to attract customers and gain market share, the common practice was to offer the lowest price. However, in recent years, Company D began to pursue customer-centrism, placing a stronger focus on service differentiation, instead of pricing only, in order to deliver a superior customer experience and gain customer loyalty. Accordingly, it sought to improve its customer interaction through individualization of its user interfaces and to extend the service value chain by also serving the customer beyond the booking.

To achieve these objectives, Company D applied BDA technologies to continually analyze how customers interact with their websites and mobile apps. Web and mobile analytics provided insights into users' online activities enabling the company to better understand their browsing and purchasing patterns. For example, when a customer visited one of the firm's websites, clickstream data were generated through cookies and logged in a database for web log analysis. These activities were supported by web analytics tools like Google Analytics. Company D ran a highperformance data warehouse to store data from multiple sources centrally, which allowed data scientists to conduct analyses. Based on the insights gained through web and mobile analytics, rule-based recommender systems automatically created targeted product- and service-related suggestions that had a high probability of meeting customer needs. Moreover, the firm used location-aware analysis of sensor data from smartphones to provide context-aware content through its mobile apps. The firm emphasized measuring users' responses (e.g., e-mail open and clickthrough rates from mail campaigns and newsletter) in order to continuously learn about customers' preferences and improve its targeting in the future:

As the company followed its new goals in terms of improving customer interaction, and extending the service value chain, material features of BDA allowed it to implement a strategy of improving customer service processes through automation. First, BDA technologies allowed to automate the adjustment of user interfaces. Second, BDA technologies supported the establishment of additional touchpoints before and during the customer's travel. Consider two examples.

First, BDA enabled the firm to adjust user interfaces automatically in terms of the types and order of the travel options presented, their visual appearance, and recommendations for complementary products and services. Instead of presenting the same user interface to all customers, it was adjusted to the customer's individual characteristics:

> *The other aspect is the personalized appearance of websites. At the moment, the online business is rather one-size-fits-all. This means I see the same website you do, although you and I are completely different target groups. I am male and live in Munich. You are female and live in Switzerland. Why should you get the same website as I do? This topic—the personalized delivery of UI [user interface] and UX [user experience] concepts and personalized website creation—is of great importance to us*. (Respondent 3, Company D)

Predictive analytics facilitated the combination of historical behavioral patterns and current navigation behavior in order to predict the probability that the customer would buy certain products. This approach allowed the firm to display related products (e.g., offering museum packages to a customer with a history of traveling to cultural sites) when the customer processed a transaction. Providing an individualized customer experience enhanced convenience by helping customers find appropriate offers much faster:

> *I believe it has added value for the customer because he gets only the offer that really interests him. He does not need to search for three hours because we already know what he wants, so this makes it easier.* (Respondent 2, Company D)

As for the second example, BDA enabled the firm to interact with customers in an automated manner beyond the transaction on the website, based on events. For example, smartphone technology allowed the firm to monitor the customer's location during the holiday and to deliver context-specific, highly personalized messages in real time:

> *If we detect the customer's current location, we can act like a kind of travel guide. Then we can tell him, "You are in London, so take a look at this tourist attraction. Keep in mind it is a weekend and there is a street festival."* (Respondent 2, Company D)

Thus, the firm could interact with its customers while they were out and about, for example, looking at tourist landmarks, thereby enriching their offline experience. The firm could also extend the service value chain beyond the online world by partnering with local service providers to create new value propositions jointly.

To summarize, Company D used web and mobile analytics to improve its service provision through automation. In contrast to the other three companies, we did not find evidence of new human-material service practices. First, BDA allowed for the automated adjustment of user interfaces (material agency).

Second, location-aware analysis based on sensors in smartphones enabled the firm to interact with customers in real time (material agency).

Table 7: BDA-enabled service innovation at Company D

Organizational goals	Material features of BDA	BDA-enabled service innovation
Provide individualized service to customers and extend the service value chain	• Clickstream data • Data warehouse • Web and mobile analytics, predictive analytics • Rule-based systems	Automatically customizing digital user interfaces in accordance with customer preferences (material agency)
	• Sensor data • Data warehouse • Mobile analytics (location-aware analysis) • Rule-based systems	Automatically customizing user interfaces (e.g., providing tailored content) in response to triggers (i.e., a customer's current location) (material agency)

Thus, Company D was afforded the ability to consider their customers' individual needs instead of treating all customers the same, thereby enhancing convenience. Moreover, Company D could interact with customers in a personalized manner, even long after the customers booked their travel, by offering additional service on-site, thereby extending service provision from the online to the offline world. Table 7 provides an overview of Company D's BDA-enabled service innovation.

A Theoretical Model of BDA-enabled Service Innovation

This section presents an integrated model of IT-enabled service innovation that is grounded in our analysis of the four cases. Our model explains how BDA technologies enable service innovation as organizations interpret them in light of new action goals that are related primarily to individualizing service. We identified two key types of service innovation afforded by BDA technologies: automation of customersensitive service provision and new human-material customer-sensitive service practices. Both types of innovation are enabled by the material features of BDA technologies in terms of sourcing, storage, event recognition and prediction, behavior recognition and prediction, rule-based actions, and visualization. When enacted, they lead to service individualization. Figure 1 visualizes this model.

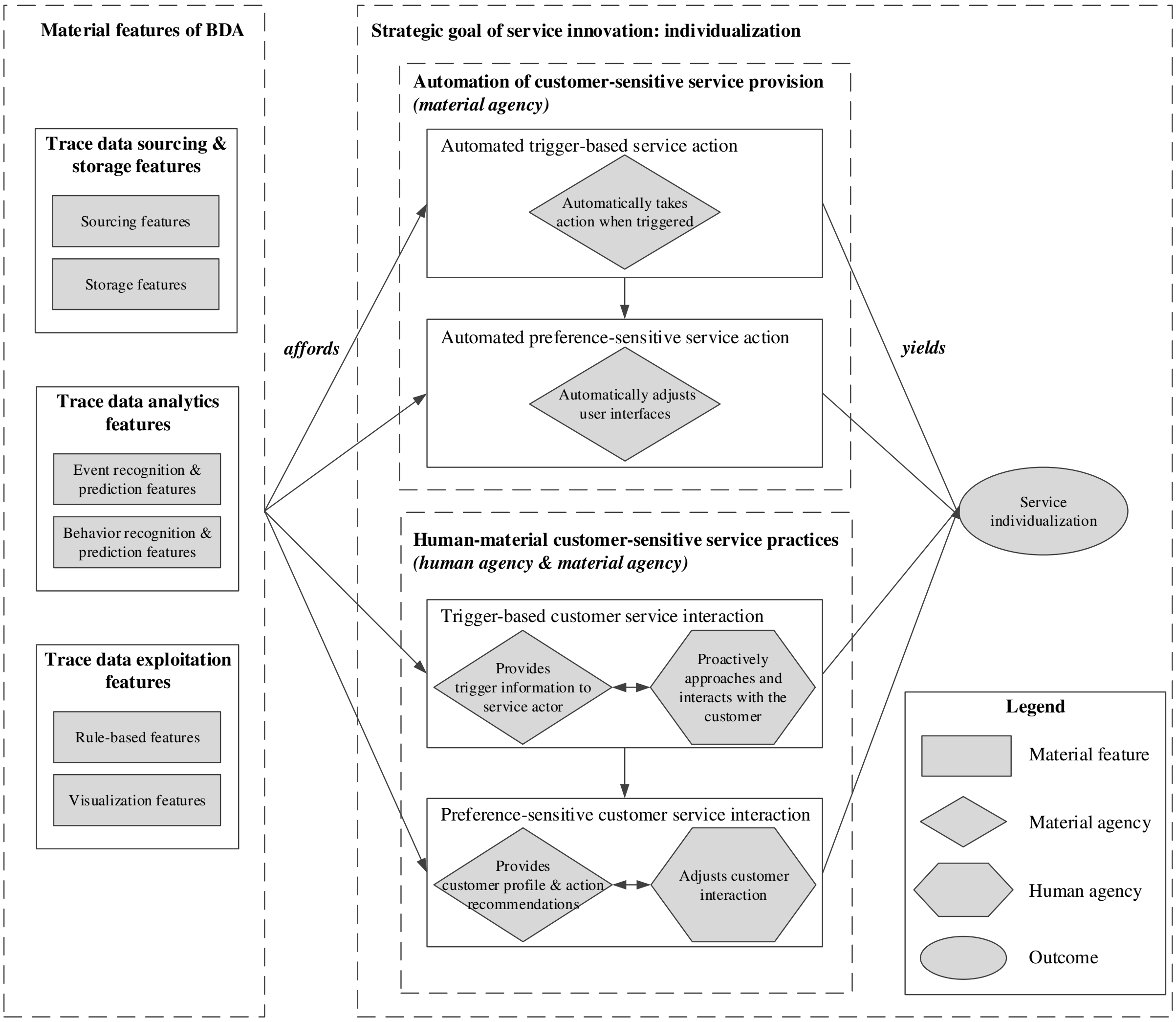

Figure 1: Theoretical model of BDA-enabled service innovation

Table 8: Service automation and human-material service practices

	Service automation	Human-material service practices
Goal	Service individualization through automated activities that are carried out without human intervention	Service individualization through interaction of the customer with a human service actor who interacts with a digital service actor
Role of agency	Focus on material agency in delivering the service	Interaction of human and material agencies in delivering the service
Nature of outcome	Deterministic provision of service	Nondeterministic provision of service: technology provides space for action

In what follows, we provide a general overview of the model and then describe its key components in terms of (1) the material features of BDA, (2) automation of service provision, and (3) human-material service practices.

By differentiating how the material features of BDA afford both service automation and human-material service practices, our model highlights how both material agency and human agency play roles in shaping organizational service processes and in creating value propositions for customers. In the case of service automation, the focus is on material agency—that is, the technology's capacity to act on its own and apart from human intervention [21]. In contrast, in human-machine service practices, human and material agencies interpenetrate in what Pickering (1995) referred to as the "mangle" of practice [36], and human agency is enacted in response to the technology's material agency [21, 51]. In the case of service automation, BDA technologies provide both necessary and sufficient conditions for service innovation, as the technology acts without the intervention of human actors. In the case of human-material service practices, BDA technologies provide only necessary conditions, as the observable practice results from the interpenetration of human and material agencies in practice. Table 8 compares the two types of service innovation.

Next, we provide detailed descriptions of the model's components, along with conceptual definitions.

Material features of BDA affording service innovation

The flexible nature of BDA technologies and their reprogrammability afford both service automation and human-material customer-sensitive service practices. BDA technologies are digital artifacts that are part of a wider ecosystem, and they derive their utility from the functional relationships they maintain [20]. Features of sourcing [3], storage [37], event recognition and prediction [53], behavior recognition and prediction [3], rule-based actions [53], and visualization [3] are built on technologies that maintain relationships and provide functions like sourcing trace data, storing trace data in databases, analyzing these data using various approaches to supervised and unsupervised learning, and exploiting the generated insights.

Table 9: Key material features of BDA technologies

BDA material features	Description	Examples of underlying BDA technologies
Sourcing features	Features for collecting and integrating digital trace data from various sources	APIs for accessing sensor data, clickstream data, social media data
Storage features	Features for storing digital trace data	Data lake
Event recognition and prediction features	Features for detecting and predicting events (i.e., deviations from a normal state)	Stream analytics, predictive analytics
Behavior recognition and prediction feature	Features for analyzing customers' behavioral patterns and predicting their future behavior	Web analytics, mobile analytics, social media analytics, predictive analytics
Rule-based features	Features for initiating automated actions	Rule-based systems
Visualization features	Features for making outcomes available to employees	Visualization applications

Table 9 provides an overview of the key categories of BDA's material features affording service individualization that emerged from our analysis.

Automation of customer-sensitive service provision

Organizations see BDA technologies as malleable technologies that afford automation of customer-sensitive service provision, consistent with new action goals related to individualized service, such as an insurance company that automatically takes action when security incidents occur. To implement service automation, organizations use algorithmic solutions that are based on the material features of BDA in terms of trace data sourcing and storage, event recognition and prediction, behavior recognition and prediction, and rule-based actions. Two types of service automation emerged as salient from our analysis: automated trigger-based service action and automated preference-sensitive service action. In the first case, the system independently carries out actions like sounding an alarm or calling the police (material agency) when triggered by an event like forced entry into a customer's home (detected by sensors), thereby, providing service at the right time. In the second case, the system automatically adjusts user interfaces, for instance, by providing tailored content (material agency) when a certain user behavior on an online channel or a customer's current location are detected, thereby, providing service in the right way. Thus, trigger-based action can lead to preference-sensitive action, as indicated in Figure 1. Table 10 provides an overview, including underlying material features and examples.

Table 10: Automation of customer-sensitive service processes

Organizational goals	Service Innovation	Material features of BDA	Example
Provide individualized service to customers	Automated trigger-based service action describes activities that are independently carried out by a system to create value for a customer.	Features of sourcing, storage, event recognition and prediction, behavior recognition and prediction, rule-based actions	Starting an alarm or calling the police in response to a forced entry into a customer's home, as detected by a sensor.
	Automated preference-sensitive service action describes activities that are independently carried out by a system to adjust user interfaces in accordance with customer preferences.	Features of sourcing, storage, behavior recognition and prediction, rule- based actions	Providing tailored content in response to certain user behavior on an online channel.

Table 11: Human-material service practices

Organizational goals	Service Innovation	Material features of BDA	Example
Provide individualized service to customers	Trigger-based customer service interaction describes the interplay of human and material agencies in providing individualized interactions with customers.	Features of sourcing, storage, behavior recognition and prediction, visualization	The system provides trigger information to human service actors who then proactively approach and interact with customers.
	Preference-sensitive customer service interaction describes the interplay of human and material agencies in providing individualized interactions with customers based on their preferences.	Features of sourcing, storage, behavior recognition and prediction, visualization	The system provides recommendations for actions based on customer profiles, which allow human service actors to adjust their customer interactions.

Human-material customer-sensitive service practices

BDA technologies afford human service actors new ways of interacting with customers, leading to human-material customer-sensitive service practices that are consistent with new action goals related to service individualization, such as proactively approaching and interacting with a customer. Two types of human-material service practices emerged as salient from our analysis: trigger-based customer service interaction and preference-sensitive customer service interaction. In the first case, the system provides service actors with trigger information (material agency), such as a customer's business-related lifetime event, after which the service actor proactively approaches and interacts with the customer (human agency). In the second case, the system uses customer profiles to make recommendations for actions (material agency), allowing the service actor to adjust interaction with the customer (human agency). Thus, trigger-based customer service interaction can lead to preference- sensitive customer service interactions, as shown in Figure 1. Table 11 provides an overview, including underlying material features and examples.

Discussion

This study presents a theoretical model of BDA-enabled service innovation that extends prior work on IT-enabled service innovation [1, 24, 34] by explaining how service automation and human-material service practices yield service individualization, grounded in the material features of BDA technologies: sourcing, storage, event recognition and prediction, behavior recognition and prediction, rule-based actions, and visualization. In this section, we discuss how our model contributes to the literature on service innovation and to the literature on digital innovation.

Contribution to service innovation scholarship

At a general level, we found that BDA allowed firms to generate customer insights and heightened awareness about customers' needs and preferences. The material features of BDA technologies facilitate firms' ability to gather and analyze the broad variety of data sources related to customers' everyday activities so firms can increase their awareness of their customers' behaviors, interests, and current situations.

Complicity of automation and human-material practices in service innovation

Our study suggests the complicity of automation and human-material practices in service innovation. Organizations follow a twofold strategy based on service automation and the implementation of new, improved human-material practices that are afforded by the material features of BDA technologies. The two are complicit in that they allow organizations to simultaneously provide their service in real time, while others still require human activity. Service automation is dominated by material agency, while human-material service provision is characterized by the interpenetration of human and material agencies to deliver value to the customer. This view is important, considering the prevalence of and emphasis on human-material-discursive practices in the recent literature (e.g., [11, 12, 19]).

Proactive service provision

BDA facilitates proactive service provision that is based on insights into the customer and the customer's context. Service provision has typically been reactive in nature, requiring customers to approach the firm with a service request. However, digitized objects enable firms to gather and analyze data generated by the customer outside the business relationship in the customer's private sphere. Using such data to initiate timely interactions enables firms to extend their service value chains and support their customers in various life situations precisely when they need it. Being aware of customers' problems in everyday life facilitates the firm's development of new value-added service and improves the customer's experience and perception of the value the firm offers. New customer interaction points can be developed both inside and outside the business relationship, thereby increasing the frequency of interactions. This nuanced view shows how organizations create new value propositions for customers under an S-D logic [1, 24].

Speed of service provision

BDA increases the speed of service provision—even real-time service provision. For this purpose, service based on BDA is often provided through automated systems that facilitate immediate action. Prominent examples of such offerings are in the field of smart homes and telematics. By acting on events, firms can convey the impression that there is no need for their customers to deal with or to worry about such things as the safety of their homes because the firms take action on their behalf. This approach to real-time service provision is in line with the basic tenets of BDA analytics in terms of the velocity with which new data are generated and analyzed [28], and it adds another nuance to how organizations create new value propositions under an S-D logic [1, 24].

Service individualization

Enabled by insights gained into the customer both inside and outside the business relationship, service can be highly individualized and tailored to customers' needs. Instead of mass customization, BDA enables firms to tailor service cost-effectively to a "segment of one" by using knowledge gained from analyzing the customer's behavioral patterns. Based on the customer's inferred preference, a firm can automatically tailor the channel used to deliver service or the user interfaces. According to den Hertog [7]. The way the firm interacts with the customer can itself be a source of innovation, and our analysis highlights how this way is grounded in the material features of BDA technologies that allow for interactions between human agency and material agency in delivering services. Our explanation of how BDA contributes to service innovation by providing customers with added value through individualized and convenient customer experiences contributes to the debate on personalization of information systems (e.g., [17, 48]) and to the emerging research on omnichannel management (e.g., [15]).

Our analysis also suggests that BDA-enabled service processes might be extended to address the customer on an emotional level, although such emotion-sensitive service was only mentioned in the interviews and has not been fully implemented in the case organizations. Knowledge about the customer's current or future emotional state, gained through BDA, might allow firms to adapt how they "speak" to the customer on an affective level, a phenomenon that is central to the emerging research field of emotion-sensitive technology (e.g., [16]). This field has started to design and build information systems that are sensitive to human emotions and that can change their behavior accordingly. This bears the potential to emphasize the "human component" in increasingly electronic and automated customer interactions and highlights the role of human agency in service delivery. Such emotion-sensitive service processes promise to deliver emotional or hedonic value, such as by providing customers with a positive feeling when they interact with the firm, thereby enriching and deepening the customer's experience.

Contribution to digital innovation scholarship

Digital technologies are reprogrammable [20, 58], so organizations explore configurations of technologies that form functional relationships to identify new potentials for action as they are confronted with new action goals. Our analysis shows that BDA technologies are an example of such malleable, flexible digital technologies and that, in order to innovate service, organizations should capitalize on the combined effects of technologies that are related to sourcing, storing, analyzing, and exploiting data. Technology is reprogrammed in some cases to automate service processes and in other cases to provide actionable spaces to human actors, leading to novel interpenetrations of human and material agencies. Our study suggests that reprogrammable digital technologies allow for innovations that are shaped by material agency and the interpenetration of human agency and material agency.

The concept of affordances helped us explain how this digital innovation occurred. Affordances are both dispositional (i.e., associated with the technology) and relational (i.e., in relation to a specific use context) [12]. As the use context changes, new, innovative applications of digital technologies emerge [41]. As our analysis of four cases from different industries suggests, these innovative affordances occur across contexts. But what explains the similarities in the occurrence of innovations across contexts? There have been advances to theorize about how such regularities occur, for instance, using arguments that draw on institutional theory [19, 41] or concepts like habit [12] or performativity [5]. Our study highlights how BDA gives rise to similar innovative affordances across our case organizations, as these organizations draw on an S-D logic, even though these similar applications are grounded in different technologies. While one company might use, for instance, Hadoop, as was the case in Company A, another company might use a different technological platform. Still, we were able to identify the material features of those technologies at an abstract level and can explain the similarities by means of the prevalence of an S-D logic, where organizations seek to implement customer centricity and service individualization. This explanation is consistent with the view that the identification and enactment of technology affordances is shaped by the institutional context and associated logics on which an organization draws [19, 41].

This view suggests that the same technology might be reinterpreted in such a way as to afford new actions in light of new action goals. The argument is that malleable digital technologies are (1) (re-)interpreted in light of changing action goals, (2) that this (re-)interpretation leads to certain development and implementation activities that enable new functional relationships among the material features of digital technology, and that (3) these new relationships afford new configurations of material and human agencies. In this view, affordances are at the organizational level (e.g., [42, 47, 59]). Therefore, our work is in line with work that has recognized the observable regularities in the enactment of information technology across contexts and time [13, 41]. Information technologies are used in strikingly similar ways across organizations, which is also the case for BDA-enabled service innovation.

Implications for IS Research and Practice

Implications for research

Our study highlights how BDA technologies enable service innovations and, thus, contribute to creating new value propositions. In so doing, the study adds an integrated perspective on IT-enabled service innovation in organizations [34]. Our research identifies material features of BDA technologies in terms of sourcing, storage, event recognition and prediction, behavior recognition and prediction, rule-based actions, and visualization—a conceptualization that accounts for both the retrospective and the prospective (e.g., in terms of predictive and prescriptive analytics) characteristics of BDA [44]. Moreover, instead of treating BDA as an undifferentiated whole, our empirical results support the notion that BDA consists of the interplay of multiple applications for gathering, storing, analyzing, and communicating big data from external and internal data sources [3], highlighting the functional relationships among digital artifacts [20] and their combined potential for service innovation [58]. We also highlight how this materiality translates into both automation and the provision of human-material service practices, a perspective that can inform future research in four primary ways.

First, our theory development suggests that future research should consider the potential of BDA technologies in developing service automation and human-material service practices. Automation can relate to both automating existing service practices and implementing new automated processes that were once impossible. Similarly, human-material service practices can be improvements of existing processes or entirely new practices.

Second, our study identifies important context factors in terms of organizational goals that are associated with an S-D logic. Future research efforts should focus on the enabling and constraining factors in actualizing the service practices and how these practices should be implemented (cf. [47]). For example, further research could investigate certain service features to determine whether a service should be automated or provided as a human-material practice.

Third, our study supports recent work highlighting that understanding technology affordances requires analytic approaches that simultaneously consider, for example, aspects of materiality, humans, and context in light of organizational level goals.

Fourth, both the dynamic changes in material features of BDA and the organizational context offer opportunities for longitudinal studies that examine the development of BDA affordances and service-provision practices.

Implications for practice

Our findings have four primary implications for practitioners who design BDA infrastructures to support service innovation. They provide guidance for the design and implementation of technologies that deliver the material features for service automation and human-material service practices.

First, the development of BDA technologies is highly dynamic, and different instantiations of a technology might provide similar material features. Practitioners can use the categories of features identified in this study (sourcing and storage features, analytic features in terms of event recognition and prediction and behavior recognition and prediction, and exploitation features) to identify suitable and scalable technologies. At the same time, they can revisit their IT infrastructures to determine to what extent such features are present that might be exploited to afford service innovation or to determine whether they can be created through reprogramming. Future research could identify additional material features and associated affordances, thereby, informing BDA research about new material features that might be beneficial or even critical to additional service innovations, such as those in the area of security and privacy.

Second, practitioners can use the theoretical model to analyze their need for service automation or human-material service practices. As our analysis shows, some organizations balance automation and human-material service practices (as in the case of Companies A and B), while others focus only on human-material practices (as in the case of Company C) or automation (as in the case of Company D). The appropriate strategy depends on the type of service as well as the customer's expectation. Our description of four cases provides some examples.

Third, the empirical insights from our case studies and our theorizing based on those cases provide fine-grained information about BDA's specific contribution to service innovation. Thereby, our results provide guidance to firms that seek to launch BDA-enabled service innovation. IT managers must have a holistic grasp on how BDA technologies afford different models of service provision such that the service provision is aligned with the organization's strategic goals. All four cases provide evidence that the companies' investments in BDA technologies and their application to service innovation was in response to specific action goals and that these goals had in common their focus on individualized service.

Fourth, the service innovations identified in this study might inspire the development of use cases for firms' specific use contexts and strategic goals.

Limitations

Despite the careful design of our research approach, our findings are subject to several limitations. First, qualitative research relies on the researchers' interpretation in coding and analyzing the data. While we applied established techniques suggested by Wallendorf and Belk [52] to ensure high-quality results, future research should repeat and refine our analysis. Second, as the use of information technologies is subject to subjective interpretations in specific contexts of use, it is unlikely that our account of the potential for service automation and human-material service practices is exhaustive. Future research could investigate whether additional uses emerge based on a comparable sample. Third, as our case organizations had a number of common characteristics with regard to ownership, business model, relevance of BDA to service innovation, and cultural proximity, our results may not be generalizable beyond this context. Future research might verify whether our results apply across contingency factors like other industries and other regulatory and cultural contexts. Fourth, although our firms have strong technological capabilities, there may be other firms, especially in the tech industry, that are pioneers in applying BDA. Future research could investigate whether these firms have put BDA to other uses, and in case of differences, shed light on why they occurred.

Conclusion

Our research lends support to the argument that BDA holds potential for service innovation [58] and identifies the factors that are pertinent to the creation of new value propositions. It identifies two key primary roles of BDA in the context of service innovation: (1) automation of customer-sensitive service provision, and (2) human-material customer-sensitive service practices, and highlights how these are grounded in material features of BDA. Together, these two types of service innovation allow organizations to revamp their value propositions.

Notes

1. The singular term "service" used here instead of the plural "services," emphasizes the focus on "service processes" instead of services in terms of "units of output" [24, 50].

2. Please note that we have adjusted our research question throughout this qualitative, exploratory study. However, the essence of our question in terms of the impact of BDA on service innovation remains the same as it was when we commenced the study.

3 While open coding is typically associated with grounded theory method, it is indeed used in exploratory, qualitative research in general [27, 43].

References

1. Barrett, M.; Davidson, E.; Prabhu, J.; and Vargo, S.L. Service innovation in the digital age: Key contributions and future directions. *MIS Quarterly, 3*9, 1 (2015), 135–154.

2. Barras, R. Interactive innovation in financial and business services: The vanguard of the service revolution. *Research Policy, 19*, 3 (1990), 215–237.

3. Chen, H.; Chiang, R.H.L.; and Storey, V.C. Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*, 4 (2012), 1165–1188.

4. Chen, D.Q.; Preston D.S.; and Swink, M. How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems, 32*, 4 (2015), 4–39.

5. D'Adderio, L. Artifacts at the centre of routines: Performing the material turn in routines theory. *Journal of Institutional Economics, 7*, 2 (2011), 197–230.

6. Constantiou, I.D., and Kallinikos, J. New games, new rules: Big data and the changing context of strategy. *Journal of Information Technology, 30*, 1 (2015), 44–57.

7. den Hertog, P. Knowledge-intensive business services as co-producers of innovation. *International Journal of Innovation Management, 4*, 4 (2000), 491–528.

8. Dubé, L., and Paré, G. Rigor in information systems positivist case research: Current practices, trends, and recommendations. *MIS Quarterly, 27*, 4 (2003), 597–635.

9. Eisenhardt, K.M. Building theories from case study research. *Academy of Management Review, 14*, 4 (1989), 532–550.

10. Faulkner, P., and Runde, J. The social, the material, and the ontology of non-material technological objects. Paper presented at the European Group for Organizational Studies (EGOS) Colloquium, Gothenburg, July 6–9, 2011.

11. Faraj, S., and Azad, B. The materiality of technology: An affordance perspective. In P. M. Leonardi, B.A. Nardi, and J. Kallinikos (eds.), *Materiality and Organizing: Social Interaction in a Technological World*. Oxford: Oxford University Press, 2012, pp. 237–258.

12. Fayard, A.L., and Weeks, J. Affordances for practice. *Information and Organization, 24*, 4 (2014), 236–249.

13. Gaskin, J.; Berente, N.; Lyytinen, K.; and Yoo, Y. Toward generalizable sociomaterial inquiry: A computational approach for zooming in and out of sociomaterial routines. *MIS Quarterly, 38*, 3 (2014), 849–871.

14. George, G.; Haas, M.R.; and Pentland, A. Big data and management. *Academy of Management Journal, 57*, 2 (2014), 321–326.

15. Hansen, R., and Sia, S.K. Hummel's digital transformation toward omnichannel retailing: Key lessons learned. *MIS Quarterly Executive, 14*, 2 (2015), 51–66.

16. Hibbeln, M.; Jenkins, J.L.; Schneider, C.; Valacich, J.S.; and Weinmann, M. How is your user feeling? Inferring emotion through human-computer interaction devices. *MIS Quarterly, 41*, 1 (2017), 1–21.

17. Ho, S.Y.; Bodoff, D.; and Tam, K.Y. Timing of adaptive web personalization and its effects on online consumer behavior. *Information Systems Research, 22*, 3 (2011), 660–679.

18. Howison, J.; Wiggins, A.; and Crowston, K. Validity issues in the use of social network analysis with digital trace data. *Journal of the Association for Information Systems, 12*, 12 (2011), 767–797.

19. Hultin, L., and Mähring, M. Visualizing institutional logics in sociomaterial practices. *Information and Organization, 24*, 3 (2014), 129–155.

20. Kallinikos, J.; Aaltonen, A.; and Marton, A. The ambivalent ontology of digital artifacts. *MIS Quarterly, 37*, 2 (2013), 357–370.

21. Leonardi, P.M. When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly, 35*, 1 (2011), 147–167.

22. Leonardi, P.M. Materiality, sociomateriality, and socio-technical systems: What do these terms mean? How are they related? Do we need them? In P.M. Leonardi, B.A. Nardi, and J. Kallinikos (eds.), *Materiality and Organizing: Social Interaction in a Technological World*. Oxford: Oxford University Press, 2012, pp. 25–48.

23. Leonardi, P.M. When does technology use enable network change in organizations? A comparative study of feature use and shared affordances. *MIS Quarterly, 37*, 3 (2013), 749–775.

24. Lusch, R.F., and Nambisan, S. Service innovation: a service-dominant logic perspective. *MIS Quarterly, 39*, 1 (2015), 155–176.

25. Majchrzak, A., and Malhotra, A. Towards an information systems perspective and research agenda on crowdsourcing for innovation. *Journal of Strategic Information Systems, 22*, 4 (2013), 257–268.

26. Markus, M.L., and Silver, M.S. A foundation for the study of IT effects: A new look at DeSanctis and Poole's concepts of structural features and spirit. *Journal of the Association for Information Systems, 9*, 10/11 (2008), 609–632.

27. Matavire, R., and Brown, I. Profiling grounded theory approaches in information systems research. *European Journal of Information Systems, 22*, 1 (2011), 119–129.

28. McAfee, A., and Brynjolfsson, E. Big data: The management revolution. *Harvard Business Review*, October 2012, 3–9.

29. Miles, M.B., and Huberman, A.M. Qualitative Data Analysis: A Methods Sourcebook. Thousand Oaks, CA: Sage, 2013.

30. Nambisan, S. Information technology and product/service innovation: A brief assessment and some suggestions for future research. *Journal of the Association of Information Systems, 14*, 4 (2013), 215–226.

31. Newell, S., and Marabelli, M. The crowd and sensors era: Opportunities and challenges for individuals, organizations, society, and researchers. In *Proceedings of Thirty Fifth International Conference on Information Systems (ICIS 2014). Auckland: Association for Information Systems, 2014*, pp. 1–17.

32. Newell, S., and Marabelli, M. Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of "datification." *Journal of Strategic Information Systems, 24*, 1 (2015), 3–14.

33. Ordanini, A., and Parasuraman, A. Service innovation viewed through a service-dominant logic lens: A conceptual framework and empirical analysis. *Journal of Service Research, 14*, 1 (2011), 387–404.

34. Orlikowski, W.J., and Scott, S.V. The algorithm and the crowd: considering the materiality of service innovation. *MIS Quarterly, 39*, 1 (2015), 201–216.

35. Paré, G. Investigating information systems with positivist case research. *Communications of the Association for Information Systems, 13*, 1 (2004), 233–264.

36. Pickering, A. *The Mangle of Practice: Time, Agency and Science*. Chicago: University of Chicago Press, 1995.

37. Porter, M.E., and Heppelmann, J.E. How smart, connected products are transforming companies. *Harvard Business Review*, (2015), 97–114.

38. Roberts, N.; Campbell, D.E.; and Vijayasarathy, L.R. Using information systems to sense opportunities for innovation: Integrating postadoptive use behaviors with the dynamic managerial capability perspective. *Journal of Management Information Systems*, 33, 1 (2016), 45–69.

39. Schatzki, T.R.; Knorr-Cetina, K.; and Von Savigny, E. *The Practice Turn in Contemporary Theory*. London: Routledge, 2001.

40. Schultze, U., and Orlikowski, W.J. A practice perspective on technology-mediated network relations: The use of Internet-based self-serve technologies. *Information Systems Research, 15*, 1 (2004), 87–106.

41. Seidel, S., and Berente, N. Toward "third wave" information systems research: Linking sociomaterial practice with broader institutional logics. In Proceedings of *Thirty Fifth International Conference on Information Systems (ICIS 2013)*. Milan: Association for Information Systems, 2013, pp. 1–14.

42. Seidel, S.; Recker, J.C.; and vom Brocke, J. Sensemaking and sustainable practicing: Functional affordances of information systems in green transformations. *MIS Quarterly, 37*, 4 (2013), 1275–1299.

43. Seidel, S., and Urquhart, C. On emergence and forcing in information systems grounded theory studies: The case of Strauss and Corbin. *Journal of Information Technology, 28*, 3 (2013), 237–260.

44. Shmueli, G., and Koppius. Predictive analytics in information systems research. MIS Quarterly, 35, 3 (2011), 553–572.

45. Skålén, P.; Gummerus, J.; von Koskull, C.; and Magnusson, P.R. Exploring value propositions and service innovation: A service-dominant logic study. *Journal of the Academy of Marketing Science, 43*, 2 (2015), 137–158.

46. Strauss, A.L., and Corbin, J. *Basics of Qualitative Research. Techniques and Procedures for Developing Grounded Theory*. London: Sage, 1998.

47. Strong, D.M.; Johnson, S.A.; Tulu, B.; Trudel, J.; Volkoff, O.; Pelletier, L.R.; Bar-On, I.; and Garber, L. A theory of organization-EHR affordance actualization. *Journal of the Association for Information Systems, 15*, 2 (2014), 53–85.

48. Thirumalai, S., and Sinha, K.K. To personalize or not to personalize online purchase interactions: Implications of self-selecting by retailers. *Information Systems Research, 24*, 3 (2013), 683–708.

49. Trantopoulos, K.; von Krogh, G.; Wallin, M.W.; and Woerter, M. External knowledge and information technology: Implications for process innovation performance. *MIS Quarterly, 41*, 1 (2017), 287–300.

50. Vargo, S.L., and Lusch, R.F. Why "service"? Journal of the Academy of Marketing Science, 36, 1 (2008), 25–38.

51. Volkoff, O.; Strong, D.M.; and Elmes, M.B. Technological embeddedness and organizational change. *Organization Science, 18*, 5 (2007), 832–848.

52. Wallendorf, M., and Belk, R.W. Assessing trustworthiness in naturalistic consumer research. In E.C. Hirschman (ed.), *Interpretative Consumer Research*. Provo: Association for Consumer Research, 1989, pp. 69–84.

53. Watson, H.J. Tutorial: Big data analytics: concepts, technologies, and applications. *Communications of the Association for Information Systems, 34*, 65 (2014), 1247–1268.

54. Woerner, S.L., and Wixom, B.H. Big data: Extending the business strategy toolbox. *Journal of Information Technology*, *30*, 1 (2015), 60–62.

55. Xiao, B., and Benbasat, I. E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly, 31*, 1 (2007), 137–209.

56. Yin, R.K. *Case Study Research Design and Methods*. Thousand Oaks, CA: Sage, 2009.

57. Yoo, Y.; Henfridsson, O.; and Lyytinen, K. The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research, 21*, 4 (2010), 724–735.

58. Yoo, Y.; Boland, R.J. Jr.; Lyytinen, K.; and Majchrzak, A. Organizing for innovation in the digitized world. *Organization Science, 23*, 5 (2012), 1398–1408.

59. Zammuto, R.F.; Griffith, T.L.; Majachrzak, A.; Dougherty, D.J.; and Faraj, S. Information technology and the changing fabric of organization. *Organization Science, 18*, 5 (2007), 749–762.

60. Zhang, D.; Guo, B.; and Yu, Z. The emergence of social and community intelligence. *Computer, 44*, 7 (2011), 21–28.

Appendix

Interview questions
A) Background

- What is your position within [case organization]?
- What projects do you typically/currently work on?
- What is your understanding of the term "big data"?
- Are you aware of big data initiatives at [case organization]?
- Do you have any tasks and responsibilities that are directly related to big data initiatives?
- What is your understanding of the term "big data analytics"?

To ensure a common understanding of big data analytics, we would like to introduce the following definition: Big data analytics refers to technologies for gathering, processing and analyzing big data, which commonly describes a vast amount of complex data.

- Based on this understanding, is [case organization] using big data analytics? And what role does it play at [case organization]?

B) Service innovation at [case organization]
In this interview, we aim to get an in-depth understanding of the role that BDA plays for service innovation at [case organization]. Therefore, we would like to ask a few questions about this topic.

- Do consumer-oriented services play a role in your organization? If yes, please describe it.

- What is your understanding of the term “service innovation”?
- Does service innovation play a role in your organization? If yes, please describe it.
- What do you think are the motivation of [case organization] with regard to service innovation?

C) The role of BDA for service innovation

- What role does BDA play for service innovation?
- What are the things you expect to be able to do with BDA in the context of service innovation?
- What do you think are the underlying goals of harnessing BDA for service innovation?
- Do you know about any BDA technology that is used at [case organization] for service innovation?

Let us now assume that your organization had all the necessary BDA technologies in place.

- What do you think could be the role of BDA for innovating or improving consumer-oriented services?

Sub-questions, especially for interviewees with a technical background:

- What does the current technological infrastructure for data collection and analysis look like at [case organization]? Please describe it in detail.
- By means of which technologies does [case organization] collect, analyze and apply big data? Or how does it plan to do this? Please describe the technologies in detail.

D) Conclusion

- Did we forget anything? Is there anything else you would like to discuss?
- Could we get back to you in case we have some (minor) further questions from our data analysis?

Anhang 2: Fachbeitrag A2 - „Approaches to the implementation of big data analytics"

Tabelle A2: Fakten zum Fachbeitrag A2

Informationstyp	Beschreibung
Titel	Approaches to the implementation of big data analytics
Autor	Alexander Wieneke, Universität St.Gallen, Schweiz
Publication type	Arbeitspapier
Jahr der Veröffentlichung	2018
Status der Publikation	Veröffentlicht
Referenz	Wieneke, A. (2018). Approaches to the implementation of big data analytics.
Zugriff	https://www.alexandria.unisg.ch/publications/254660

Approaches to the implementation of big data analytics

Alexander Wieneke

Everyone is talking about big data analytics

It seems that there is no area in our everyday lives that is not influenced by big data and big data analytics (BDA). The term big data refers to a high volume, variety, velocity, and veracity of data, while BDA refers to methods and tools for gathering, processing, and analyzing big data (Chen et al. 2012).

Besides the constantly increasing number of individualized applications enabled by the gathering and analysis of big data, BDA also attracts attention from a social-policy perspective. The debate about the downsides of BDA has broadened, especially in the last five years. Many newspapers address stolen or illegal capture of personal data and its unethical use (e.g., Lieber 2017, Tufekci & King 2014), and experts warn about unfair classification of individuals that leads to discrimination (Markus 2015; Newell & Marabelli 2014). The limitations of our decision-making abilities are also frequently cited as problematic, as when political parties use information about individuals to influence their opinions (e.g., Hern 2017). Accordingly, people increasingly see in BDA a threat to privacy, freedom, and democracy, a view that is often accompanied by fear. For example, according to one US survey, more than 45 percent of those who use wearable devices are concerned about the devices' ability to breach their privacy (Mills 2015). Paradoxically, consumers enjoy using mobile apps that provide individualized service, reading individualized newsfeeds, and using wearable devices for self-tracking (IDC 2015).

Despite the potential for negative consequences, many companies use BDA to provide new services that can make our lives easier. As BDA has proliferated and data sources have increased in number and volume, companies seek to leverage the transformational impact of BDA for service innovations (Woerner & Wixom 2015) that benefit customers and create competitive advantages (Skålén et al. 2016). Specifically, service innovation focuses on new ways of creating value for customers by establishing new activities or realigning existing ones to improve service delivery (Orlikowski & Scott 2015). For example, industrial companies like Schindler and the Swiss Federal Railways (SBB) Company see in BDA an enabler for creating smart cities (SBB 2018, Schindler 2017) that will enhance the habitants' quality of life. Car manufacturers like Porsche use BDA to create innovative services in the context of connected cars (Freimark 2014) that provide the consumer with a safer and more efficient driving experience. Similarly, insurance companies like AXA are designing analytics-based services like the AXA drive coach app that make lives safer (Tardy 2015). Consumer goods companies use BDA to adapt their products to individual needs and improve the customer's experience. For example, Whirlpool, the home-appliances manufacturer, put sensors in its products to track how customers use them and combining these data with user-generated content from social media platforms (e.g., product reviews) to offer predictive maintenance services, reducing customers' stress and increasing their products' reliability (Woerner & Wixom 2015).

Against this background, it is clear that BDA should not be associated only with its negative potential but also with the potential to add value for the consumer (Woerner & Wixom 2015). Despite the impression that BDA is in league with the devil, companies can use new approaches to harness its positive potential.

Bringing the scientific and practical perspective together – A guide addressing the challenges of BDA

Data about a company's actual and potential consumers, their environment, and the products they use is extremely valuable to that company. Statements like that of Peter Sondergaard of the Gartner Group that "*information is the oil of the 21st century, and analytics is the combustion engine*" (Goes, 2014, p. iii) and The Economist's observation that "*Data are becoming the new raw material of business*" (2010, as cited in Goes, 2014, p. iii) are well known. McAfee and Brynjolfsson (2012) labeled BDA a "*Management Revolution*" (p. 3).

However, in reality, many companies struggle to capitalize on BDA (Chen et al. 2015). Thus, I explain and provide insights into three fundamental challenges companies face when implementing BDA—failure to understand the term "BDA," lack of knowledge about the potential for its use, and missing information about the required practices and process for implementing it.

The insights are based on my experiences during a practice-oriented research project I started in 2014. I spoke to several experts in the BDA field and made several observations about its application to service innovation. I also held several workshops with executives of companies in Switzerland and Germany who were exploring new application areas for BDA. I also referred to the scientific literature to extend the practical viewpoints.

This paper contributes to practice-oriented BDA (e.g., McAfee & Brynjolfsson, 2012) and provides a novel perspective on how BDA influences companies' business success. Specifically, it contributes to the idea of Analytics 3.0 introduced by Davenport (2013) by providing companies with insights into how BDA can empower customer service processes.

Challenges regarding BDA – What is it? Why is it valuable? How to implement it?

What is BDA?

In many companies I observed a lack of understanding of the term "BDA." Some companies' employees label BDA data analytics because they do not see many differences between BDA and the conventional way of analyzing data. As a result, these companies may focus solely on improving their business intelligence initiatives or fail to consider the specific requirements of BDA, and they wander about making slight improvements that focus primarily on their existing reporting landscapes. Failing to work at conceptualizing the term, they do not extend their mind sets to consider new possibilities. Companies' employees that have a more advanced understanding of BDA use, for example, the term "advanced analytics" to highlight the new opportunities BDA provides. However, the term "advanced analytics" can also be interpreted in a variety of ways, so many companies struggle to agree internally on a common understanding of what is "in scope" and what it "out of scope" when they talk about "advanced analytics."

These observations are in line with the scientific literature's ongoing discussion about how to define big data and BDA. Amott and Pervan (2014) stated that "*there is no accepted definition of big data*" (p. 271), while Baesens et al. (2016) differentiated BDA from business intelligence when they introduced the term "business analytics" as "*encompass[ing] all aspects of the data process to facilitate predictive and/or causal inference-based business decision making*" (p. 808).

Why is BDA valuable?

How BDA contributes to the overall company's success remains unclear for many executives. Based on my experiences, there is scarce knowledge about BDA's potential in the context of service innovation, and executives struggle to derive a strategic approach to implementing BDA. These observations are comparable to the assumptions made by several researchers. For example, Chen et al. (2015, p. 5) stated, "*a majority of companies have still not begun to engage in the practice of capitalizing on big data*" and

Lavalle et al. (2011, p. 23) explained that "*the leading obstacle to widespread analytics adoption is lack of understanding of how to use analytics to improve the business*."

How to implement BDA

Many firms do not understand how to implement BDA, so they do not use a systematic approach in implementing their BDA-related initiatives. Some companies follow a bottom-up approach and start by investing in technological solutions like Data Lake. These companies invest considerable money without having a concrete idea about promising ways to use the technology, how to define promising use cases, and how to link their BDA initiative to the company's overall objectives. I recognized that firms lack a systematic approach to the required practices and processes and the tools and techniques that provide guidance in problem-solving when implementing BDA. These observations are in line with the scientific literature, such as the work of LaValle et al. (2011, p. 21), who stated that "*the biggest challenge in adopting analytics are managerial and cultural*."

Three approaches to the implementation of BDA

BDA – An explorative approach to data analytics

BDA describes a new stage of business intelligence (Chen et al. 2012). The ongoing development of business intelligence and analytics solutions occurs primarily because of the unprecedented amount of data generated by an increasing number of sources and the widening possibilities for gathering, processing, and analyzing them (Chen et al. 2012). To explain BDA, I decompose the term into its two parts: big data and BDA.

When we use e-commerce, social media platforms, and digitized objects like smartphones and wearables, we leave a digital trace of data about our behavior and thoughts that is often referred to as digital trace data (Müller et al. 2016; Newell & Marabelli 2015). In addition, many companies generate a vast amount of data by, for example, using sensors in their products or digitalizing their business processes (e.g., paper-less customer interaction). These kinds of internal and external data can be encompassed under the umbrella term "big data" (Debortoli et al. 2014; Newell & Marabelli 2014). Big data has specific characteristics. For example, web-based and sensor data are both generated in high volumes (large-scale data), at high velocity (high-speed data), in wide variety (e.g., text-based data and numerical data), and with high veracity (e.g., sensor data) (Debortoli et al. 2014). These "four Vs" are well known, but there is an ongoing debate about which is the most important (Goes 2014).

The volume of data collected is central to big data's potential. Practitioners and scientists (e.g., Clarke 2016) have found that the unprecedented volume of data now available creates new possibilities for data analysis that provide, for example, new opportunities for data-driven decision-making (Constantiou & Kallinikos 2015). However, with the help of powerful business warehouse solutions, companies have already been able to analyze vast amounts of data. According to scientists like Belanger and Xu (2015), the opportunity to combine data from a multitude of unrelated data sources is central to big data's potential. This characteristic provides the opportunitiy to improve the representation of reality and facilitating the recognition of new, previously unpresentable relationships and patterns (Belanger & Xu, 2015). Of course, combining a small set of data in variousdifferent formats has been, was also already done for years in the past.

Against this background, I support the view that big data is valuable for firms when they have datasets that can be characterized by all four Vs. As Goes (2014, p. vi) pointed out, big data should not be focused on only one dimension, as "*the new paradigm comes by combining these dimensions. The hard core science disciplines have been working on volume and perhaps velocity, but it's the 4 V's together*."

In addition, by working with experts in the field of BDA, I recognized that many experts consider data as big data only if it originates from external data sources. This discussion is also being taken up by different researchers, e.g., Baesens et al. (2016). Associating big data only with data from external sources diminishes the value of BDA, as this definition ignores internal sources like mails, contracts, voice records, and data generated by products equipped with sensors. These kinds of data also occur in high volumes, velocity, variety, and veracity and support the generation of insights (Baesens et al. 2016). Big data should not be differentiated by its sources, a view that is in line with George et al. (2014, p. 321), who described big data as being "*generated from an increasing number of sources of sources, including Internet clicks, mobile transactions, user-generated content, and social media as well as purposefully generated content networks as sales queries and purchase transactions*."

While the term "big data" is clearly defined, the question is why "analytics" was added to big data. I refer to Chen et al. (2012), who argued that BDA should be used as an umbrella term to describe the processes, methods, and technologies for collecting, processing, and analyzing big data. Although many articles about BDA, especially those published by software vendors, give the impression that the technologies and methods for collecting, processing, and analyzing big data constitute an information technology revolution, from my point of view, these technologies and methods are an evolutionary stage of business. This view is also supported by the scientific literature (e.g., Debortoli et al. 2014). However, besides specific technologies like application programming interfaces (API) for data collection, data lakes for data storage, and Hadoop for data processing and analysis that differentiate BDA from conventional business intelligence and analytics initiatives (Chen et al. 2012, Chen et al. 2015, Porter & Heppelmann 2015), we should also consider new methods for analyzing collected data (Baesens et al. 2016). Data analytics once focused primarily on descriptive analytics to answer questions about why something happened (Baesens et al. 2016). Today, data analytics and data scientists conduct predictive and prescriptive data analysis to create insights into what will happen and what to do in future situations (Baesens et al. 2016, Lavalle et al. 2011).

As I discussed with several experts from several companies during a workshop, BDA also refers to a new approach to analyzing data. With the unprecedented opportunities for gathering and analyzing data (Chen et al. 2012), the approach to working with data should be more scientific. Instead of executing analyses in a way that generates pre-defined insights, data scientists need the freedom to explore new data sets with the aim of finding unexpected insights that help to achieve business goals (i.e., service innovation) more effectively. Accordingly, BDA can be extended by an explorative way of analyzing data, an approach that is comparable to that of Netflix. The company honored data scientists who developed the best approach (i.e., algorithm) to improving Netflix's recommendation engine (Davenport & Patil 2012). My insight relates to Baesens et al. (2016, p. 810), who stated, "*State-of-the-art big data research and practice draws on a variety of techniques from machine learning, classical statistics, and econometrics to design of experiments (industry calls this A/B or multivariate testing) to test existing theories and hypotheses, develop new theories, and create large-scale business value*". Accordingly, data scientists get the chance to work in a "real-word laboratory" (Baesens et al. 2016, p. 810) where they can answer a wide variety of new questions.

Against this background, I emphasize that BDA should not be seen as a support function but as an enabler of business process improvements and disruptive innovation.

Three potential uses of BDA

I present three approaches to using BDA for service innovation. The approaches emphasize that the technologies related to BDA enable companies to monitor and analyze a broad variety of external and internal data sources so they can increase their awareness of their customers' behavior, interests, actual context, and emotions and establish innovative behavior-, event-, and emotion-sensitive services that provide new value propositions.

Behavior-based services take into account the insights gained from customers' behavioral patterns, which are leveraged to tailor service-related activities to individual customers. Based on a customer's preferences inferred from his or her behavior, firms can tailor the channel used to promote services to the customer and increase the degree of individualization. The channels' user interfaces can be adapted once—or even dynamically in real time—based on behavioral patterns and the customer's current situation. For example, based on choices that the user makes in navigating a website and the device he or she is using, the user interface can be adapted to shorten the customer's journey to the buy-it-now-option and adapt the functionalities provided to increase simplicity and security.

By establishing behavior-sensitive services, companies can adapt each activity to their customers' preferences, habits, and needs. By providing the customer a highly individualized customer experience, companies can improve their overall service quality and increase the customer's net promoter score and engagement. Moreover, adapting the user interface in real-time to support the customer in shortening the buying process increases the conversion rate and revenue and reduces the required server utilization and operating costs.

In short, behavior-based services enable companies to provide individualized services that are adapted to their customers' interests and preferences. This goal is similar to that of CRM systems, but the intention in using BDA is not only to maximize profit but also to do so by creating a unique customer experience that is informative, convenient, and engaging. BDA is particularly useful when the firm already has a high number of touchpoints that allow it to interact frequently with its customers.

Event-sensitive services refer to services triggered by events, such as a birthday or wedding; specific activities, such as driving on a crowded highway; the condition of a digitized object, such as damages to a car; the external environment, such as weather); or the customer herself, such as health-related events. Companies can also identify future events, but, in general, each event is related to a specific customer need or interest that is triggered by an event that has happened, is happening, or is likely to happen. When these events occur, firms provide helpful interactions (e.g., recommendations, information, and warnings) or take action on the customer's behalf (e.g., starting the sprinkler system in case of a fire).

The difference between event-sensitive and behavior-sensitive services is that event-sensitive services can create new customer touchpoints and new opportunities for interacting with and adding value for the customer. By addressing the customer's need exactly when he or she has a demand, firms improve the customer's experience. Because of the new possibilities for gathering data about customers' everyday lives, BDA allows companies to identify events that go beyond those revealed in a conventional business relationship so they can create new service offers and revenue streams. Companies can also establish a new customer relationship in which they are positioned as the "customer's friend," who offers support in every situation, thereby influencing the customer's perception about the firm and restructuring its branding.

In summary, event-sensitive services enable companies to support their customers proactively exactly when a need or interest occurs and to create new touchpoints that enhance their conventional approaches to customer service. BDA can help companies create a "wow effect" by providing supportive information the customer does not expect, thereby contributing to a unique customer experience and differentiating themselves as a way out of the commodity trap.

Emotion-sensitive services serve the customer in a way that considers her or his affective state. Instead of addressing the customer on a cognitive level by providing behavior- and event-sensitive information, knowledge gained through BDA about the customer's current or future emotional state allows firms to adapt how they "speak" to the customer on an affective level. Thus, firms adjust the content, tonality, channel, or flow of a dialog with a customer or even choose the right front-line employee to deal with the customer. By analyzing customers' statements about the company, such as those made on social media platforms, over a period of time, companies can recognize a customer's moods. For instance, if the customer appears annoyed or dissatisfied, the firm might avoid certain words or topics, instead offering supportive advice or an apology. When the user appears to be pressed for time, the firm may focus on making the interaction short, to the point, and via digital communication, such as text message. In addition, based on historical data, firms can learn about their customers' affective reactions to instances like network failures (in the case of a telecommunications firm) and anticipate how she will feel when failures occur.

By addressing the customer according to her or his emotional state, companies can interact in a way that the customer expects and needs, thereby bringing a personal touch back into mass communication. Making the customer feel understood on an emotional level could makes the firm appear friendlier and more empathic to its customers, improving the customer's perception of the firm. While the other two service-provision practices provide functional value to the customer, emotion-sensitive services promise emotional or hedonic value—the feeling of being understood—which improves customer engagement, acts as a differentiator, and decreases the likelihood of churn.

Emotion-sensitive services enable companies to provide their customers with emotional understanding and support, especially when there is direct personal contact with a service employee. Large numbers of customers, significant time pressure, and increasing amounts of digitalized communication make it all but impossible to create a personal, caring relationship with each customer. Gaining emotional intelligence through BDA can help firms develop an emotional bond with their customers and interact with them as though they were friends.

Implementing BDA – It's not all about technology and data.

Implementing BDA involves not only deciding what technology is needed and which data sources should be used for data gathering but also requires company-wide participation, including stakeholder and management attention (Lavalle et al. 2011). In the following, I give an overview of a systematic approach to realizing the potential of BDA, which consists of three key dimensions: the strategic layer, the organizational layer, and the technological layer.

The strategic layer holds the definition of the strategic framework in which the BDA strategy is connected to the overall corporate strategy and the outcome the company wants to achieve with BDA are described. Accordingly, companies should define the use cases they want to realize with BDA, starting with a list of concrete expectations from relevant stakeholders that can be realized in the short run and the long run. It is important to consider how BDA could be used in an ideal world.

This approach is related to research like that of Lavalle et al. (2011), who argued that one must "*first [define] the insights and questions needed to meet the big business objective and then [identify] those pieces of data needed for answers*" (p. 26). However, as early as 2008, when talking about the use of customer data in general, not about BDA in specific, Piccoli and Watson (2008, p. 113) provided four strategies that enable companies "*to envision how they can adopt the most appropriate strategy (or strategies) for exploiting customer data to improve profitability*." As a first step, they recommended deciding which of the four strategies are most suitable and only then to define the required data sets and technologies.

Customer needs must be taken into account when a company defines the use cases in the context of service innovation (Piccoli & Pigni 2013; Wieneke & Lehrer 2016). Such a customer-centric view enables companies to define use cases that allow them to use BDA to offer their customers the right value propositions (Orlikowski & Scott 2015, Yoo et al. 2012). In addition, creating value for the customers increases customers' willingness to share personal data with the company. Picolli and Pigni (2013, p. 55) also highlighted the use of digital data streams as indispensable for value creation "*to increase customers' willingness to pay for [a company's] product or service or to reduce opportunity cost of the resources it uses to create existing value propositions.*"

I suggest that companies cluster the identified use cases along the three dimensions of behavior-, event-, and emotion-sensitive services) to get an idea of the kinds of use cases that will help them realize their vision. Doing so provides important guidance for the next steps of defining the organizational, technological, and governance requirements and helps to identify potential for uses the company has not considered yet.

The organizational layer consists of the tasks required to set up the BDA team, including how employees should be managed to realize the defined types of use cases, the organizational structure, and the employees' required skill set (Lavalle et al. 2011, Piccoli & Pigni 2013). The organizational structure describes how the company delivers value through BDA that is, how it gathers, processes, analyzes, and uses generated insights in innovating customer services (Wieneke & Lehrer 2016).

As a first step the company highlights the interfaces between the BDA team and relevant stakeholders, including which stakeholders need to communicate with each other and how they will do so. The interface between the business and the BDA team may require a new way of communicating because it must ensure the user-centric work of the analytics team and facilitate the definition of valuable insights (Wieneke & Lehrer 2016) in an environment of high volatility of generated data and fast-changing customer needs (Lavalle et al. 2011, Wieneke & Lehrer 2016). Therefore, communication between the BDA team and the business must be agile, speedy, and customer-centric (Wieneke & Lehrer 2016). In second step, the company defines the required skill sets and roles for the team's employees, determines the number of employees needed, and decides whether external sources should be used for the ramp-up phase and whether it needs to educate its own employees in the field of data science (Lavalle et al. 2011, Piccoli & Pigni 2013).

Finally, in the technological layer, companies should identify from the technical perspective what is necessary to realize the strategic framework, starting by analyzing how their current IT architectures and available data enable them to realize the defined types of use cases. Next, they define the improvements in the current technology and the data management processes. This recommendation is in line with Lavalle et al. (2011), Piccoli and Pigni (2013), and Piccoli and Watson (2008), the last of whom suggest determining the technologies required for analytic needs and the data required to implement the overall strategy. As a last step, the analytics team and the data stewards or chief data officers should decide whether the company needs more data to provide the required insights (Lavalle et al. 2011). New sources for gathering customer data could come from a detailed analysis of the customer's journey and highlighting what kinds of data can be gathered at each touchpoint. They should also check opportunities to use external sources like open data sources.

Summary

BDA is not a technological revolution but an umbrella term for an evolutionary step in the development of business intelligence (Chen et al. 2012). Implementing BDA has many steps that are also necessary in other strategic projects. From my perspective, it is common sense for a company to start by establishing a common understanding of BDA, defining its potential for the company, and finally answering strategy-related, organization-related, and technology-related questions. Moreover, to implement BDA effectively, companies must change their mindsets so employees will be willing to follow the recommendation based on the created insights (Lavalle et al. 2011), as when employees are not willing to accept data-driven recommendations, all the effort spent on the implementation of BDA is useless

(Wieneke & Lehrer 2016). Therefore, companies should not neglect the importance of change management (Lavalle et al. 2011).

However, with regard to the new service offers afforded by BDA, I hypothesize that this technological evolution has the potential to revolutionize how companies do business and interact with their customers. Therefore, companies must address the implementation of BDA on a highly detailed and especially customer-centric level.

References:

Arnott, D., & Pervan, G. (2014). A critical analysis of decision support systems research revisited: the rise of design science. *Journal of Information Technology 29*, 269–293.

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., & Zhao, J. L. (2016). Transformational issues of big data and analytics in networked business. *MIS Quarterly, 40*(4), 807-818.

Belanger, F., & Xu, H. (2015). The role of information systems research in shaping the future of information privacy. *Information Systems Journal, 25*(6), 573-578.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly, 36*(4), 1165-1188.

Chen, D. Q., Preston D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems, 32*(4), 4-39.

Clarke, R. (2016). Big data, big risks. *Information Systems Journal, 26*(1), 77-90.

Constantiou, I. D., & Kallinikos, J. (2015). New games, new rules: big data and the changing context of strategy. *Journal of Information Technology*, *30*(1), 44-57.

Davenport, T. (2013). Analytics 3.0: in the new era, big data will power consumer products and services. *Harvard Business Review*, *December*, 2-9.

Davenport, T., & Patil, D. J. (2012). Data scientist: the sexiest job of the 21st century. *Harvard Business Review*, *October*, 61-67.

Debortoli, S., Müller, O., & vom Brocke, J. (2014). Comparing business intelligence and big data skills. *Business & Information Systems Engineering, 6*(5), 289-300.

Freimark, A. (2014). *Arbeiten bei Porsche*. Available under https://www.computerwoche.de/a/arbeiten-bei-porsche,3060790. Accessed 4th of July, 2018.

Goes, P. G. (2014). Big data and IS research. *MIS Quarterly*, 38(3), iii-viii.

Hern, A. (2017). *How social media filter bubbles and algorithms influence the election*. Available under https://www.theguardian.com/technology/2017/may/22/social-media-election-facebook-filter-bubbles. Accessed 23th of January, 2018

IDC (2015). *Worldwide wearables market forecast to reach 45.7 million units shipped in 2015 and 126.1 Million Units in 2019*. Available under http://www.idc.com/getdoc.jsp?containerId=prUS25519615. Accessed 3th of January, 2016.

LaValle, S., Lesser, E., Shockley, R., Hopkins M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21-31.

Lieber, R. (2017): *How to protect yourself after the equifax breach.* Available under https://www.nytimes.com/interactive/2017/your-money/equifax-data-breach-credit.html. Accessed 23th of January, 2018.

Markus, M. L. (2015). New games, new rules, new scoreboards: The potential consequences of big data. *Journal of Information Technology, 30*(1), 58-59.

McAfee, A., & Brynjolfsson, E. (2012). Big data: the management revolution. *Harvard Business Review*, *October*.

Müller, O., Junglas, I., vom Brocke, J., & Debortoli, S. (2016). Utilizing big data analytics for information systems research: challenges, promises and guidelines. *European Journal of Information Systems*, *25*(3), 289-302.

Newell, S., & Marabelli, M. (2014). The crowd and sensors era: opportunities and challenges for individuals, organizations, society, and researchers. In *Proceedings of Thirty Fifth International Conference on Information System*s (ICIS 2014), Association for Information Systems, New Zealand, Auckland.

Newell, S., & Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: a call for action on the long-term societal effects of 'datification'. *Journal of Strategic Information Systems, 24*(1), 3-14.

Orlikowski, W.J., & Scott, S.V. (2015). The algorithm and the crowd: considering the materiality of service innovation. *MIS Quarterly, 39*(1), 201-216.

Piccoli, G., & Pigni, F. (2013). Harvesting external data: the potential of digital data streams. *MIS Quarterly Executive, 12*(1), 53-64

Piccoli, G., & Watson, R. (2008). Profit from customer data by identifying strategic opportunities and adopting the 'Born Digital' approach. *MIS Quarterly Executive, 7*(3), 113-122.

Porter, M. E., & Heppelmann, J. E. (2015). How smart, connected products are transforming companies. *Harvard Business Review, October*.

SBB (2018). *Smart City: Beitrag der SBB*. Available under https://www.sbb-immobilien.ch/sites/default/files/inline-files/SBB_SmartCity_Zielbild_A4_V13_DE.pdf. Accessed 4th of July, 2018.

Schindler (2017). *Schindler ahead debuts at HUAWEI CONNECT 2017: smart city, grow with the cloud*. Available under https://www.schindler.com/cn/internet/en/about-us/news/press-releases-2017/schindler_ahead.html. Accessed 4th of July, 2018.

Skålén, P., Gummerus, J., von Koskull, C., & Magnusson, P.R. (2015). Exploring value propositions and service innovation: a service-dominant logic study. *Journal of the Academy of Marketing Science, 43*(2), 137-158.

Tardy, F. (2015). *The AXA drive coach app, an innovative contribution to safer driving, now on the Apple Watch*. Available under https://www.axa.com/en/newsroom/press-releases/drive-coach-apple-watch-en. Accessed 4th of July, 2018.

Tufekci, Z., & King, B. (2014). *We can't trust Uber*. Available under https://www.nytimes.com/2014/12/08/opinion/we-cant-trust-uber.html. Accessed 23th of January, 2018.

Wieneke, A., Lehrer C. (2016). Generating and exploiting customer insights from social media data. *Electronic Markets, 26*(3), 245-268.

Woerner, S. L., & Wixom, B. H. (2015). Big data: extending the business strategy toolbox. *Journal of Information Technology,* 30(1), 60-62.

Yoo, Y., Boland Jr., R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science, 23*(5), 1398-1408.

Anhang 3: Fachbeitrag B - „Generating and exploiting customer insights from social media data“

Tabelle A3: Fakten zum Fachbeitrag B

Informationstyp	Beschreibung
Titel	Generating and exploiting customer insights from social media data
Autor(en)	Alexander Wieneke, Universität St.Gallen, Schweiz Christiane Lehrer, Universität St.Gallen, Schweiz
Publikationsorgan	Electronic Markets - The International Journal on Networked Business
Publication type	Fachjournal
Jahr der Veröffen-tlichung	2016
Ranking	B (VHS Jourqual 3.0 Ranking)
Status der Publikation	Veröffentlicht
Referenz	Wieneke, A., & Lehrer, C. (2016). Generating and exploiting customer insights from social media data. *Electronic Markets, 26*(3), 245-268.[5] [6]
Zugriff	https://link.springer.com/article/10.1007/s12525-016-0226-1

[5] Wie von der Prüfungsordnung der Universität St.Gallen (HSG) vorgeschrieben, findet sich im Folgenden eine Kopie sämtlicher Inhalte des erstellten Fachbeitrages. Als Quellenangabe ist die in Tabelle A3 angegebene Referenz zu verwenden. Diese verweist auf die veröffentlichte Originalversion des Fachbeitrages.

[6] “The final publication is available at link.springer.com”

Generating and Exploiting Customer Insights from Social Media Data

Alexander Wieneke[1] & Christiane Lehrer[1]

Abstract

Previous research has emphasized the virtues of customer insights as a key source of competitive advantage. The rise of customers' social media use allows firms to collect customer data in an ever-increasing volume and variety. However, to date, little is known about the capabilities required of firms to turn social media data into valuable customer insights and exploit these insights to create added value for customers. Based on the dynamic capabilities perspective, in particular the concept of absorptive capacity (ACAP), the authors conducted multiple case studies of seven mid-sized and large B2C firms in Switzerland and Germany. The results provide an in-depth analysis of the underlying processes of ACAP as well as contingent factors – that is, physical, human and organizational resources that underpin the firms' ACAP.

Keywords: *Customer insights, Customer data, Social media, Absorptive capacity, Capabilities*

[1]Institute of Information Management, University of St. Gallen (HSG), Unterer Graben 21, 9000 St. Gallen, Switzerland

Introduction

The proliferation of social media has radically changed the way people communicate and interact with each other. Today's "social customers" have a powerful voice in the marketplace and expect a similar level of interaction from the firms they choose to buy from (Greenberg 2010). The empowered customers' demands make it critical for businesses to manage their customers in an interactive, collaborative, and personalized way in order to survive (Greenberg 2010; Setia et al. 2013; Woodcock et al. 2011). For example, Barclays Bank has integrated various social media applications such as blogs and wikis to collaborate with customers and respond to their needs in an interactive way, in order to improve its overall business performance (Setia et al. 2013).

At the same time, firms have recognized the potential of social media as an external source of knowledge to learn about their customers' opinions, attitudes, and "emotional temperature" (Canhoto et al. 2013; Choudhury and Harrigan 2014; Woodcock et al. 2011). In today's dynamic marketplace, management scholars have emphasized the virtues of knowledge as a key source of competitive advantage (Jansen et al. 2005). To remain competitive, firms need to recognize and make sense of new valuable knowledge located outside of the firm's boundaries and incorporate it into their value creation processes (Jansen et al. 2005). Knowledge about customers has been cited as an especially precious competitive tool for two main reasons. First, a profound understanding of customer characteristics and preferences allows firms to offer products and services that provide superior value to the customer (García-Murillo and Annabi 2002). Second, knowledge about customers is invisible and thus difficult for competitors to imitate (Salojärvi and Sainio 2006). Social media constitutes a particularly rich source for obtaining customer knowledge. The rise of customers' social media usage allows firms to acquire customer data in an ever-increasing volume and variety (Choudhury and Harrigan 2014). Information from social media profiles (e.g., interests, preferences, life events) and online conversations (e.g., sentiment regarding a product or brand) can enrich master and transactional data (e.g., purchase history, visits to websites, response to marketing campaigns) (Greenberg 2010; Newell and Marabelli 2014). For example, Burberry combines enterprise data with social media data to accelerate the identification of emerging customer trends in order to make timely adjustments throughout its supply chain (Palmer et al. 2013). Cost-effective storage and advanced business intelligence and analytics technologies (e.g., text and big data analytics) enable firms to gather and analyze these huge sets of customer data (Chen et al. 2012; Dinter and Lorenz 2012).

Firms that have the capability not only to acquire but also to make sense of social media data in their business context can turn this data into valuable customer insights, that is, in-depth and actionable knowledge of customer needs and underlying motivations. These insights can be exploited to create added value to customers by tailoring offerings to their needs and serving "*what they want, the way they want it, and when they want it*" (Setia et al. 2013, p. 566). For example, Walmart analyzes a wide variety of social media data, including user updates, comments, transactions, images, and check-ins, and uses the derived customer insights to predict product demand and launch new products (Palmer et al. 2013). Thus, customer insights are becoming more and more valuable for improving business performance and gaining competitive advantage in target markets (Choudhury and Harrigan 2014; Greenberg 2010; Woodcock et al. 2011).

Despite the relevance of customer insights as a source of competitive advantage, there is a lack of research on how to capitalize on them (García-Murillo and Annabi 2002). Particularly little is known about the capabilities through which firms can utilize social media data to generate and exploit customer insights. Previous research in the field of information systems (IS) investigating how businesses use social media data to generate customer insights has primarily focused on technological aspects, that is, methodologies for gathering and analyzing customer data (e.g., Chau and Xu 2012; Lewis et al. 2013; Li et al. 2014), technical requirements for data analytics (e.g., Gallinucci et al. 2015; Rosemann et al.

2012), and application possibilities for social media analytics (e.g., He et al. 2013; Kalampokis et al. 2013; Rao and Kumar 2011). Only a small number of marketing studies examined specific organizational aspects, such as governance structures for the firm-wide communication of customer insights (Barwise and Meehan 2011; Stone and Woodcock 2014), challenges regarding their effective application (Greenberg 2010; Woodcock et al. 2011) and the impact of social media technology use on firms' customer relationship performance (Choudhury and Harrigan 2014; Trainor et al. 2014).

A strong focus on technology also prevails in practice. Firms heavily invest in technologies like social media gathering and analytics tools (e.g., social media monitoring) to make use of social media data (Choudhury and Harrigan 2014; Kleindienst et al. 2015). However, valuable customer insights cannot be achieved by relying on technology alone. While information technology (IT) is effective for gathering and processing social media data, the generation of customer insights also requires transforming the data into meaningful knowledge that is subsequently disseminated throughout the firm and acted upon (Smith et al. 2006). This implies, for example, that firms require human skills to interpret and understand the data, as well as organizational structures and processes to share and use the generated insights within the organization. A holistic understanding of the required capabilities and resources would enable firms to derive business value from social media data by developing and refining their knowledge-related mechanisms. This paper aims to close the existing research gap and poses the following research question:

How can firms generate and exploit customer insights from social media data?

We address this question by applying the theoretical lens of the dynamic capabilities perspective, especially the concept of absorptive capacity (ACAP). ACAP explains how firms can absorb externally generated knowledge and deploy it internally (Zahra and George 2002). Applying the four dimensions of ACAP, that is, acquisition, assimilation, transformation, and exploitation, allows us to investigate in detail the required capabilities through which firms can generate and exploit customer insights from social media data. Moreover, we study contingent factors that influence firms' ACAP, with a particular emphasis on internal factors. Methodologically, our study is based on multiple case studies of seven mid-sized and large B2C firms in Switzerland and Germany. With this approach, we follow Ambrosini and Bowman's (2009) call for more empirical research, in particular case studies, to shed light on the detailed micro-foundations of how firms deploy dynamic capabilities. Our research contribution is threefold. First, we contribute to the theoretical understanding of ACAP by shedding light on the fundamental building blocks of ACAP. Based on empirical findings, we show how firms deploy the underlying processes in the context of social media. Second, we identify and specify new contingent factors of ACAP in the context of social media, namely physical, human and organizational resources. By investigating technological and non-technological resources in combination we contribute to prior research in the IS field and strategic management. Third, our research highlights the unique characteristics of social media data and how they affect the required capabilities and contingent factors. Moreover, we discuss the limitations of social media data for customer insights generation and exploitation. From a practitioner's perspective, we provide a comprehensive overview of the organizational prerequisites necessary to turn social media data into actionable customer insights. By underlining the need to complement technological with non-technological resources and better integrate the two, we challenge the widespread practice of heavily investing in IT only. A better understanding of the capabilities and resources should be of great interest to practitioners eager to leverage social media data. It will allow managers to assess their current capabilities and resource setup, to identify gaps, and to allocate financial and personnel efforts accordingly.

This paper proceeds as follows. The next section introduces the concept of customer insights as well as the dynamic capabilities perspective, with a particular focus on the ACAP concept. Next, we describe the methodical approach of multiple case studies, followed by a presentation of our results regarding the underlying processes of ACAP and relevant contingent factors. We then turn to a discussion of the results and present implications for research and practice. The paper concludes with reflections on its limitations and suggestions for further research.

Theoretical background

This section presents the paper's theoretical background. We begin with a definition of customer insights and discuss the unique characteristics of social media data. Next, we present the dynamic capabilities perspective with specific emphasis on the ACAP concept. This section then discusses the factors influencing ACAP, which are further validated and specified in the multiple case studies conducted.

Customer insights generated from social media

Firms depend more and more on social media to interact with their customers (Choudhury and Harrigan 2014). Social media is defined as "*a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content*" (Kaplan and Haenlein 2010, p. 61). Social media include, among others, social networks (e.g., Facebook or hosted online communities), microblogging services (e.g., Twitter), video sharing (e.g., YouTube), and blogs. In this paper, we focus on social media aimed at existing and new customers as opposed to internal social media aimed at employees. About 80 % of executives have recognized the importance of social media for customer interaction and consider it a highly relevant aspect of business success (Hennig-Thurau et al. 2010). Research also highlights the usability of social media to achieve significant performance gains. First, social media increases the effectiveness of customer acquisition activities (Reinhold and Alt 2012). Second, social media offers new digital service channels (e.g., online brand communities) for co-creation activities and better customer service (Lehmkuhl and Jung 2013). Third, social media yields new strategies to generate customer insights (Greenberg 2010; Woodcock et al. 2011).

Customer insights are defined as the firm's "*understanding of current customer needs, the reasons behind these needs, and how these change over time*" (Hillebrand et al. 2011, 595), which can be exploited in the firm's value creation process. A firm with customer insights has profound knowledge about customer characteristics and preferences; it not only knows very well who its customers are, where they shop, and what they buy, but also has a deep understanding of the underlying motivations that trigger customers' attitudes and actions. Valuable customer insights are actionable, that is, they support decision-making and inform concrete business actions (e.g., personalization of marketing campaigns, creation of new products and services). Users' social media profiles, activities, and conversations constitute a promising source of customer data encompassing, among other things, sociodemographic characteristics, interests, life events, and opinions. These interactions lead to richer data compared to structured data from transactions, and they can help explain the drivers behind customer decisions and actions (García-Murillo and Annabi 2002). Yet, to generate customer insights from social media data, firms must be effective not only in collecting and analyzing this data but also in connecting it with existing customer records and synthesizing it in the context of the firm's objectives (Smith et al. 2006).

However, social media data has unique characteristics, which set it apart from other data sources and need to be considered when using this promising data source to generate customer insights. Social media data can be described as "big data" characterized by high volume, variety, and velocity (Holsapple et al. 2014). When tapping into social media, firms gain a vast number of heterogeneous data sets that usually originate from multiple sources, that is, social media platforms such as Facebook, Twitter, LinkedIn, Pinterest, internet forums, or microblogs (Dinter and Lorenz 2012). Each of these platforms provides data in different formats (Holsapple et al. 2014). Furthermore, processing the vast quantity of social media posts floods firms with unstructured data (Kurniawati et al. 2013). Unlike structured data (e.g., master or transactional customer data), unstructured data from social media platforms can be textual, based on human natural language, or non-textual, such as pictures, audio, or videos (Kurniawati et al. 2013). Comments on a firm's Facebook page, for example, are written in free form. They include abbreviations, special symbols, or different slangs. The creation of unstructured data distinguishes social media from other sources generating big data, for example, sensors in smartphones and wearables. In addition, many pieces of information published in these posts (e.g., holiday location, opinion, relationship status) have a high velocity and do not represent long-lasting states in customers' lives. This places particularly high demands on data quality management, as acquired social media data needs to be validated and updated at frequent intervals to ensure that data is current and consistent (Dinter and Lorenz 2012; Fan and Gordon 2014).

In sum, generating customer insights from social media data poses new challenges for firms' capabilities to explore and exploit this external knowledge source. Yet, firms that are able to analyze this data faster and feed valuable insights into their business units more frequently can potentially realize a competitive advantage and improve business performance (Choudhury and Harrigan 2014; Hillebrand et al. 2011).

Dynamic capabilities perspective and absorptive capacity

The dynamic capabilities perspective is an influential theoretical framework in strategic management literature for understanding how firms generate and sustain a competitive advantage (Teece et al. 1997). The dynamic capabilities perspective extends the resource-based view (RBV), which explains a firm's superior economic performance through its resource endowment. If a firm possesses resources that are simultaneously valuable (i.e., can be used to guide decisions), rare (i.e., not commonly held by competitors), inimitable (i.e., difficult and costly for others to replicate), and non-substitutable by other resources (Barney 1991), it enjoys a competitive advantage (Barney 1991). These four properties are commonly referred to as the VRIN criteria. Resources are broadly defined as "*all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm*" (Barney 1991, p. 101). In essence, resources encompass both tangible and intangible assets, as well as processes (Helfat and Peteraf 2003; Winter 2003).

However, the possession of VRIN resources at one point in time does not suffice to sustain a competitive advantage amid changing market conditions. As the RBV does not explain how valuable resources can be created or how the extant resource base can be altered over time, Teece et al. (1997) introduced the dynamic capabilities perspective as an extension of the RBV. Dynamic capabilities are a set of learned processes and activities that allow firms to change by enabling them to "*integrate, build, and reconfigure internal and external competences*" (Teece et al. 1997, p. 516). Adapting Teece et al.'s definition, many authors have formulated their own definitions of dynamic capabilities (Ambrosini and Bowman 2009). Eisenhardt and Martin (2000) define them as "*the firm's processes that use resources – specifically the processes to integrate, reconfigure, gain and release resources – to match and even create market change. Dynamic capabilities thus are the organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve, and die*" (1107). Despite multiple definitions, there is consensus that dynamic capabilities are intentional, persistent, and repeatable organizational processes that alter the firm's extant resource base with the aim of creating a new set of valuable resources (Ambrosini and Bowman 2009). In contrast, dynamic capabilities do not encompass ad hoc problem solving (Winter 2003), spontaneous interventions, or disjointed reactions to market changes (Ambrosini and Bowman 2009).

Eisenhardt and Martin (2000) suggest four types of dynamic capabilities: those that integrate resources (e.g., product development routines), reconfigure resources (e.g., organizational restructuring), gain resources (e.g., knowledge creation routines, acquisition), and release resources (e.g., exit routines). Knowledge creation routines focus on gaining new knowledge to build new thinking and capabilities within the firm. This concept is particularly important to the present study, as the process of generating customer insights from social media data can be regarded as a knowledge creation routine.

A key knowledge-based dynamic capability is ACAP, which helps firms understand how to absorb externally generated knowledge and deploy it internally. Cohen and Levinthal (1990) define it as "*the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to a commercial end*" (p. 128). Absorbing knowledge from the outside is of vital importance to firms' innovation orientation, since they cannot develop all relevant knowledge within the organization. Moreover, knowledge needs to be updated regularly to avoid obsolescence (Cohen and Levinthal 1990; Zahra and George 2002). Zahra and George (2002) state that ACAP is "*a dynamic capability that influences the firm's ability to create and deploy the knowledge necessary to build other organizational capabilities*" (p. 188). They explain that ACAP allows firms to create new knowledge from sources outside the firm's boundaries and deploy it to build other organizational capabilities (e.g., innovation or improvements in marketing, distribution, production). This enhances the firm's ability to adapt to changing market conditions and sustain competitive advantage.

To understand the concept of ACAP, it is important to differentiate between dynamic and organizational capabilities. ACAP, a dynamic capability, consists of a set of organizational capabilities to manage knowledge, in other words, "*a set of organizational routines and processes by which firms acquire, assimilate, transform, and exploit knowledge to produce a dynamic organizational capability*" (Zahra and George 2002, 186). Organizational capabilities, also called operational or ordinary capabilities, refer to a firm's ability to deploy resources, usually in combination. They are rooted in processes and routines that produce outputs by combining different resources (Helfat and Peteraf 2003). In essence, they are basic, functional processes that turn inputs into outputs and permit the firm to earn revenue and profit in the present (Winter 2003). While organizational capabilities support the firm's current operations, dynamic capabilities are change-oriented processes that impact and modify extant organizational capabilities.

Zahra and George (2002) propose that four organizational capabilities compose a firm's ACAP: (1) knowledge acquisition, (2) assimilation, (3) transformation, and (4) exploitation. Conceptualizing ACAP as a multidimensional construct is in line with Eisenhardt and Martin (2000), who argue that while often described vaguely, dynamic capabilities "*actually consist of identifiable and specific routines*" (p. 1107) that show "*commonalities in key features*" (p. 1110) across firms. The four organizational capabilities are distinct, but they need to build upon each other to create ACAP – a dynamic capability. This implies that firms must "*accurately sense changes in their competitive environment, including potential shifts in technology, competition, customers, and regulation*" (Harreld et al. 2007, p. 24, emphasis in the original) as well as "*act on these opportunities and threats; to be able to seize them by reconfiguring both tangible and intangible assets to meet new challenges*" (Harreld et al. 2007, p. 25, emphasis in the original). The extent to which a firm can perform each organizational capability depends on the implementation of structural, systematic, and procedural mechanisms within the firm. In the following we describe the four dimensions of ACAP in more detail.

(1) Acquisition describes a "*firm's capability to identify and acquire externally generated knowledge that is critical to its operations*" (Zahra and George 2002, 189). In this study, acquisition refers to the firm's ability to identify and acquire customer data through social media platforms and import it into the organization.

(2) Assimilation refers to "*the firm's routines and processes that allow it to analyze, process, interpret, and understand the information obtained from external sources*" (Zahra and George 2002,

p. 189). In this study, assimilation entails adequate internal routines to make sense of the social media data and turn it into customer knowledge.

Processes (1) and (2) represent a firm's potential ACAP (Zahra and George 2002), that is, the extent to which a firm can acquire and process external social media data.

(3) Transformation denotes "*a firm's capability to develop and refine the routines that facilitate combining existing knowledge and the newly acquired and assimilated knowledge*" (Zahra and George 2002, p. 190). In this study, transformation refers to the internal routines that relate the new customer knowledge to the existing knowledge base of the firm by updating, deleting, or interpreting existing customer knowledge in a different manner or adding new knowledge. The alignment of new and existing knowledge creates customer insights, that is, actionable customer knowledge.

(4) Exploitation is defined as the firm's capability "*to refine, extend, and leverage existing competencies or to create new ones by incorporating acquired and transformed knowledge into its operations*" (Zahra and George 2002, p. 190). In this study, exploitation represents a firm's ability to recognize new value-creating opportunities to better serve their customers and incorporate customer insights into concrete applications (e.g., new or improved products and services, new business models, or processes).

Processes (3) and (4) represent a firm's realized ACAP (Zahra and George 2002), in other words, the extent to which a firm can utilize the externally acquired customer insights.

Only a few studies have applied the ACAP concept to the context of social media. Ooms et al. (2015) examined how the use of social media in innovation processes affects socialization and coordination capabilities for ACAP. Hu and Schlagwein (2013) aimed to identify which use types of external and internal social media increase firms' ACAP and create business benefits. Other authors investigating social media in the organizational context have based their research on the dynamic capabilities perspective and the RBV. In a quantitative study, Choudhury and Harrigan (2014) and Trainor et al. (2014) used this theoretical framework to explain how firms use social media technology (e.g., Twitter or firm blogs), organizational resources (e.g., customer engagement initiatives), and internal capabilities (e.g., relational information processing) to achieve performance gains (e.g., customer relationship performance). However, to the best of our knowledge, no research has provided an in-depth investigation of the micro-foundations of ACAP's deployment by firms to generate customer insights from social media data.

Contingent factors

As explained above, organizational capabilities refer to processes that use and combine different resources (Eisenhardt and Martin 2000; Helfat and Peteraf 2003; Verona and Ravasi 2003). In other words, resources form the basis of a firm's capabilities, which deploy these resources to attain a desired goal (Wang and Ahmed 2007). However, to date, little is known about which resources a firm actually needs in order to develop and nurture the underlying capabilities of ACAP. Therefore, we aim to investigate the resources required in generating and exploiting customer insights from social media data and examine how these resources affect the capabilities of ACAP. In their conceptualization of ACAP, Zahra and George (2002) emphasized the need to examine the contingent conditions under which ACAP creates value. Of particular interest in this study are internal resources and their effects on ACAP. While previous research has provided initial insights into how organizational parameters affect ACAP, most studies have largely ignored this aspect (Jansen et al. 2005).

In their theoretical ACAP model, Zahra and George (2002) included the contingent factor of social integration mechanisms, which influences the components of ACAP, in particular assimilation and transformation. Social integration refers to informal and formal mechanisms that facilitate the sharing and eventual exploitation of knowledge. Meanwhile, Jansen et al. (2005) empirically investigated the effects of different organizational factors on the potential and realized ACAP of a business unit. The findings indicate that organizational mechanisms associated with coordination capabilities (i.e., cross-functional interfaces, participation in decision making, and job rotation) positively affect a unit's potential ACAP, while mechanisms associated with socialization capabilities (i.e., connectedness and socialization tactics) increase a unit's realized ACAP. Van den Bosch et al. (1999) showed the impact of different organizational forms (functional, divisional, and matrix organizational structure) and combinative capabilities (systems capabilities, coordination capabilities, and socialization capabilities) on a firm's ACAP. While these studies provide evidence on the influence of organizational determinants on ACAP, they do not give profound insight into which factors firms can actively manipulate in order to increase their ACAP. In line with the dynamic capabilities perspective, which serves as the theoretical foundation of our study, we argue that it is crucial to identify and examine the specific resources that form the basis of the ACAP capabilities. Studying the effects of organizational resources on the dimensions of ACAP would clarify how this dynamic capability can be developed and would help explain why some firms are better than others at managing the underlying processes of ACAP.

In this study, we adopt the widely used classification by Barney (1991), which groups resources into three categories: (1) physical, (2) human, and (3) organizational resources. We suggest that these are linked, in different ways, to the capabilities forming ACAP. This is in line with the definition of capabilities as processes that leverage specific resources (Eisenhardt and Martin 2000; Verona and Ravasi 2003). In the following, we discuss the three types of resources in more detail.

Physical resources refer to the physical infrastructure and technology used in a firm, such as plants, equipment, and finances (Barney 1991), as well as the IT infrastructure comprising computer and communication technologies, technical platforms, and databases (Bharadwaj 2000; Ross et al. 1996). In this study, we are concerned with the role of physical resources, in particular IS, as a factor influencing ACAP. IS has great potential to enhance a firm's ability to acquire, store, process, and analyze large amounts of data and deliver and distribute meaningful insights throughout the organization. Previous research suggests that IS impact on ACAP (Roberts et al. 2012) and that ACAP benefits from the judicious deployment of IT-based resources, for example, business intelligence tools (Yeoh et al. 2013).

Human resources relate to the firm's workforce, that is, non-management employees as well as managers. This factor takes into account their knowledge and skills coupled with their experience, judgment, intelligence, and relationships (Barney 1991). In this study we are interested in the role of the firm's workforce vis-à-vis ACAP. Past studies have shown the relevance of human resources for ACAP. Verona and Ravasi (2003) found that employees' special skills and expertise as well as their motivation positively affected knowledge creation and absorption, integration, and reconfiguration. Lane et al. (2006) pointed out that prior research neglected the role of individuals in developing, deploying, and maintaining ACAP. They underlined the high relevance of individuals for knowledge processing and argued that "*what creates competitive advantage out of knowledge is the unique and valuable ways in which it is combined and applied. This uniqueness arises from the personal knowledge and mental models of the individuals within the firm, who scan the knowledge environment, bring the knowledge into the firm, and exploit the knowledge in products, processes, and services*" (Lane et al. 2006, p. 854). Consequently, they called for further research on the role of individuals for ACAP.

Organizational resources relate to configuration of an organization's various parts. This resource category encompasses corporate governance mechanisms such as formal reporting lines as well as planning, controlling, and coordination systems. Moreover, it includes informal inter-departmental relationships and external networks (e.g., relationships with other firms or customers) (Barney 1991). In this research, we are interested how organizational resources impact a firm's ACAP. Zahra and George (2002) proposed social integration mechanisms as an important contingent factor that lowers the barriers between assimilation and transformation, thus increasing ACAP. Verona and Ravasi (2003) noted that structures and systems (roles, incentives, etc.) as well as the organizational culture (values, norms) constitute the organizational context that guides people's behavior and affects knowledge flows within the firm.

Research method

In this study, we aim to examine the underlying processes of ACAP and relevant contingent factors that allow firms to generate and exploit customer insights from social media data. We chose a case study approach, following the recommendations of Eisenhardt (1989), Paré (2004), and Yin (2009). According to Easterby-Smith et al. (2008), qualitative approaches are better suited than quantitative methods to capture the nature of ACAP and its underlying processes. The case study is undertaken within the positivist research paradigm, because our aim is to generate generalizable results (Eisenhardt 1989; Paré 2004). In the following four sub-sections, we describe the identification of preliminary constructs, the case study design, the data collection, and the data analysis procedure to ensure a rigorous and transparent research process.

Identification of preliminary constructs

When following the positivist research paradigm, the researcher should draw on preliminary constructs (Eisenhardt 1989; Paré 2004). Preliminary constructs, also called "seed categories," can be described as "*potentially important variables, with some reference to extant literature*" (Eisenhardt 1989, p. 536). They should guide the researcher during the research process when handling the vast amount of collected field data (Yin 2009). Furthermore, preliminary constructs help avoid results that are biased because "*investigators reach premature and even false conclusions*" (Eisenhardt 1989, p. 540). To enhance the generalizability of the case study results, the core constructs should be derived from existing literature; if they prove important, the researchers have a firmer empirical grounding for their findings (Eisenhardt 1989).

Since the dimensions of the ACAP concept and the contingent factors are rather general, we aimed to specify them by conducting a literature review in accordance with previous research (e.g., Eisenhardt and Bourgeois 1988; Keil 1995; Mehta and Hirschheim 2007; Olsson et al. 2008). Appendix A describes the methodology used to identify relevant publications.

A systematic and comprehensive literature search resulted in a coding set of 29 articles. When analyzing these articles, we extracted quotations on required capabilities and contingent factors. In a first round, we clustered them into 11 candidate preliminary constructs: data gathering, data analysis, data integration, transformation into actionable insights, definition of action possibilities, technology as an enabler, analytical knowledge, interpretative knowledge, customer insight governance, cross-functional communication, customer value creation. To avoid duplicates or constructs with a low degree of selectivity, the list was refined continuously by renaming or summarizing the candidate preliminary constructs. For example, "technology as an enabler" became "information and communication technology" (ICT), while "data gathering," "data analysis," "data integration," "transformation into actionable insights," and "definition of action possibilities" were consolidated into "absorptive capacity." During the entire analysis of the identified articles, the authors jointly read the papers and extracted relevant quotations. Conflicts were discussed with a senior researcher, which limited the risk of bias in data collection and inconsistency of the obtained data. Table 1 presents the six preliminary constructs identified from the literature. Further details on the coding process and the preliminary constructs are provided in Appendix B.

As shown in Table 1, none of the identified articles covers all six of the preliminary constructs. Moreover, the small number of identified studies indicates that previous research has paid relatively little attention to the topic under investigation. In fact, most of the authors mentioned the potentially relevant constructs only in passing and did not provide detailed descriptions. Following Paré (2004), we considered the identified preliminary constructs to be tentative and did not restrict ourselves to these constructs during the case studies.

Case study design

Perceived asmore robust than single case studies, we conducted multiple case studies to ensure the generalizability of the constructs identified (Eisenhardt 1989; Paré 2004). Multiple case studies allow us to identify the commonalities of the processes that underlie ACAP across firms. With this approach, we concur with Eisenhardt and Martin (2000), who argue that dynamic capabilities show identifiable commonalities across firms and do not have to be firm-specific. The authors explain that "*while dynamic capabilities are certainly idiosyncratic in their details, the equally striking observation is that specific dynamic capabilities also exhibit common features that are associated with effective processes across firms*" (Eisenhardt and Martin 2000, p. 1108). They conclude that "*the functionality of dynamic capabilities can be duplicated across firms*" (p. 1106) and that many firms share similar dynamic capabilities.

The unit of analysis focuses on the management of customer insights in the context of social media at the firm's level. Applying literal replication logic, we selected cases with intrinsic similarities that were expected to yield similar results (Paré 2004). The cases included in this study were chosen based on the selection criteria of firm size, sales model, country, strategy, and level of maturity with regard to leveraging social media. As the generation of a comprehensive and coherent picture of the customer involves substantial efforts (Choudhury and Harrigan 2014; Wills and Williams 2004), only mid-sized and large B2C firms were considered in the sampling process. To rule out cultural differences, the cases were drawn from Switzerland and Germany as countries with significant cultural closeness.

Table 1: Results of the literature review

Identified articles	Absorptive capacity	Information and communication technology	Analytical skills	Understanding of the business context	Customer insight governance	Customer-oriented culture
Bailey et al. (2009)			x	x	x	
Baird und Gonzalez-Wertz (2011)	x					x
Barwise and Meehan (2011)	x				x	x
Berman and Korsten (2014)	x	x	x		x	x
Bijmolt et al. (2010)	x	x			x	x
Bingham (2005)	x				x	x
Brown et al. (2008)	x	x			x	x
Canhoto et al. (2013)	x	x	x		x	
Choudhury and Harrigan (2014)	x	x	x		x	x
Clauser (2001)	x					x
Dinter and Lorenz (2012)	x	x	x	x	x	
Greenberg (2010)	x	x			x	x
Hauser (2007)	x	x	x	x		
Hillebrand et al. (2011)	x		x			x
Hirschowitz (2001)	x	x			x	
Hubbell and Redding (2003)	x	x	x		x	x
Jayachandran et al. (2005)	x	x			x	x
Langford and Schulz (2006)	x					x
Lemke et al. (2011)	x					x
Malthouse et al. (2013)	x				x	x
Peltier et al. (2013)	x	x			x	x
Reinhold and Alt (2012)	x	x			x	
Saarijärvi et al. (2013)	x				x	
Saraf et al. (2013)	x		x		x	x
Smith et al. (2006)	x					x
Stone and Woodcock (2014)		x	x	x	x	
Verhoef et al. (2010)	x	x				x
Wills and Williams (2004)	x	x			x	x
Woodcock et al. (2011)	x				x	x
Sum	27	16	10	4	21	21

Moreover, all selected firms shared comparable strategies and levels of maturity with regard to leveraging social media as a data source for generating customer insights.The firms aimed to improve their customer relationship managementby enhancing their customer orientation. Due to competitive pressure, they had recognized the necessity to respond to their customers' needs in a more personalized way and to increase customer satisfaction and loyalty. Addressing these market requirements, the case organizations had enhanced their capability to absorb external customer knowledge and use it internally. To this end, they had utilized social mediachannels and implemented technologies to improve customer data management and analytics. All firms had already run successful pilot projects endorsed by the management board, in which they extracted social media data to generate customer insights. Case variance was attained based on industry sector in order to verify that the prerequisites were not industry- or firmspecific, enhancing the generalizability of the results (Paré 2004). We stopped gathering cases when we recognized that we had reached theoretical saturation (Eisenhardt 1989). In sum, seven firms from Switzerland and Germany from different industry sectors took part in this study (see Table 2).

Data collection

As the primary data source, we used semi-structured interviews, "*a highly efficient way to gather rich, empirical data, especially when the phenomenon of interest is highly episodic and infrequent*" (Eisenhardt and Graebner 2007, 28). For each case, we acquired two to four participants.

Table 2: Case description

Case name	Country	Industry sector	Total number of employees	Revenue in 2015 (in billion EUR)
A	Switzerland	Telecommunication	~ 20.000	~ 11
B	Switzerland	Health insurance	~ 3.000	~ 5
C	Switzerland	Insurance	~ 4.000	~ 10
D	Germany	Aviation	~ 100.000	~ 30
E	Germany	Railway	~ 300.000	~ 30
F	Germany	E-commerce	~ 1.000	~ 0.1
G	Germany	Automotive	~ 70.000	~ 50

The interviewees were selected based on the heuristic of purposeful sampling (Paré 2004). Since generating customer insights involved different business units in each firm, we deliberately chose experts from the respective functional areas and hierarchical levels. All of the participants were key informants with direct involvement in the management of customer insights or related processes and could provide a strategic perspective on the application of social media and data management in the respective firm. This resulted in 19 interviews, which were conducted over a period of three months from January to March 2015 (see Table 3). The rather small number of interviews per case is still sufficient to generate robust case study results, as the primary goal of our study is to identify generalizable constructs across all cases rather than conduct in-depth cross industry or cross-firm comparisons (Paré 2004). Interviewing experts from different functional areas and hierarchical levels across all cases allowed us to capture the relevant required processes and resources from multiple perspectives, which enhances the reliability of the case study results (Paré 2004).

Table 3: Interview partners

Case name	Interview number	Interviewee's position
A	1	Business owner social media customer experience
	2	Team leader social media marketing
B	3	Community manager
	4	CIO
C	5	Senior social media manager
	6	Head of market research
	7	IT project manager
	8	Head of CRM
D	9	Project lead web analytics
	10	Head of marketing communication
	11	Senior manager dialogue marketing
E	12	Social media manager
	13	Social media manager
	14	Head of CRM
F	15	Head of digital analytics
	16	Head of CRM
	17	Senior expert social media
G	18	Project lead data analytics
	19	Head of online communication

We conducted interviews with open-ended questions, which allowed us to follow up on interesting and unexpected responses, while the interviewees were free to elaborate their perceptions, experiences, and reflections (Paré 2004). The participants were first asked about their understanding of customer insights before a definition of customer insights was provided to ensure a common understanding. Then, questions were asked about how the firms generate and exploit customer insights, the role of social media, and the firm's pursued goals. Following this, the interviewees were asked to state prerequisites for generating customer insights through social media and using them in the firm. The subsequent questions addressed the required capabilities and the required physical, human, and organizational resources. However, since we did not want to impose our theoretical framework on the interviewees' interpretations, we deliberately refrained from including the identified preliminary constructs in the interview guide. This way, we ensured unbiased data collection instead of simply confirming the preliminary constructs. The interview concludedwith questions about challenges and potentially relevant trends (for the interview questions, see Appendix C). The interviews lasted between 45 and 60 min and were recorded and transcribed verbatim to analyze the data in a rigorous and transparent manner.

In addition, we used data triangulation because the development of converging lines of data collection leads to greater confidence in the findings (Yin 2009). Thus, as a further source of data, we collected relevant documentation about the management of customer insights for each case (Paré 2004; Yin 2009), including internal presentations, project schedules, external press releases, and business reports. These documents primarily served the purpose of providing valuable background information to clarify the information gathered during the interviews (Paré 2004).

Data analysis

Cross-case analysis was used as the study's data analysis strategy. First, the technique treats each case as a separate study (Eisenhardt 1989; Paré 2004; Yin 2009). In this way, the investigator is able to focus on the collected case data separately in order to become familiar with each case. In a second step, the findings of the "within-case analyses" are aggregated to investigate whether they make sense beyond each individual case and to reach generalizability (Eisenhardt 1989; Paré 2004).

We used the coding technique as the analysis technique, leading to data reduction and generalization. To examine our data, we followed a three-stage process of open, axial, and selective coding (Bhattacherjee 2012). Each step of the coding process was conducted independently by the different authors, accompanied by regular discussions to avoid subjective interpretation and enhance validity. First, we openly coded the interview transcripts and the documents, line by line, and identified initial constructs (e.g., "customer orientation," and "cultural change"). Second, these initial constructs were assigned to dynamic capabilities or the respective contingent factor (e.g., the initial constructs "customer orientation," and "cultural change" were assigned to "organizational resources"). Third, we aggregated the initial constructs into meaningful core categories. To ensure that we did not "*reach premature and even false conclusions*" (Eisenhardt 1989, 540) during the coding process, we used the preliminary constructs previously identified in our literature review as an orientation framework (Paré 2004). When we found similarities between the field data and the preliminary constructs, we used the latter as the final core category (e.g., "customer orientation," and "cultural change" were aggregated to "customer-oriented culture"). Where the field data deviated from the preliminary constructs, we created a new core construct (e.g., "iterative customer insight generation"). This way we remained open to the field data; none of the preliminary constructs were guaranteed to be part of the research outcome and could be modified or supplemented with new constructs if necessary. As a result, one additional dimension was identified through the case study approach, namely iterative customer insight generation. Table 4 provides an overview of our results and presents a short description of each required capability and the relevant contingent factors.

Results

The following sections present our findings on the required capabilities and resources that allow firms to generate and exploit customer insights from social media data. Based on our case study interviews, we identify a total of seven dimensions – processes underlying the firms' ACAP and resources that they rely on – required of firms to carry this out effectively. However, before explaining each dimension in detail, it is helpful to elaborate on what the case organizations identified as unique characteristics of social media data. We use this as a starting point, referring to specific characteristics if they are relevant for the required capabilities and resources.

Unique characteristics of social media data

Our case organizations highlighted the great potential ofsocial media data to generate customer insights. In particular, they underlined the possibility of gathering psychographic data in order to understand and predict customer behavior. The team leader of social media marketing in Case A described the new opportunities best: "*Social media is where the party is happening. We have the opportunity to observe them [the customers] in their private lives and gather data about the customers' everyday lives, for example, their hobbies and interests*" (Interview 2). However, the case organizations confirmed the challenge of managing social media data because of its unique characteristics. Compared to other data sources, the volume, variety, and velocity of social media data is particularly pronounced. The firms collect data on multiple platforms in order to gain information on different facets of people's lives, gathering large and heterogeneous data sets. In addition, the volume and variety of social media data is high due to the fact that one unique user activity on a social media platform (e.g., publishing a post) generates several types of data. For example, one post can include pictures, comments, location-based information, and cross-links to other users. With regard to velocity, the case organizations mentioned the high change frequency of social media data: "*We have found that social media data can only be described as current within an average period of six months. That means we have to update the data base as often as possible*" (Interview 2). Another characteristic of social media is its controversial validity. Almost all case organizations stated that much social media data is useless because the demographic data provided by the users is often wrong or outdated: "*Many of our customers state false information about themselves. They use wrong names or enter the wrong place of residence. That's why it is really complicated to identify our customers on social media platforms and make use of the gathered data*" (Interview 19). Considering the unique characteristics of social media data, the firms recognized the specific challenges regarding the capabilities required to generate and exploit customer insights. The head of market research in Case C specifically emphasized this point: "*The generation of insights from social media data poses great challenges because of the unique characteristics of social media data. In order to tackle the challenge, we need to change several aspects regarding the collection, analysis, interpretation, and use of the data sources*" (Interview 6). In the following section, the required capabilities and relevant contingent factors are explained in detail.

Table 4: Description of required capabilities and contingent factors

Required capabilities and contingent factors		**Description**
Dynamic capabilities	Absorptive capacity	Firm's ability to acquire, assimilate, and transform social media data into actionable customer insights and exploit these insights to build other organizational capabilities.
	Iterative customer insight generation	Iterative process of improving the ability to acquire, assimilate, and transform social media data into actionable customer insights and exploit these insights based on learning-by-doing.
Physical resources	Information and communication technology	IT landscape, including applications and database systems that support a firm in gathering and analyzing unstructured social media data in combination with structured internal data, as well as communicating the insights throughout the organization.
Human resources	Analytical skills	Employees' knowledge of analytical methods and ability to handle advanced data analytics tools.
	Understanding of the business context	Employees' understanding of the firm's business context, the relevant business problems, and the ability to leverage the available customer data in a way that provides actionable customer insights, which enable the business to make decisions.
Organizational resources	Customer insight governance	Organizational and operational structures that enable cross-departmental cooperation and communication of the right insights to the right place, at the right time. Internal rules based on legal regulations and ethical norms for the responsible use of private customer data.
	Customer-oriented culture	Mindset of employees in considering customer needs in their daily work. This implies the consideration of customers' added value when defining application purposes grounded in customer insights.

Dynamic capabilities perspective

Absorptive capacity

The participant organizations value social media as an important source of customer knowledge located outside of the firm's boundaries. In order to generate customer insights from social media data and incorporate them into value creation processes, they draw on capabilities for acquiring, assimilating, transforming, and exploiting social media data.

For data acquisition from social media, the case organizations utilize multiple social media platforms, in particular social networks (e.g., Facebook or hosted online communities) and microblogging services (e.g., Twitter). They reported that the high volume, velocity, and variety of social media data make it critical to gather the relevant data in a fast and targeted manner. It is not efficient to gather all available social media data; this would overstrain the firms, requiring too much effort to handle the vast amount of heterogeneous data and prepare the raw data for analysis. Due to the high velocity of social media data, the firms would risk letting the data become outdated before they could make use of it: "*It is not efficient to gather all available data on all available platforms. We are not able to handle such a vast amount of data. Before we are ready to analyze these data sets, the data is already outdated. Therefore, we must act in a targeted manner and collect only data that is valuable for the insight generation*" (Interview 19). Consequently, the case organizations screen different platforms regularly and assess which of them provide valuable data for insight generation. Furthermore, the firms underlined the importance of IT to enhance their acquisition capability. They cited specific IT tools that can automatically filter out non-valuable and non-critical data. The head of marketing communication in Case D emphasized: "*One social media platform alone already provides way too much data. Additionally, many data sets are useless because of the controversial validity. Therefore it is important that only the valid and valuable data sets are automatically collected*" (Interview 10).

Assimilation capability was described by the case organizations as the ability to process and analyze social media data. The data, they emphasized, should be analyzed in a way that generates valuable knowledge for all internal stakeholders. Due to the high volume and variety of social media data, the analysis can provide many opportunities for knowledge creation. However, to support evidence-based decision-making, it must be based on relevant business needs. In order to ensure the value of generated knowledge for internal stakeholders, the case organizations first define relevant questions and hypotheses about customer behavior. Several interview partners cited the example of cross- and upselling opportunities for a specific customer segment. As described by the Head of CRM in Case F, these questions and hypotheses were discussed regularly in meetings between the analysts and the relevant stakeholders. Analysts thereby gained an in-depth understanding of the stakeholders' knowledge requirements to improve their decision-making. "*For the customer insight department, it is important to have a concrete question to answer. Only then it is possible to say what you want to know and to precede in a purposeful analysis*" (Interview 1). In order to generate a profound database for data analysis, the participant organizations combine the data absorbed from different social media platforms and create a holistic picture of customers' behavior. Afterwards, the data is analyzed with regard to the predefined questions. The assimilation capability relies on employees with advanced analytical skills.

Transformation capability was described by the case organizations as the ability to communicate newly generated knowledge to the relevant stakeholders and connect it with existing knowledge. Due to the velocity of social media data, the case organizations establish lean and unbureaucratic communication routines to ensure that the newly generated knowledge be communicated to the right stakeholder in a timely and direct manner. "*Of course it's already a success if we have generated relevant insights. But in the end, it is vital to communicate the insights to the department that needs them for the improvement of their business processes*" (Interview 5). Transformation capability is underpinned in the firms by specific technological applications that visualize the knowledge and increase its understandability. However, to follow through on transformation capability, the employees must be willing to combine the newly generated knowledge with their existing knowledge and to update their perceptions about their firm and its market environment. To increase acceptance of social media data and thus the firm's transformation capability, the case organizations stressed that employees require special training on how to select and interpret the relevant information in order to avoid information overload (e.g., Interview 12). Moreover, the firms educate their employees on how to make use of the new knowledge, for example, through customer oriented campaigns and offers.

The participant organizations described exploitation capability as the ability to identify relevant applications for customer insights. The firms stated that insights from social media regarding customer preferences and behavior as well as market trends and patterns could be applied to several fields, including strategic management, business model innovation, product and service development, process improvement, and individualization of customer interactions. For example, the participating health insurance firm (Case B) reported analyzing customer complaints on its Facebook page, with the goal of identifying failures in its customer service chain and reacting as soon as possible. The challenge lies in identifying applications for the generated customer insights that provide the most value to the firm: "*To generate actionable insights in an effective and efficient manner, we need to ask ourselves: What are the insights for? We need to analyze the whole value chain as well as the customer journey to find relevant touch points that can be improved by customer insights*" (Interview 7).

Iterative customer insight generation

By using social media as external source, firms enter a new, unknown field (e.g., Interview 10). For this reason, the case organizations mentioned that generating and exploiting customer insights should be treated as an iterative process (e.g., Interview 9). In other words, the acquisition, assimilation, transformation, and exploitation capabilities should be developed and optimized through feedback loops. First, with regard to data acquisition, the firms find it important to predefine criteria in order to collect only relevant social media data. At the same time, they have to screen the available social media platforms and the data provided with open minds: "*Subsequent to an interaction with the customer, we should analyze whether the gained data offers new possibilities and ideas for insight generation*" (Interview 9). To make things more complex, technological innovation constantly produces new social media platforms and thus new data to be identified and assessed with regard to opportunities for customer insight generation. Second, with regard to assimilation, the case organizations explained that their employees redefine the underlying questions and hypotheses for data analysis at frequent intervals based on their experiences, which helps them to communicate their knowledge needs to the analysts more precisely. This feedback loop enables analysts to adapt their activities to changing objectives and requirements and to improve the effectiveness of the data analysis process. Third, the case organizations regularly scrutinize the application fields for customer insights. They reported that altering or extending the application fields can result from either changes in a firm's strategy because of changes in the market environment or technological advancements that provide new opportunities to exploit customer insights. In sum, the firms need to scrutinize their processes and routines regularly in order to constantly develop new ideas for customer insight generation and exploitation and adapt to changes in the environment (e.g., Interview 13). Ideally, a firm's ACAP can be enhanced over time through learning-by-doing.

Physical resources

Information and communication technology

The case organizations stated that ICT plays an important role in underpinning various ACAP processes. To be useful in the context of social media data, a firm's ICT has to be adapted to the specific characteristics of this data source. The project lead for data analytics in Case G summarized: "*In sum, I would say that we require an IT architecture that enables us to exploit the potential of big data gathered from a vast amount of different sources*" (Interview 18). In order to acquire data from the variety of social media platforms, the case organizations use several application programming interfaces (APIs), or web crawlers. The IT project manager in Case C highlighted the importance of rule-based engines in facilitating the acquisition capability and avoiding the collection of useless data sets. Rule-based engines help firms to automatically classify social media data in terms of relevance. To enhance assimilation capability, some case organizations use data aggregation tools, which enable them to transform the unstructured text-based data sets into data formats useful for data analysis. "*Overall, specific tools help us to overcome the challenges of semantic computing*" (Interview 4). In particular, several firms cited a need for text analysis tools, that is, natural-language processing engines. These tools identify salient entities (e.g., names of products or names of customers) or facts (e.g., low quality or dissatisfaction) in large amounts of unstructured textual data. This allows firms to interpret the vast amount of user generated content and determine customers' opinions and sentiment. Moreover, interview partners stressed the importance of connecting data sets gathered from different social media platforms with internal data and storing everything in a central database: "*One of the most important aspects from a technological perspective is the integration of social media and internal data to build a central database*" (Interview 18). The majority of case organizations referred to "Hadoop" database technology, which facilitates the storage and rapid analysis of huge amounts of heterogeneous, unstructured data. The team leader of social media marketing in Case A highlighted the importance of Hadoop: "*Because of the high velocity of customer data, the data must be processed as soon as possible. If it takes too long, the data is no longer current and its impact is low*" (Interview 2). Interview partners also described ICT as a facilitator of transformation capability by making the right social media data readily available to the right employees. In particular, visual analytics tools enable business users to query the data and produce visualizations such as maps of social networks or key performance indicators of social media campaigns in real time. These visualized reports help stakeholders to understand and interpret the knowledge, combine it with existing knowledge, and generate actionable customer insights.

Human resources

Analytical skills

The case organizations noted the importance of specialized analysts familiar with advanced analytical methods to make sense of the social media data and turn it into customer knowledge. Having such analysts available, interview partners argued, positively affects a firm's assimilation capability. According to the senior social media manager in Case C: "*It is essential that the employees who are responsible for data analysis have a certain level of statistical knowledge*" (Interview 5). The case organizations highlighted the need for analysts to be familiar with building complex data models; in particular, they should have the skills to perform sentiment analysis and opinion mining to identify current trends and new behavioral patterns. In order to understand the concrete meaning of the analyzed posts, they have to define particular characteristics without technological support (e.g., a post's importance, whether it was meant ironically). Therefore, compared to other data sources (e.g., sensor data generated by digital devices), social media data analysis requires additional empathy. In addition, the firms stressed that their analysts should be aware of techniques related to topic modelling, social network analysis, and influencer analysis in order to expose relationships between social media users and to identify valuable influencers.

Understanding of the business context

Despite the high relevance of analytical skills, data analysts are ultimately much more than "*number crunchers*" (Interview 19). In order to generate valuable knowledge, the case organizations explained, data analysts need to understand the firm's business context: "*Our data scientists should be aware of the purpose of analyzing the data. They need to understand the questions that are posed by the front-office employees and the expected value from answering those questions. This way we can be ensured that the data analysis does not miss the target*" (Interview 1). The participant organizations mentioned strategic management, business model innovation, product and service development, process improvement, and individualization of customer interactions as relevant business areas that can benefit from customer insights generated from social media data. For example, to support strategic decision-making, social media data can be transformed into competitive intelligence. Analyzing the social media presence and posts of competitors (e.g., social media page performance, promoted products) as well as comments about competitors (e.g., sentiment about brands and offers) helps firms to know where they stand and what needs to be improved. Consequently, to generate this valuable knowledge, the analysts should be aware of relevant competitors and benchmarks. They should be aware of the firms' marketing strategy to support the marketing department with relevant analyses. For example, to evaluate the performance of a social media campaign, the analysts need to understand the overall campaign objectives and be familiar with relevant key performance indicators, such as engagement rate (Interview 2). Thus, employees must be capable of deciding which data from social media platforms fulfills which specific purpose and answers which specific question. In sum, to exploit the potential of social media data, analysts require both analytical skills and the ability to anticipate the relevance of social media data and the derived customer insights.

Organizational resources

Customer insight governance

Customer insight governance, including organizational structures and operational processes as well as legal and ethical frameworks, is an important factor influencing a firm's ACAP. The case organizations referred to cross-departmental cooperation as an effective organizational structure: "*The management of customer insights is a joint effort by different departments like marketing, sales, or service. Our department alone is not capable of interpreting all data. Technical and statistical aspects need to be merged with the customer perspective that other employees have*" (Interview 18). Some case organizations took the argument one step further, proposing a centralized customer insight department that pools all expertise relevant to generating customer insights (e.g., Interview 13). To ensure that the customer insight department gets sufficient financial resources as well as an adequate hierarchical position to improve the impact of customer insights within the firm, it is necessary for the management board to confirm its commitment (e.g., Interview 3).

Customer insight governance also relates to legal and ethical frameworks. Using social media to gather customer data increases the risk of violating customers' privacy (e.g., Interview 4). To ensure that the social media monitoring initiatives and the integration of social media into existing databases neither libel the customers nor violate laws, the case organizations argued for a better development of legal and ethical frameworks that define the proper handling of customer insights. "*First, we have to convince the customer that we are a reliable and trustworthy partner. When this is achieved, the customers will share* *more data*" (Interview 5). In contrast to internal customer data, in most instances, firms need the customer's permission to use her personal social media data (e.g., Interview 13). To increase a customer's willingness to give permission to use her personal social media data, the case organizations proposed a "code of conduct" across firms that defines "ethical rules" for the use of customer data and insight generation (e.g. Interview 1). For example, by communicating the why, how, and when of data collection in a transparent and reassuring manner, firms send a strong message to the customer (e.g., Interview 19).

Customer-oriented culture

In this study, culture refers to the mindset, values, and beliefs of a firm and how these affect its ACAP. Participant organizations emphasized that in order to foster ACAP, a willingness to generate and apply customer insights must be inherent in the firm's culture. Employees in all departments should be aware of the importance of actively seeking out new knowledge as well as updating their data and maintaining data consistency (e.g., Interview 7). It is especially crucial for customer-facing units to base all of their actions on customer insights to individualize the customer interaction (e.g., Interview 14). To this end, according to the case organizations, employees must be willing to "listen to the crowd." Customer-oriented culture also takes into account the degree to which employees consider customer needs in their daily work. Due to the sensitivity of social media data, the case organizations highlighted that customers expect an added value from giving their personal data to the firm (e.g., Interview 15). "*We started to form personas that describe our target groups and then we define relevant use cases based on customer insights that generate benefits for each of them*" (Interview 14). Establishing a customer-oriented culture lived by the entire staff can support the acquisition of social media data by giving the employees the right mindset to create the necessary added value to the customer (e.g. Interview 5).

To summarize, Table 5 provides an overview of all required processes and resources. As shown in Table 5, all seven required processes and resources were mentioned in at least five of the seven case organizations from different industries. Although the primary goal of this study was to identify generalizable constructs across all cases rather than conduct case comparisons, it is interesting to point out a few minor differences. When analyzing the quantitative results in Table 5, slight differences emerge among the cases regarding their mentions of dynamic capabilities and contingent factors. ACAP, as well as the contingent factors ICT and customer insight governance, were explicitly mentioned as important dimensions in all seven cases and by nearly all interviewees. Understanding of the business context, customer-oriented culture, and iterative customer insight generation were mentioned in six of the seven cases, while only five cases cited the need for analytical skills. While these differences should not be overstated, they may indicate varying importance of the prerequisites across industries. Interestingly, interview partners from the telecommunications and railway cases did not explicitly state analytical skills as a required human resource for the successful generation of customer insights.

Table 5: Required processes and resources mentioned in case studies

Case / Inter-view	Interviewee's position	Absorptive capacity	Iterative customer insight gen-	Information and communica-	Analytical skills	Understanding of the business	Customer insight governance	Customer-oriented culture
A	Telecommunication	x	x	x		x	x	x
1	Business owner, social media customer experience	x	x			x	x	x
2	Team leader, social media marketing	x	x	x		x	x	x
B	Health Insurance	x	x	x	x	x	x	
3	Community manager	x		x	x	x	x	
4	CIO	x	x	x	x	x	x	
C	Insurance	x	x	x	x	x	x	x
5	Senior social media manager	x	x	x	x	x	x	x
6	Head of market research				x	x	x	
7	IT project manager	x	x	x	x		x	x
8	Head of CRM	x		x		x	x	x
D	Aviation	x	x	x	x	x	x	x
9	Project lead, web analytics	x	x	x	x	x	x	x
10	Head of marketing communication	x	x	x	x	x	x	x
11	Senior manager, dialogue marketing	x		x	x	x	x	
E	Railway	x	x	x		x	x	x
12	Social media manager	x	x	x		x	x	
13	Social media manager	x	x				x	x
14	Head of CRM	x		x			x	x
F	E-commerce	x	x	x	x		x	x
15	Head of digital analytics	x		x	x		x	x
16	Head of CRM	x		x				
17	Senior expert, social media	x	x				x	x
G	Automotive	x		x	x	x	x	x
18	Project lead, data analytics	x		x	x	x	x	x
19	Head of online communication	x		x	x	x	x	x
Number of mentions in interviews		18	10	15	11	13	18	13
Number of mentions in cases		7	6	7	5	6	7	6

It is possible that the experts in these two cases did not attribute particular relevance to analytical skills for different reasons. While data analytics departments were introduced a long time ago in the telecommunications industry and may be taken for granted, railway companies, as stated by the interviewees, do not yet possess large amounts of customer data, including social media data, whose analysis requires advanced analytical skills (Interview 14).

Understanding of the business context may not have been mentioned in the e-commerce case because, according to the experts from this firm, close coordination between marketers and data scientists is an established routine. The fact that customer-oriented culture was not addressed in the health insurance case may reflect the heavy data privacy regulation in this industry, which does not allow insurance firms to be as transparent and open in their customer interaction, especially via social media, as other industries (Belbey 2015). Additionally, from a customer perspective, the sensitivity of personal health data and the low interaction of many customers with their insurance companies decreases customer engagement on social media and their willingness to give permission for the use of their personal social media data (Levine 2015; Osakwe 2015). The interviewees in the automotive case specified the necessary steps for customer insight generation and exploitation, but did not explicitly highlight the need for an iterative process.

Despite these slight differences, the overall results show that there is broad consensus across the cases regarding the required capabilities and relevant contingent factors for the effective generation and exploitation of customer insights from social media data.

Discussion and implications

The aim of this study was to improve our understanding of how firms can generate and exploit customer insights from social media data. We addressed this question by applying the theoretical lens of the dynamic capabilities perspective, especially the ACAP construct. ACAP describes the firm's ability to create and deploy new external knowledge necessary to build other organizational capabilities (Zahra and George 2002). In today's dynamic marketplace, developing ACAP is relevant for firms as it positively affects innovativeness, firm performance, and competitive advantage (e.g., Jansen et al. 2005; Zahra and George 2002). Based on multiple case studies of seven mid-sized and large B2C firms in Switzerland and Germany, we shed light on the detailed micro-foundations of how firms deploy ACAP in the context of social media. As stipulated by Zahra and George (2002) we confirmed the relevance of all four dimensions of ACAP, that is, acquisition, assimilation, transformation and exploitation capabilities. Prior empirical research has mainly focused on the outcome of ACAP and thereby overemphasized the dimensions transformation and exploitation (Zahra and George 2002). Furthermore, we presented contingent factors, that is, physical, human and organizational resources, which are required by the firm to develop and nurture the underlying capabilities of ACAP. Having conducted multiple case studies allows us to generate generalizable results that can be applied across different industries.

In summary, we found evidence how firms can generate valuable insights about customer preferences and needs as well as market trends and patterns based on social media data. Our analysis and interpretation of the case interviews underlines that firms need to develop acquisition, assimilation, transformation and exploitation capabilities to harness the potential of social media as an external knowledge source. Firms require processes that facilitate acquiring social media data, understanding this data and sharing the generated customer insights internally. Ultimately, firms need to be skilled at applying the customer insights to develop products and services, create new business models, improve internal processes, and maneuver strategically. This way, firms can act more customer-oriented and potentially increase firm performance and competitive advantage. However, the unique characteristics of social media data, in particular its high volume, variety, velocity and controversial validity, pose new challenges for firms' processes to explore and exploit this external knowledge source. Furthermore, the processes need to be underpinned by specific physical, human and organizational resources that allow the firm to handle social media data internally.

In the following, we discuss the main findings of our empirical study with regard to the underlying capabilities of ACAP. On the one hand, we discuss how the unique characteristics of social media influence the required processes of a firm's ACAP. On the other hand, we relate specific aspects of the resources to the different processes. Furthermore, we highlight the limitations of social media data for customer insights generation and exploitation.

First, we discuss the acquisition and assimilation capabilities, which represent the firm's potential ACAP (Zahra and George 2002). In particular, these processes include the collection, analysis and interpretation of social media data. Our findings show that screening user-generated content on multiple social media platforms allows a fast and comprehensive absorption of real-time marketplace information. However, we found that the variety and constantly changing nature of social media platforms, the volume of generated data, and the multiplicity of opportunities for data analysis increase the complexity of acquisition and assimilation processes. This high complexity overwhelms firms and jeopardizes the successful generation of customer insights. In order to reduce the complexity, firms establish filter mechanisms, which reduce the amount of information influx and thus counteract the risk of information overload. Simplification and focus is achieved, for example, through screening the available social media platforms regularly and evaluating, which of them constitute a useful data source. Additionally, firms define criteria to assess the data in terms of relevance, validity and quality. With regard to data analysis, firms prefer a targeted approach and first define relevant questions and hypotheses about customer behavior in order to guarantee that the generated knowledge meets the business needs.

We found that specific resources underpin the acquisition and assimilation capabilities. In particular, technological applications are relevant facilitators. Data collection on several social media platforms is enabled by APIs and web crawlers, while rule-based engines support the automatic classification of data in terms of relevance and thereby serve as a filter. Natural-language processing engines enhance the firm's assimilation capability by transforming unstructured text-based data sets into data formats useful for analysis. Moreover, technology facilitates the storage and rapid analysis of huge amounts of heterogeneous and unstructured data, such as Hadoop database technologies. Beyond technology, human skills are required to interpret and understand the acquired data. One the one hand, experts with specific statistical skills and a profound understanding of the firm's business context can derive valuable and applicable knowledge. One the other hand, domain experts do not suffice to handle and interpret all the incoming data. In addition, it requires intense cross-departmental communication and cooperation or a centralized customer insight department to bring together all expertise relevant to make sense of the data. This finding is in line with Zahra and George (2002) who suggested the importance of social integration mechanisms, which link assimilation and transformation. Jansen et al. (2005) empirically confirmed that crossfunctional interfaces such as liaison personnel, task forces, and teams to enable knowledge exchange positively affect a business unit's potential ACAP.

Second, we turn to the transformation and exploitation capabilities. Transformation refers to the internal routines that communicate and relate the new customer knowledge to the existing knowledge base of the firm in order to allow for the creation of customer insights, that is, actionable customer knowledge (Zahra and George 2002). The aim of exploitation is to apply the customer insights to create new commercial outputs (Lane et al. 2006). Our results suggest that the effort spent on the acquisition and assimilation of social media data is worthless, when the generated knowledge is not communicated across the organization and transmuted in a timely manner. The velocity of social media data bears the risk that the knowledge is already outdated when it is applied and thus, the outcome falls short of the firm's expectations. To ensure knowledge is recent and relevant, lean and unbureaucratic communication processes need to be established across the whole organization. They need to ensure that the right knowledge is communicated to the right places, at the right time. Technological resources can support the transformation capability as shown by our analysis. In particular, visual analytic tools provide access to and increase the understandability of the generated knowledge. Thereby, they reduce the "*time to value*" (LaValle et al. 2011, 24). With regard to exploitation, we found that firms can capitalize on the customer insights generated from social media data by deploying them in strategic management, business model innovation, product and service development, process improvement, and individualization of customer interactions. Acting on customer insights allows firms to connect better with the marketplace by developing and commercializing new offerings faster and tailoring them to customer needs.

Furthermore, our results indicate that all four dimensions of ACAP are enhanced by a corporate culture, which recognizes the value of data and cultivates data generation and exploitation. Employees need to be willing and able to seek out data and apply customer insights, for example, to support decision-making regarding strategies and the fine-tuning of daily activities. However, traditional, non-tech firms often find that their employees lack the knowhow and confidence to make data-based decisions (Chen et al. 2012). Moreover, given the velocity and controversial validity of social media data, there is skepticism and distrust limiting employees' reliance on this data. As also suggested by Dinter and Lorenz (2012) employees require special training on how to explore and exploit social media data in order to increase acceptance. According to our results, another important aspect of corporate culture is the appreciation of the customer as the key provider for user-generated content. In order to increase the customers' willingness to share personal social media data, firms need to respect privacy regulations, earn the customers' trust and provide added value (Smith et al. 2011).

Third, we highlight the relevance of developing ACAP through an iterative approach. Firms that aim to generate customer insights from social media data are faced with an external data source that is not stable and constantly changes its nature. Technological innovation constantly brings about new social media platforms targeting new customer segments and supporting new use purposes. This continuously increases the amount of potential data for insights generation. Furthermore, over time, customers change their use behavior as well as their attitude towards sharing personal data on social media platforms. These changes must be identified and assessed with regard to opportunities and threats for customer insights generation. Firms must regularly screen the available social media platforms and the data provided for data acquisition. Regarding assimilation, the underlying questions and hypotheses for data analysis need to be redefined at frequent intervals based on experiences. Last but not least, in the light of technological advancements and changes in the marketplace firms need to regularly scrutinize possible application areas for customer insights. Thus, we argue that the ACAP concept proposed by Zahra and George (2002) should be extended by feedback loops.

Fourth, we discuss the limitations of social media data for customer insights generation and exploitation. Besides the new opportunities, our results indicate that social media data has constraints regarding the generation and exploitation of customer insights. As firms often rely on platforms offered by third parties, such as Facebook, firms have only limited access to customer data and there is a threat that access is restricted even further (Ghoshal 2015). Additionally, the handling of social media data is regulated by complex legal frameworks (Dinter and Lorenz 2012). Our findings highlight that there are specific legal restrictions to gathering and processing data from third-party platforms. In contrary to platforms offered by the firms (e.g., own online community), additional permissions of the customer are required. Both issues decrease the value of social media as an external data source. Furthermore, our results indicate that the controversial validity of social media data poses a challenge to firms and increases skepticism. On the one hand, the demographic data provided by the users is often wrong (e.g., false name or place of residence). This restricts opportunities to match internal data with social media data. Therefore, for example, a post on Facebook cannot be assigned to one specific customer. On the other hand, the fact that most usergenerated content consists of natural human language increases the probability of error when analyzing and interpreting the data (e.g., irony does not become clear). These constrains bear the risk of making wrong assumptions about individual customers' needs. Acting on these wrong customer insights, can lead to mistakes, which upset the customer and impair the customer relationship. Based on these findings, we call attention to the limitations of social media data and question the opinion often stated in practice and research that social media data provides great potential for "segment-of-one marketing" and individualized customer interaction (e.g., Greenberg 2010). Instead, we concur with Newell and Marabelli (2014) who see the value of social media in providing big data allowing aggregated analyses to identify general customer needs and new customer trends.

Implications for research

From a research perspective, the contribution of our study is threefold. First, we contribute to the theoretical understanding of ACAP by shedding light on the detailed micro-foundations of how firms deploy this dynamic capability. Based on empirical findings, we show how firms deploy the underlying processes in the context of social media. This way, we contribute to prior quantitative research on firms' use of social media technology (Choudhury and Harrigan 2014; Trainor et al. 2014). Furthermore, we suggest that the ACAP concept should be extended by feedback loops that allow the iterative improvement of firms' ACAP. This is in line with research in the field of big data analytics (e.g., Lavalle et al. 2011), which claims that firms are well advised to continuously refine their information processing routines.

Second, this research contributes to the ACAP concept by identifying and specifying new contingent factors in the context of social media, namely physical, human and organizational resources. Unlike previous conceptualizations of ACAP found in strategic management literature (e.g., Cohen and Levinthal 1990; Lane et al. 2006; Zahra and George 2002), we underline the need to include technology in the theoretical framework. In line with previous IS research, we demonstrated that technology is necessary to generate customer insights from social media. However, it needs to be combined with human skills and organizational resources. By investigating technological and non-technological resources in combination we contribute to prior research in the IS field, which has examined technological aspects of social media data use in isolation (e.g., Chau and Xu 2012; Lewis et al. 2013; Li et al. 2014). Additionally, we expand studies from marketing that have focused only on specific organizational aspects such as governance structures (e.g., Barwise and Meehan 2011). In contrast to prior quantitative (e.g., Choudhury and Harrigan 2014; Trainor et al. 2014) or conceptual studies (e.g., Greenberg 2010; Woodcock et al. 2011) related to the use of social media data in IS and marketing research, the case study approach enabled us to gain an indepth understanding of each contingent factor.

Third, our research highlights the unique characteristics of social media data and how they affect the required capabilities and contingent factors. Moreover, we discuss the limitations of social media data for customer insights generation and exploitation. In particular, we point out how the reliance on third party platforms, complex legal frameworks and controversial validity limits the value of social media data for firms. Thereby, we challenge previous research that highlighted the potential of social media data for individualized customer interaction (e.g., Greenberg 2010). In line with Newell and Marabelli (2014) we argue that social media data is mainly suited for aggregated analyses to identify general customer needs and new customer trends.

Implications for practice

For practitioners, our results allow firms with the capability to harness the vast and increasing amount of social media data to gain a deeper understanding of their customers' needs and make more informed customer-oriented decisions, such as providing personalized products and services. This, in turn, holds a potential to achieve competitive advantage.

Our study provides a comprehensive overview of the processes and resources necessary to turn social media data into actionable customer insights. By underlining the need to complement technological resources with non-technological resources and integrate the two, we challenge the widespread practice of heavily investing in IT only. While technology is indeed an important prerequisite for capturing customer data, maximum benefits can only be achieved if human and organizational resources are developed equally. Based on the seven dimensions – processes underlying the firms' ACAP and resources that they rely on – required of firms, managers can evaluate their firm's maturity in these areas and initiate suitable measures and investments in IT, HR development, organizational restructuring, and extensive change management. However, instead of developing and optimizing each resource in isolation, firms should place particular focus on the efficient interplay among the resources. However, it must be noted that ACAP, a dynamic capability, cannot be acquired overnight. Instead, it is the result of a long-term learning process that involves an iterative process of continuously improving the ability to acquire, assimilate, and transform social media data into actionable customer insights and exploit these insights based on learning-by-doing.

In sum, our research argues for expanding the common saying, "data is the new gold", to "the skillful use of data is the new gold." According to LaValle et al. (2011), this will determine the future winners in competitive markets. Firms that tackle the generation and use of customer insights through a comprehensive organizational approach have a realistic chance to be the future market leader. In contrast, firms that primarily focus on gathering data from all available sources and heavily investing only in technology in order to make quick performance gains, as promised by the software vendors, may remain in the race but will not realize the full potential of social media data.

Limitations and further research

Despite the careful design of our research approach, the findings are subject to some limitations that should be addressed by further research. First, the empirical data from the case studies enabled us to identify a set of seven capabilities and contingent factors that should be in place in order to generate and exploit customer insights from social media data. Regarding the significance of the contingent factors for customer insight generation and exploitation, further research should quantify the effect of each contingent factor on the ACAP. This will allow researchers to determine whether some contingent factors are more important than others. Furthermore, in order to fully understand the cumulative effect of the contingent factors, future studies should investigate potential relationships among them. This will help explore whether changes to specific contingent factors influence other factors and thereby have a positive or negative effect on the firm's ACAP. Our results also indicate that the importance of specific contingent factors may vary across industries. Further research should investigate this issue in more detail.

Second, only firms from Switzerland and Germany were included in the case study design. Therefore, we could not observe if and how the capabilities and contingent factors vary across cultural contexts. However, we do not expect the set of identified capabilities and contingent factors – what is required – to differ significantly between firms from different cultural backgrounds. Nevertheless, the specific implementation of the processes and resources – how they are arranged – might vary. For example, legal regulations related to the processing of social media data, such as the combination with other data sources, differ between countries and are likely to affect customer insight governance. Additionally, customers from different cultural backgrounds differ in their attitudes toward data privacy and their willingness to share personal data (Bellman et al. 2004; Dwyer et al. 2007). Future research efforts should examine the implementation of the capabilities and contingent factors in other cultural contexts.

Third, firms can only derive customer insights from social media if customers are willing to share their private data on social media platforms and if firms are able to access this data. Since firms often rely on platforms offered by third parties, such as Facebook, there is a threat that access to the customer data will be restricted (Ghoshal 2015). Additionally, there are indications of an emerging social media fatigue corresponding to decreasing customer willingness to share private data on social media (Maier et al. 2015). Against this backdrop, further research should investigate the potential of additional data sources (e.g., mobile apps, sensor data) run directly by the firms. In order to motivate customers to disclose their data to the firm voluntarily, further research should provide scientific evidence on the drivers behind customers' trust and derive measures to offer customers added value.

Conclusion

The aim of our research was the investigation how firms can generate and exploit customer insights from social media data. For this purpose, we conducted multiple case studies using the theoretical lens of the dynamic capabilities perspective, in particular the ACAP construct. We identified required capabilities as well as contingent factors, namely physical, human and organizational resources. From a research perspective, the findings from the case study approach shed light on the fundamental building blocks of ACAP in the context of social media. From a practical perspective, we provide guidance for managers by presenting a comprehensive overview of the processes and resources necessary to turn social media data into actionable customer insights.

Appendix A

Methodology used to identify research publications

Following the approach proposed by vom Brocke et al. (2009), our methodology for identifying publications that provided valuable information about preliminary constructs proceeded in four stages. First, we performed a search spanning multidisciplinary databases with access to academic journals and conference proceedings. The databases were queried on the basis of a keyword search in December 2014. Use form “customer insight”) in the search fields title, keywords, and abstract identified a total of 228 candidate articles from various disciplines. Second, we excluded duplicates and articles not published in peer-reviewed outlets. Additionally, we examined the title, abstract, and introduction to evaluate whether the paper appeared to be concerned with the management of customer insights in the context of social media or at least in the context of customer relationship management (e.g., sales, marketing, and service). After the first evaluation round, the list included 86 articles. Third, the remaining articles were read thoroughly to extract those that provided valuable information on the dimensions of the ACAP concept and the contingent factors. As a result, our pool comprised 21 relevant articles. Fourth, conducting a forward and backward search (Levy and Ellis 2006), we identified 8 additional articles.

This systematic and comprehensive literature search resulted in a coding set of 29 articles. Table 6 shows the number of identified papers after each step.

Table 6: Results of literature search

Database	Step 1	Step 2	Step 3	Step 4	
				Forward search	Backward search
EBSCOhost	69	35	6	0	
Emerald	8	7	4	0	
ProQuest	121	36	8	0	
Science Direct	8	4	2	0	
Web of Knowledge	9	4	1	0	-
AISel	4	0	0	0	
ACM DL	9	0	0	0	
Google Scholar	-	-	-	6	
Sum	228	86	21	6	2
Total Net Hits	29				

Appendix B

Identification of preliminary constructs: Examples for the coding process

Table 7: Examples of the coding process

Preliminary constructs	Candidate preliminary constructs	Examples of relevant quotations
Absorptive capacity	Data gathering	• "*This poses a challenge for marketers to gathering such a vast amount of data*" (Choudhury and Harrigan 2014, 155). • "*We don't automatically correlate data gathered on social media with segment data on the CRM system*" (Canhoto et al. 2013, 420).
	Data analysis	• "*Analysis must take place in all phases of the customer involvement process*" (Hauser 2007, 40). • "*Customer insight leaders – companies that optimize data analysis*" (Baird and Gonzalez-Wertz 2011, 16).
	Data integration	• "*Given the diversity of data sources, data integration is a key challenge for the retailer*" (Verhoef et al. 2010, 123). • "*Companies … were seeing significant benefits by using a big data approach involving data integration and sophisticated analytics to generate customer insight*" (Stone and Woodcock 2014, 8).
	Transformation into actionable insights	• "*Closing the CRM loop involves deploying customer insight into the operational CRM environment*" (Hirschowitz 2001, 168). • "*In practice, this means the capability of translating data about customers into customer preference and hence shareholder value*" (Smith et al. 2006, 135).
	Definition of action possibilities	• Determining the value of customer "*relies on defining what insight is needed and when and how it can be applied*" (Baird and Gonzalez-Wertz 2011, 22). • "*It is imperative to know the when, why and how of data collection and whether the data can accurately be used to meet the marketer needs/understanding the unique business context*" (Hauser 2007, 41).
Information and communication technology	Technology as an enabler	• "*Technological advances are making it feasible to understand customers – based on actual, real-time behavior – and engage them as individuals*" (Berman and Korsten 2014, 41).
Analytical skills	Analytical knowledge	• "*They will need stronger analytics capabilities to uncover patterns and answer questions they never thought to ask*" (Hirschowitz 2001, 37).

Understanding of the business context	Interpretative knowledge	• *"Marketing analytics not only demands good data, but also it mandates a good understanding of it"* (Hauser 2007, 42). • *"Rather they should adopt it based on an in-depth understanding of the value and goals of CRM"* (Hillebrand et al. 2011, 603).
Customer insight governance	Customer insight governance	• *"This data-driven orientation requires a cross-functional integration of processes, people, operations, and marketing capabilities that is enabled through information, technology, and applications"* (Peltier et al. 2013, 2). • *"Improved planning and governance is needed to cope with a powerful, self-servicing CI community"* (Stone and Woodcock 2014, 11).
	Cross-functional communication	• *"The goal is to communicate it widely and to get it into the heads of all those who should be using it"* (Wills and Williams 2004, 401). • *"Building strong brands based on actionable customer insights flowing freely through the business and ultimately leading to consistently great customer experience"* (Barwise and Meehan 2011, 342).
Customer-oriented culture	Customer value creation	• *"It will come by being the best at understanding the many and varied needs and characteristics of customer, and developing products and services that truly meet those needs"* (Wills and Williams 2004. 396). • *"First, as a framework, CRM should better address the possible uses of customer data for the benefit of the customer, as suggested in the emerging data sharing wave"* (Saarijärvi et al. 2013, 595).

Appendix C

Interview questions

Introductory questions about customer insights
At first, I would like to ask you a couple of questions about your personal understanding of customer insights:

- How would you describe customer insights in your own words?

General questions on firms' generation and use of customer insights
To ensure a common understanding of customer insights, I would like to suggest the following definition: Customer insights describe the firm's understanding of their customers, their needs, the reasons behind these needs, and how these change over time.

- To what extent does your firm generate customer insights? And how are these insights used?
- What role do social media play?

- Which goals does your firm pursue with the generation and use of customer insights in general and through social media in particular?

Organizational prerequisites
In the following, I would like to learn more about your opinion concerning the prerequisites that should exist in your firm to effectively generate customer insights through social media and use them in your firm.

- In your opinion, which prerequisites should exist in your firm to generate and exploit customer insights?
  - What processes are required to gather and process the data from social media? What does it take to turn the data into valuable customer insights?
  - Are there specific prerequisites regarding the technical infrastructure?
  - Are there specific prerequisites regarding the skills and knowledge of the employees?
- Are there specific prerequisites regarding the corporate setup, e.g., governance mechanisms?

Challenges and outlook

- What problems and challenges do you face when generating and using customer insights based on social media?
- Which trends regarding customer insights do you expect to be relevant in the future?

References

Ambrosini, V.,& Bowman, C. (2009). What are dynamic capabilities and are they a useful construct in strategic management? *International Journal of Management Reviews, 11*(1), 29–49.

Bailey, C., Baines, P. R., Wilson, H., & Clark, M. (2009). Segmentation and customer insight in contemporary services marketing practice: why grouping customers is no longer enough. *Journal of Marketing Management, 25*(3–4), 227–252.

Baird, C. H., & Gonzales-Wertz, C. (2011). How top performers achieve customer-focused market leadership. *Strategy & Leadership, 39*(1), 16–23.

Barney, J. (1991). Firm resource and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Barwise, P., &Meehan, S. (2011). Customer insights that matter. *Journal of Advertising Research, 51*(2), 342–344.

Belbey, J. (2015). How healthcare can use social media effectively and compliantly. *Forbes*. Retrieved from http://www.forbes.com/sites/ joannabelbey/2015/01/21/how-healthcare-can-use-social-mediaeffectively- and-compliantly/#b5ec79f3bc8e.

Bellman, S., Johnson, E. J., Kobrin, S. J., & Lohse, G. (2004). International differences in information privacy concerns: a global survey of consumers. *The Information Society, 20*(5), 313–324.

Berman, S., & Korsten, P. (2014). Leading in the connected era. *Strategy & Leadership, 42*(1), 37–46.

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS Quarterly, 24*(1), 169–196.

Bhattacherjee, A. (2012). *Social science research: principles, methods, and practices*. Tampa: Global Text Project.

Bijmolt, T. H. A., Leeflang, P. S. H., Block, F., Eisenbeiss, M., Hardie, B. G. S., Lemmens, A., & Saffert, P. (2010). Analytics for customer engagement. *Journal of Service Research, 13*(3), 341–356.

Bingham, C. N. (2005). Hottest new title in the executive suite? Chief customer officer. *Handbook of Business Strategy, 6*(1), 289–296.

Brown, L., Gallagher, S. M., & Brown, C. (2008). How CEOs can promote a strong market culture. *Strategy & Leadership, 36*(5), 28–33.

Canhoto, A. I., Clark, M., & Fennemore, P. (2013). Emerging segmentation practices in the age of the social customer. *Journal of Strategic Marketing, 21*(5), 413–428.

Chau, M., & Xu, J. (2012). Business intelligence in blogs: understanding consumer interactions and communities. *MIS Quarterly, 36*(4), 1189–1216.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly, 36*(4), 1165–1188.

Choudhury, M. M., & Harrigan, P. (2014). CRM to social CRM: the integration of new technologies into customer relationship management. *Journal of Strategic Marketing, 22*(2), 149–176.

Clauser, R. (2001). Offline rules, online tools. *Brand Management, 8*(4–5), 270–287.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152.

Dinter, B., & Lorenz, A. (2012). Social business intelligence: a literature review and research agenda. In Proceedings of the 33rd International Conference on Information Systems (ICIS 2012), Orlando, FL.

Dwyer, C., Hiltz, S. R., & Passerini, K. (2007). Trust and privacy concern within social networking sites: a comparison of Facebook and MySpace. In *Proceedings of the 13th Americas Conference on Information Systems (AMCIS 2007)*. Keystone, CO.

Easterby-Smith, M., Graça, M., Antonacopoulou, E., & Ferdinand, J. (2008). Absorptive capacity: a process perspective. *Management Learning, 39*, 483–501.

Eisenhardt, K.M. (1989). Building theories from case study research. The Academy of Management *Review, 14*(4), 532–550.

Eisenhardt, K. M.,&Bourgeois, L. J. (1988). Politics of strategic decision making in high velocity environments: toward a mid-range theory. *Academy of Management Journal, 31*(4), 737–770.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: opportunities and challenges. *The Academy of Management Journal, 50*(1), 25–32.

Eisenhardt, K.M.,& Martin, J. A. (2000). Dynamic capabilities: what are they? *Strategic Management Journal, 21*(10–11), 1105–1121.

Fan, W., & Gordon, M. D. (2014). The power of social media analytics. *Communications of the ACM, 57*(6), 74–81.

Gallinucci, E., Golfarelli, M., & Rizzi, S. (2015). Advanced topic modeling for social business intelligence. *Information Systems, 53*, 87–106.

García-Murillo, M., & Annabi, H. (2002). Customer knowledge management. *Journal of the Operational Research Society, 53*, 875–884.

Ghoshal, A. (2015). Facebook is shutting down access to hashtags in its API. *The Next Web*. Retrieved from http://thenextweb.com/facebook/2015/04/03/facebook-might-be-shutting-down-access-to-hashtags-in-its-api/#gref.

Greenberg, P. (2010). The impact of CRM 2.0 on customer insight. *Journal of Business & Industrial Marketing, 25*(6), 410–419.

Harreld, J. B., O'Reilly, C. A., & Tushman, M. L. (2007). Dynamic capabilities at IBM: driving strategy into action. *California Management Review, 49*(4), 21–43.

Hauser, W. J. (2007). Marketing analytics: the evolution of marketing research in the twenty-first century. *Direct Marketing: An International Journal, 1*(1), 38–54.

He, W., Zha, S., & Li, L. (2013). Social media competitive analysis and text mining: a case study in the pizza industry. *International Journal of Information Management, 33*(3), 464–472.

Helfat, C. E.,& Peteraf, M. A. (2003). The dynamic resource-based view: capability lifecycles. *Strategic Management Journal, 24*, 997–1010.

Hennig-Thurau, T., Malthouse, E. C., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A., & Skiera, B. (2010). The impact of new media on customer relationships. *Journal of Service Research, 13*(3), 311–330.

Hillebrand, B., Nijholt, J. J., & Nijssen, E. J. (2011). Exploring CRM effectiveness: an institutional theory perspective. *Journal of the Academy of Marketing Science, 39*(4), 592–608.

Hirschowitz, A. (2001). Closing the CRM loop: the 21st century marketer's challenge: transforming customer insight into customer value. *Journal of Targeting, Measurement and Analysis for Marketing, 10*(2), 168–178.

Holsapple, C., Hsiao, S.-H., & Pakath, R. (2014). Business social media analytics: definition, benefits, and challenges. In *Proceedings of the 20th Americas Conference on Information Systems (AMCIS 2014)*. Savannah, GA.

Hu, M., & Schlagwein, D. (2013). Why firms use social media: an absorptive capacity perspective. In *Proceedings of the 21th European Conference on Information Systems (ECIS 2013)*. Utrecht, Netherlands.

Hubbell, A., & Redding, M. (2003). Customer relationship management—Today and tomorrow. *The Journal of Bank Cost & Management Accounting, 16*(2), 44–52.

Jansen, J. J. P., Van den Bosch, F. A. J., & Volberda, H. W. (2005). Managing potential and realized absorptive capacity: how do organizational antecedents matter? *Academy of Management Journal, 48*(6), 999–1015.

Jayachandran, S., Sharma, S., Kaufman, P., & Raman, P. (2005). The role of relational information processes and technology use in customer relationship management. *Journal of Marketing, 69*(4), 177–192.

Kalampokis, E., Tambouris, E., & Tarabanis, K. (2013). Understanding the predictive power of social media. *Internet Research, 23*(5), 544–559.

Kaplan, A. M., & Haenlein, M. (2010). User of the world, unite! The challenges and opportunities of social media. *Business Horizons, 53*, 59–68.

Keil, M. (1995). Pulling the plug: software project management and the problem of project escalation. *MIS Quarterly, 19*(4), 421–447.

Kleindienst, D., Pfleger, R., & Schoch, M. (2015). The business alignment of socialmedia analytics. In *Proceedings of the 23th European Conference on Information Systems (ECIS 2015)*. Münster, Germany.

Kurniawati, K., Shanks, G., & Bekmamedova, N. (2013). The business impact of social media analytics. In *Proceedings of the 21th European Conference on Information Systems (ECIS 2013)*. Utrecht, Netherlands.

Lane, P. J., Koka, B. R.,&Pathak, S. (2006). The reification of absorptive capacity: a critical review and rejuvenation of the construct. *Academy of Management Review, 31*(4), 833–863.

Langford, R.,& Schulz, K. (2006). Gaining 3-D customer insight to drive profitable growth. *Strategy & Leadership, 34*(2), 21–27.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big Data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21–31.

Lehmkuhl, T., & Jung, R. (2013). Towards social CRM—Scoping the concept and guiding research. In *Proceedings of the 26th International Bled eConference (Bled 2013)*. Bled, Slovenia.

Lemke, F., Clark,M., &Wilson, H. (2011). Customer experience quality: an exploration in business and consumer contexts using repertory grid technique. *Journal of theAcademy ofMarketing Science, 39*(6), 846–869.

Levine, D. S. (2015). *Is your insurance company using social media to snoop on you?* Retrieved from http://www.safebee.com/tech/yourinsurance-company-using-social-media-snoop-you.

Levy, Y.,&Ellis, T. J. (2006). A systems approach to conduct an effective literature review in support of information systems research. *Informing Science, 9*, 181–212.

Lewis, S. C., Zamith, R., & Hermida, A. (2013). Content analysis in an era of big data: a hybrid approach to computational and manual methods. *Journal of Broadcasting & Electronic Media, 57*(1), 34–52.

Li, Y. M., Chen, H. M., Liou, J. H.,&Lin, L. F. A. (2014). Creating social intelligence for product portfolio design. *Decision Support Systems, 66*, 123–134.

Maier, C., Laumer, S., Weinert, C., & Weitzel, T. (2015). The effects of technostress and switching stress on discontinued use of social networking services: a study of facebook use. *Information Systems Journal, 25*, 275–308.

Malthouse, E. C., Haenlein, M., Skiera, B., Wege, E., & Zhang, M. (2013). Managing customer relationships in the social media era: introducing the social CRM house. *Journal of Interactive Marketing, 27*(4), 270–280.

Mehta, M., & Hirschheim, R. (2007). Strategic alignment in mergers and acquisitions: theorizing IS integration decision making. *Journal of the Association for Information Systems, 8*(3), 143–174.

Newell, S., & Marabelli, M. (2014). The crowd and sensors era: opportunities and challenges for individuals, organizations, society, and researchers. In *Proceedings of Thirty Fifth International Conference on Information Systems (ICIS 2014)*. Auckland, New Zealand.

Olsson, H. H., Conchuir, E. O., Agerfalk, P. J., & Fitzgeral, B. (2008). Two-stage offshoring: an investigation of the Irish bridge. *MIS Quarterly, 32*(2), 257–279.

Ooms, W., Bell, J., & Kok, R. A. W. (2015). Use of social media in inbound open innovation: building capabilities for absorptive capacity. *Creativity and Innovation Management, 24*(1), 136–150.

Osakwe, M. (2015). Do insurance companies look at your social media profiles? *Huffington Post*. Retrieved from http://www. huffingtonpost.com/nextadvisorcom/do-insurance-companies-lo_b_7844070.html.

Palmer, D., Mahldhar, V., Gallzia, T., & Sharma, V. (2013). *Reengineering business intelligence.* Westlake: Deloitte UniversityPress.

Paré, G. (2004). Investigating information systems with positivist casestudy research. *Communications of the Association for Information Systems, 13*, 233–264.

Peltier, J.W., Zahay, D., & Lehmann, D. R. (2013). Organizational learning and CRM success: a model for linking organizational practices, customer data quality, and performance. *Journal of Interactive Marketing, 27*(1), 1–13.

Rao, G. K., & Kumar, R. (2011). Framework to integrate business intelligence and knowledge management in banking industry. *Review of Business and Technology Research, 4*(1).

Reinhold, O., & Alt, R. (2012). Social customer relationship management: state of the art and learnings from current projects. In *Proceedings of the 25th International Bled eConference (Bled 2012)*. Bled, Slovenia.

Roberts, N., Galluch, P. S., Dinger, M., & Grover, V. (2012). Absorptivecapacity and information systems research: review, synthesis, and directions for future research. *MIS Quarterly, 36*(2), 625–648.

Rosemann, M., Eggert, M., Voigt, M., & Beverungen, D. (2012). Leveraging social network data for analytical CRM strategies—The introduction of social BI. In *Proceedings of the 20th European Conference on Information Systems (ECIS 2012)*. Barcelona, Spain.

Ross, J. W., Beath, C. M., & Goodhue, D. L. (1996). Develop long-term competitiveness through IT assets. *Sloan Management Review, 38*(1), 31–42.

Saarijärvi, H., Karjaluoto, H., & Kuusela, H. (2013). Customer relationship management: the evolving role of customer data. *Marketing Intelligence & Planning, 31*(6), 584–600.

Salojärvi, H. &Sainio, L.-M. (2006). Applying absorptive capacity construct to customer-related knowledge processing. In *Proceedings of the ICEP and eBRFConference*. Global Venture Lab, Tampere, Finland.

Saraf, V., Thakur, P., & Yadav, L. (2013). CRM with data mining & warehouse: "Optimizes customer insight". *International Journal of Marketing & Technology, 3*(4), 177–187.

Setia, P., Venkatesh, V., & Joglekar, S. (2013). Leveraging digital technologies: how information quality leads to localized capabilities and customer service performance. *MIS Quarterly, 37*(2), 565–590.

Smith, B., Wilson, H., & Clark, M. (2006). Creating and using customer insight: 12 rules of best practice. *Journal of Medical Marketing, 6*(2), 135–139.

Smith, H. J., Dinev, T., & Xu, H. (2011). Information privacy research: an interdisciplinary review. *MIS Quarterly, 35*(4), 989–1016.

Stone, M. D., & Woodcock, N. D. (2014). Interactive, direct and digital marketing: a future that depends on better use of business intelligence. *Journal of Research in Interactive Marketing, 8*(1), 4–17.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533.

Trainor, K. J., Andzulis, J. M., Rapp, R., & Agnihotri, R. (2014). Social media technology usage and customer relationship performance: a capabilities-based examination of social CRM. *Journal of Business Research, 67*(6), 1201–1208.

Van Den Bosch, F. A., Volberda, H. W., & De Boer, M. (1999). Coevolution of firm absorptive capacity and knowledge enviroment: organizational forms and combinative capabilities. *Organization Science, 10*(5), 551–568.

Verhoef, P. C., Venkatesan, R., McAlister, L., Malthouse, E., Krafft, M., & Ganesan, S. (2010). CRM in data-rich multichannel retailing environments: a review and future research directions. *Journal of Interactive Marketing, 24*(2), 121–137.

Verona, G., & Ravasi, D. (2003). Unbundling dynamic capabilities: an exploratory study of continuous product innovation. *Industrial and Corporate Change, 12*(3), 577–606.

Vom Brocke, J. M., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R.,& Cleven, A. (2009). Reconstructing the giant: on the importance of rigour in documenting the literature search process. In *Proceedings of the 17th European Conference on Information Systems (ECIS 2009)*. Verona, Italy.

Wang, C. L., & Ahmed, P. K. (2007). Dynamic capabilities: a review and research agenda. *International Journal of Management Reviews, 9*(1), 31–51.

Wills, S., & Williams, P. (2004). Insight as a strategic asset—The opportunity and the stark reality. *International Journal of Market Research, 46*(4), 393–410.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal, 24*, 991–995.

Woodcock, N., Green, A., & Starkey, M. (2011). Social CRM as a business strategy. *Journal of Database Marketing & Customer Strategy Management, 18*(1), 50–64.

Yeoh, W., Richards, G., & Wang, S. (2013). Linking BI competency and assimilation through absorptive capacity: a conceptual framework. In *Proceedings of the 17th Pacific Asia Conference on Information Systems (PACIS 2013)*.

Yin, R. K. (2009). *Case study research design and methods*. Thousand Oaks: Sage.

Zahra, S. A., & George, G. (2002). Absorptive capacity: a review, reconceptualization, and extension. *Academy of Management Review, 27*(2), 185–203.

Anhang 4: Fachbeitrag C - „Privacy-related decision-making in the context of wearable use“

Tabelle A4: Fakten zum Fachbeitrag C

Informationstyp	Beschreibung
Titel	Privacy-related decision-making in the context of wearable use
Autor(en)	Alexander Wieneke, Universität St.Gallen, Schweiz Christiane Lehrer, Universität St.Gallen, Schweiz Raphael Zeder, Universität St.Gallen, Schweiz Reinhard Jung, Universität St.Gallen, Schweiz
Publikationsorgan	Proceedings of the Pacific Asia Conference on Information Systems (PACIS)
Publication type	Konferenzbeitrag
Jahr der Veröffentlichung	2016
Ranking	C (VHS Jourqual 3.0 Ranking)
Status der Publikation	Veröffentlicht
Referenz	Wieneke, A., Lehrer, C., Zeder, R., & Jung, R. (2016). Privacy-related decision-making in the context of wearable use. In *Proceedings of the 20th Pacific Asia Conference on Information Systems (PACIS 2016),* Chiayi, Taiwan.[7]
Zugriff	http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1069&context=pacis2016

[7] Wie von der Prüfungsordnung der Universität St.Gallen (HSG) vorgeschrieben, findet sich im Folgenden eine Kopie sämtlicher Inhalte des erstellten Fachbeitrages. Als Quellenangabe ist die in Tabelle A4 angegebene Referenz zu verwenden. Diese verweist auf die veröffentlichte Originalversion des Fachbeitrages.

Privacy-related decision-making in the context of wearable use

Alexander Wieneke, Institute for Information Management, University of St.Gallen, St.Gallen, Switzerland, alexander.wieneke@unisg.ch

Christiane Lehrer, Institute for Information Management, University of St.Gallen, St.Gallen, Switzerland, christiane.lehrer@unisg.ch

Raphael Zeder, Institute for Information Management, University of St.Gallen, St.Gallen, Switzerland, raphael.zeder@gmail.com

Reinhard Jung, Institute for Information Management, University of St.Gallen, St.Gallen, Switzerland, reinhard.jung@unisg.ch

Abstract

The widespread use of wearables for self-tracking activities despite potential privacy risks is an intriguing phenomenon. For firms, the data collected from individuals' wearable use are highly valuable for generating in-depth customer insights. Accordingly, firms have an increasing desire for these data. Despite the undisputed relevance of self-tracking activities in practice, there is scarce knowledge among information systems (IS) scholars about the perceived values of wearables that drive individuals' use and the reasons why these values prevail over the privacy risks. Against this background, our research set out to better understand why people use wearables despite privacy risks by investigating the perceived values of wearables that drive individuals' use and disclosure of data and the reasons why these values prevail over privacy risks of wearable use. Based on the concept of the privacy calculus and concepts from behavioural decision-making, we conducted in-depth interviews with 22 wearable users from Switzerland. As a result, we reveal eight values that individuals perceive through the use of wearable devices. Furthermore, we illustrate the low awareness regarding privacy risks and explain how the reliance on prominent dimensions and heuristics are influencing individuals' value-risk assessment.

Keywords: *Information privacy, Laddering, Privacy-related decision-making, Wearables*

1. Introduction

Recent advances in battery longevity, cheap massive storage and low-cost sensors have spawned a new generation of devices, so-called wearables (Trickler 2013). Wearables are digital devices in the shape of watches, wristbands, glasses or textiles with the ability "*to monitor the minutiae of our everyday lives*" (Newell & Marabelli 2015, p. 3). The embedded sensors track daily activities or vital parameters and collect personal data (Buchwald et al. 2015; Sjöklint et al. 2015; Trickler 2013). Individuals often use wearables to quantify various aspects of their lives with the objective of generating *"insight and even predict certain realities about oneself"* (Trickler 2013, p. 197). In fact, this individual activity, also called self-tracking, has become an emerging trend in society (Sjöklint et al. 2015). The use of wearables is constantly increasing, and it is forecasted that the worldwide wearables market will grow from fewer than 20 million units in 2014 to more than 126 million units in 2019 (IDC 2015). However, the use of wearables, especially in the context of self-tracking, is a double-edged sword, simultaneously presenting value and risks (Buchwald et al. 2015; Xu et al. 2009). The overall values are "*built upon the explanatory power of continuously collected data*" (Buchwald et al. 2015, p. 3). The risks arise from individuals wearing the devices whenever possible and becoming a "*walking data generator*" (McAfee & Brynjolfsson 2012, p. 5). New techniques for advanced data analytics (Chen et al. 2012) allow firms to collect the data and compile customers' "*digital footprints into a comprehensive picture of an individual's daily-life facets*" (Zhang et al. 2011, p. 21). Unsurprisingly, much has been written in the press and the scientific community about the possible loss of privacy caused by, for example, stolen data or illegal capture of data (Markus 2015; Markus & Topi 2015). Accordingly, more than 45% of wearable users are concerned about breaches of privacy through wearable use (Mills 2015). The paradox between the increasing diffusion of wearables and the extensively discussed privacy risks illustrates a general phenomenon of digital technology whereby individuals are willing to disclose personal data despite their privacy concerns if the values outweigh the costs (Newell & Marabelli 2015).

Firms, such as insurance companies or sporting goods manufacturers, have developed an insatiable desire for data gathered by fitness apps or digital devices (Newell & Marabelli 2014; Trickler 2013). This type of data provides them with valuable information for the generation of in-depth customer insights (Newell & Marabelli 2014). Despite this undisputed relevance in practice, there is scarce knowledge among information systems (IS) scholars about the perceived values of wearables that drive individuals' use and the reasons why these values prevail over the privacy risks (Markus & Topi 2015; Min & Kim 2015; Newell & Marabelli 2015). Previous studies in the field of information privacy primarily focused on identifying privacy concerns (e.g., Motti & Caine 2015) and how to reduce privacy risks (e.g., Xu et al. 2009). Another stream in this research field investigates how individuals react to information privacy policies (e.g., Zhao et al. 2012), practices (e.g., Xu et al. 2011) and tools (e.g., Sutanto et al. 2013). Further research studied the role of situation-specific considerations influencing the assessment of privacy risks and values (e.g., Acquisti et al. 2012; Dinev et al. 2015; Kehr et al. 2015). Only a small number of studies empirically investigated the influence of perceived values (e.g., personalisation, financial rewards) on individuals' willingness to disclose personal data (e.g., Sun et al. 2015; Zhao et al. 2012). However, most of this research was conducted in the context of e-commerce, social network applications, location-based services (LBS) or mobile apps. Research in the context of wearables focusing on perceived value or individuals' value-risk assessment has been scarce to date. However, there are some pioneering studies about privacy concerns regarding mobile health (e.g., Anderson & Agarwal 2011), individuals' adoption of wearables in healthcare (e.g., Gao et al. 2015) or behavioural change through wearable use (e.g., Sjöklint et al. 2015).

To close this research gap and better understand why people use wearables despite privacy risks, our research focuses on investigating the perceived values of wearables that drive individuals' use and data disclosure and the reasons why these values prevail over privacy risks of wearable use. In the privacy literature, the perceived risks are generally understood as the "*potential for loss associated with the release of personal information*" (Smith et al. 2011, p. 1001). The perceived values are described as the potential for enjoying positive consequences from data disclosure (Wilson & Valacich 2012). For our research purposes, we focus on wearables in the shape of bracelets and watches used in the context of self-tracking and offered by service providers, such as Fitbit, Jawbone, Apple or Samsung. Together, these types of wearables account for more than 90% of the worldwide wearables market (IDC 2015). The research questions of our paper are:

RQ 1. *What are the perceived values of wearables that drive individuals' use and disclosure of personal data?*

RQ 2. *Why do these values prevail over the privacy risks?*

We address these questions by applying the theoretical lens of the privacy calculus and conducting in-depth interviews with 22 wearable users from Switzerland. To gather detailed information about the actual perceived values of wearables that drive individuals' use and the actual reasons why these values prevail over privacy risks of wearable use, we focus solely on individuals using wearables in their everyday lives. This means that our research primarily focuses on aspects influencing the continuance wearable use. To answer both research questions, we applied different interview techniques. First, we applied the means-end chain analysis approach (Gutman 1982) and used the laddering interview technique (Reynold & Gutman 1988) to examine how individuals translate the attributes of wearables into meaningful value. Second, we used the semi-structured interview technique (Lacity & Janson 1994) to obtain an in-depth understanding of the reasons why the values prevail over privacy risks. With regard to the first research question, our findings reveal eight values that individuals perceive through the use of wearable devices. Regarding the second research question, we illustrate the low awareness of privacy risks and explain how the reliance on prominent dimensions and heuristics are influencing individuals' privacy-risk assessment.

Our theoretical contribution is threefold. First, we identify and illustrate the perceived values of wearables that drive individuals' use. We suggest that hedonic values are dominant in wearable use. Thereby, we contribute to prior research, which has examined perceived values in the context of e-commerce, social networks and LBS. Second, we emphasise individuals' low awareness in terms of how their data are being used and their low interest in obtaining more information on this topic. Finally, our findings suggest that individuals, under normal circumstances, ignore privacy risks and do not base their decisions on a rational value-risk assessment. Moreover, they appear to base their decision to use wearables predominantly on intuitive processes. Thereby, we contribute to IS research in the field of information privacy, which has emphasised the rational process of privacy-related decision-making (e.g., Dinev & Hart 2004; Dinev et al. 2006). Our results inform practitioners about the value that consumers perceive in the use of wearables and the underlying cognitive processes involved in their privacy-risk assessment. This knowledge helps firms configure their services to provide customers with the perceived value and motivate them to disclose their personal data.

The rest of the paper is organised as follows. The next section gives an overview of the general use of wearables and explains the privacy calculus in detail. Then we present our research approach, followed by a presentation of the identified values and the cognitive processes involved in individuals' value-risk assessment. We then turn to a discussion of the results and emphasise why individuals use wearables despite privacy risks. Additionally, we highlight our theoretical and practical implications. The paper ends with a conclusion providing limitations and suggestions for further research.

2. Conceptional Background

2.1. Wearables

In recent years, several firms entered the market for wearable devices. The majority of these service providers offer wearables in the shape of bracelets (e.g., Jawbone) and watches (e.g., Fitbit, Apple, Samsung) (IDC 2015). Despite slight differences in appearance, wearable devices usually have the same fundamental technical properties, i.e., integrated sensors, massive storage and software applications. Integrated sensors and massive storage afford the gathering of several data types (e.g., pace, position, step rate, sleep, blood pressure, caloric intake and expenditure, body mass index) over a long period of time (Li & Wu 2014; Trickler 2013). Different technologies for data transfer (e.g., Bluetooth, WiFi network, headphone port) allow the utilisation of these data sets within applications on mobile devices or desktop computers (Sjöklint et al. 2015). These applications use advanced data analytics to generate insights about different aspects of individuals' lives (Buchwald et al. 2015). Based on these abilities, service providers describe wearables as a "*revolutionary system that guides you every step of the way to a better, healthier you*" (Jawbone 2016) or as devices that "*fit seamlessly into your life so you can achieve your health and fitness goals, whatever they may be*" (Fitbit 2016). Accordingly, more and more individuals use these devices for self-tracking activities. Self-tracking is described as the collection of quantitative "*data about the individual's performance in everyday life, such as (…) daily activities, workouts, food consumption, finances or even blood sugar levels*" (Sjöklint et al. 2015, p. 1). Although the activity of self-tracking has already been performed with different tools, such as handwritten notes or smartphone apps, wearables enable individuals to track the activities of their daily lives in a more convenient manner (Buchwald et al. 2015; Newell & Marabelli 2015). When one wears a device in the form of a bracelet or watch all day long, it becomes a part of oneself (Sjöklint et al. 2015). This, in turn, enables service providers to implicitly collect personal data about all facets of individuals' everyday lives (McAfee & Brynjolfsson 2012; Newell & Marabelli 2014). The evolution of business intelligence and analytics allows firms to use mobile, location-aware, person-centred and context-relevant analysis techniques for generating insights about actual market and consumer trends and individual customers' preferences and behavioural patterns (Chen et al. 2012; Setia et al. 2013). Based on these insights, firms are able to provide more individualised products or services and align customer-oriented work practices with customers' needs. Despite the existence of privacy regulations designed for keeping the data safe, firms' use of data gathered through wearables is associated with several privacy risks (Buchwald et al. 2015; Newell & Marabelli 2015). The sensitivity of these data sets (e.g., location-based data, health data) in particular prompt heated discussion about potential privacy intrusion (Buchwald et al. 2015).

It is irrefutable that information gathered by wearables is extremely valuable for several stakeholders, such as businesses and criminals. For example, health insurance companies can use these data sets to assess individuals' health risks to reject potential customers with unhealthy lifestyles or raise the premiums. This could lead to unfair classification or labelling of and unjust discrimination against individuals (Markus 2015; Newell & Marabelli 2014). For criminals, the data can be useful by facilitating analysis of individuals' movement patterns to identify the optimal time for burglary. It is possible that these stakeholders may come into possession of the data sets. Service providers can sell the data to third parties without the explicit consent of the user (Maddox 2016). Additionally, the data can be stolen through a data breach and illegally sold to other people or firms (Markus 2015; Markus & Topi 2015). Moreover, the collected data can be stored for several decades. Over time, "*new laws could be passed that change access to the data that you willingly gave up your privacy rights to share*" (Maddox 2016). Then, it could be legal to use the data for different purposes and share the data with every firm that the service provider wants to share it with. However, paradoxically, the use of wearables is constantly increasing (Buchwald et al. 2015, IDC 2015). According to Newell and Marabelli (2015), "*individuals seem to be* *likely to accept the 'dark side' of datification through digital traces (always there), and constant monitoring through sensors because they are persuaded that the benefits outweigh the costs*" (p. 11). Thus, to generate scientific evidence about the privacy-related decision-making process, we seek to explore the perceived values of wearables that drive individuals' use and disclosure of data and the reasons why these values prevail over the privacy risks of wearable use. Therefore, in the next section, we discuss the privacy calculus that provides us with a lens suitable to understand the rational and emotional factors underlying people's willingness to disclose data.

2.2. Privacy calculus

In general, information privacy is regarded "*as a human right integral to society's moral value system*" (Smith et al. 2011, p. 992). With the evolution of IT, especially the rise of the internet, the so-called "*general privacy as a right*" concept was reconsidered (Belanger et al. 2011; Smith et al. 2011). The widespread opportunities to voluntarily disclose information (e.g., on websites) in exchange for several values has eroded the societal tendency to consider information privacy an absolute legal right. For some, information privacy has become "*subject to the economic principles of cost-benefit analysis and trade-off*" (Smith et al. 2011, p. 994). From this perspective, personal data is a currency that can be traded against value-added privileges or advantages (Belanger et al. 2011). Against this background, the "*privacy as a commodity*" concept was established (Smith et al. 2011). According to this concept, many scholars describe the cognitive process of privacy-related decision-making as an economical calculation. They rely on the privacy calculus model, which views privacy-related decision-making as a rational process, "*where individuals weigh the anticipated risks of disclosing personal data against the potential benefits*" (Kehr et al. 2015, p. 607). The privacy risks can be specified as the potential loss of control over personal data due to unauthorised access and theft or transfer of data to other stakeholders (Smith et al. 2011). Moreover, when firms classify their customers, this may lead to discrimination, unfair treatment and even financial disadvantages (Newell & Marabelli 2014; Xu et al. 2009). With regard to the perceived values, prior research typically refers to financial rewards, personalisation and social adjustment as exemplary positive consequences. In summary, the privacy calculus perspective claims that individuals are willing to share personal data voluntarily if they expect to perceive value from data disclosure outweighing the perceived risks (Wilson & Valacich 2012; Xu et al. 2009). However, prior research in the field of information privacy primarily focuses on the identification of perceived risks "*rather than identifying the benefits that people want to gain despite that cost*" (Min & Kim 2015, p. 842). Thus, the perceived values that drive individuals' use of wearables are still underexplored (Min & Kim 2015; Newell & Marabelli 2015).

In recent years, the privacy calculus has become one of the most applied frameworks for analysing the underlying cognitive processes of privacy-related decision-making (Xu et al. 2009). It was widely used by scholars in previous empirical studies (e.g., Dinev et al. 2006; Dinev & Hart 2004; Xu et al. 2009; Zhao et al. 2012). However, as shown by Dinev et al. (2015) and Kehr et al. (2015), the value-risk assessment may not necessarily be based on an objective and rational mathematical calculation. More than likely, the rational assessment process is "*bereft of biased assumptions or cognitive shortcuts*" (Dinev et al. 2015, p. 640). This means that individuals' privacy-related decision-making is affected by psychological limitations. Normally, individuals do not have the ability to process all the information required to make a rational and objective value-risk assessment (Min & Kim 2015). This is reflected in individuals' employment of "*low-effort cognitive processes*" (Dinev et al. 2015, p. 640), such as heuristics, to simplify decision-making (Dinev et al. 2015; Min & Kim 2015). In relation to information privacy, Min and Kim (2015) describe heuristics as cognitive processes "*through which people evaluate costs and benefits (…) by attaching subjective values to them, although those may be completely arbitrary*" (p. 841). In more detail, Kehr et al. (2015) identified the influence of the affect heuristic on individuals' risk and value perception. The affect heuristic emphasises the key role of emotions in decision-making (Bazerman & Moore 2008). Furthermore, Kehr et al. (2013) demonstrated the influence of dispositional factors on the weighing of values and risks (Kehr et al. 2013; Kehr et al. 2015). Dispositional factors may be individuals' subjective sense of privacy concerns and institutional trust (Kehr et al. 2013). Against this background, there has been a call in IS research to scrutinise the assumption of rational decision-making and examine the influence of intuitive processes on privacy-related decision-making (Dinev et al. 2015).

With regard to our research questions, we identify the perceived values of wearables that drive individuals' use. Additionally, we aim to understand why the perceived values prevail over the privacy risks of wearable use. For this purpose, we study the cognitive processes involved in individuals' value-risk assessment.

3. Methodical Background

3.1. Research approach

This study aims to provide a better understanding of why people use wearables despite privacy risks. For this purpose, we employed a qualitative research approach and conducted 22 in-depth interviews with wearable users from Switzerland. This approach allowed us to gain a deep understanding of the underlying cognitive processes in individuals' privacy-related decision-making (Constantiou et al. 2014). Because research on wearable use has been scarce to date, the interviews were exploratory in nature. To gather detailed information about the perceived values of wearables that drive individuals' use and the reasons why these values prevail over the privacy risks of wearable use, we interviewed actual users of wearables. In our sample, we did not include people who had never adopted wearables or those who had discontinued their use. For our sample, we targeted wearable users of both genders (i.e., 7 females and 15 males) ages 23 to 59 years old (Table 1). Our sample contains an over-representation of males. This is in line with the specific target groups of similar studies examining the use of mobile devices or mobile applications in Europe (e.g., Constantiou et al. 2014). Additionally, the majority of wearable users in Switzerland are men (Statista 2016a). Because the diffusion of wearables in Switzerland is limited, i.e., only 3% percent of the population use wearables (Statista 2016b), the respondents can be described as early adopters (Rogers 1995). Accordingly, most of the respondents described themselves as very health-conscious and technology affine. The interviews were conducted in German from January to February 2016. Each interview lasted between 35 and 45 minutes and was audio recorded and transcribed. In sum, we generated 188 pages of interview transcripts. To answer both of the research questions of this paper, we used two different interview techniques. First, we applied the means-end chain analysis (MECA) approach (Gutman 1982) and the laddering interview technique (Reynolds & Gutman 1988) to identify the perceived values of wearables that drive individuals' use. Second, we used the semi-structured interview technique (Lacity & Janson 1994) to investigate why these values prevail over the privacy risks of wearable use.

Table 1: Descriptive statistics of participants

Contextual factors	Interviewees' characteristics
Gender	32% female; 68% male
Age	From 23 to 59 years; average 36
Occupational area	18% students; 50% private sector; 32% public sector

3.2. Research design

Means-end chain analysis is a qualitative research approach used for in-depth analysis of individuals' cognitive decision-making processes (e.g., Jung 2014; Schäfer 2013; Wagner 2007). It helps scholars uncover the underlying drivers of individuals' decisions, e.g., purchase or use decisions (Reynold & Gutman 1988). The approach is based on the assumption that product and service attributes are associated with consequences and personal values that the product or service can provide to individuals. The MECA approach "*specifically focuses on the linkages between the attributes that exist in products (the "means"), the consequences for the consumer provided by the attributes and the personal values (the "ends") the consequences reinforce*" (Reynold & Gutman 1988, p. 11). Accordingly, the result is a means-end chain linking attributes to consequences to underlying personal values. Attributes are defined as "*perceived qualities or features of products or services*" (Reynolds & Olson 2001, p. 92) (e.g., pulse monitor, altimeter). Consequences "*may be defined as any result (…) accruing directly or indirectly to the consumer (sooner or later) from his/her behaviour*" (Gutman 1982, p. 61). According to Olson and Reynolds (2001), consequences can be separated into functional and psychological consequences. Functional consequences represent qualitative outcomes that are directly related to the use of the product or service (Schäfer 2013; Wagner 2007) (e.g., universally applicable, profiling oneself). Psychological consequences "*reflect the personal and social outcomes of product usage*" (Reynolds et al. 1995, p. 258) (e.g., self-awareness, self-control). Values "*imply highly abstract motivation that guides usage behaviour*" (Jung & Kang 2010, p. 220) and illustrate the desirable end states of product or service use (e.g., success, health). Designing a means-end chain in the context of wearables allows us to uncover the drivers, i.e., the underlying values behind individuals' decision to use wearables and thereby disclose their personal data despite the privacy risks.

To uncover the means-end chain and define the attributes, functional consequences, psychological consequences and values and the linkages between the key elements, Reynolds and Gutman (1988) proposed the use of the in-depth interviewing and analysis methodology named laddering. Laddering can be described as a "*one-on-one interviewing technique used to develop an understanding of how consumers translate the attributes of products into meaningful associations with respect to self, following means-end theory*" (Reynolds & Gutman 1988, p. 12). The overall objective is the creation of a cognitive hierarchical value map (HVM) illustrating the interrelations between the key elements (i.e., attributes, functional and psychological consequences and values) of a given product or service (Gutman 1982, Reynolds & Gutman 1988, Wagner 2007). Thus, a HVM provides insights into individuals' hierarchical cognitive structures and allows drawing conclusions about the expected values of product or service use. To ensure rigor in qualitative research and avoid potential subjective biases, we followed the established guidelines of Reynolds and Gutman (1988) for conducting and analysing laddering interviews. As a first step in a laddering interview, the interviewee is asked about the relevant attributes of a product or service. The stated attributes then serve as a starting point for the laddering procedure. This means that the interviewer refers to one attribute and asks the responder questions along the lines of "Why is this important to you?" After the interviewee's answer, the question is repeated until the level of the terminal value is reached. This procedure enables the interviewer to ascend the "ladder" of the means-end chain hierarchy. Thus, as a result, the interviewer gains a set of ladders for each interviewee (Reynolds & Gutman 1988). For our research purposes, we began with questions about the contexts of wearable use, the reasons for use and personal experiences. We then asked the respondents "What attributes make wearables attractive to you?" To focus on the relevant attributes, we applied the direct elicitation method, as suggested by Bech-Larsen and Nielsen (1999). In this method, the interviewees note the attributes most important for them without prioritising or assigning the attributes to specific products. The procedure comes close to a "'*natural speech' interviewing technique, which compared to the other techniques is believed to lead to a stronger focus on idiosyncratic and intrinsically relevant attributes* *and to less focus on extrinsic product differences*" (Bech-Larsen & Nielsen 1999, p. 317). We noted the answers to conduct the laddering procedure for each attribute named by the respondents. To identify the functional and psychological consequences, we asked questions such as "Why exactly is this attribute important to you?" or "What positive consequences do you expect from this attribute?" Finally, to reach the terminal end state, we asked questions such as "Why exactly is this consequence important for you?" or "What value do you expect to derive from this consequence?" If the interviewees were unwilling to answer due to sensitive questions or an inability "*to articulate a 'ready' reason*" (Reynold & Gutman 1988, p. 15), we made use of specific laddering techniques, such as "negative laddering" and "third-person probe". To help the interviewees find reasons why an element is important to them, the negative laddering includes questions "*asking what would happen if the attribute or consequence was not delivered*" (Reynolds & Gutman 1988, p. 16). Using the third-person probe techniques means "*ask[ing] how others they know might feel in similar circumstances*" (Reynolds & Gutman 1988, p. 17).

Following Reynolds and Gutman (1988), we analysed the interview data in three steps. First, we conducted a content analysis "*to develop a set of summary codes that reflect everything that was mentioned*" (Reynolds & Gutman 1988, p. 18) and illustrate the elements of the means-end chain. Two scholars independently analysed the empirical data by carefully reading and reflecting the interview transcripts. To produce consistency, the two scholars compared their results regularly. Differences were discussed with a third senior scholar to seek reliable compromises. Then each code was related to one of the four levels of the means-end chain hierarchy. In an iterative process, similar codes on similar hierarchical levels were combined with the goal "*to achieve broad enough categories of meaning to get replications of more than one respondent saying one element leads to another*" (Reynolds & Gutman 1988, p. 18). After the first coding round, the scholars agreed on 59 elements. By combining replications (e.g., "self-confidence" and "special emphasis" were aggregated to "distinguish oneself"), the number of codes was reduced to 43 relevant elements. Second, the two scholars analysed the interviews for a second time to identify the linkages between the identified elements and define a set of "ladders" for each interview. In sum, we reached a number of more than 200 individual ladders. Third, the ladders of all the respondents were aggregated in an implication matrix. The rows and columns in the matrix contained the elements identified as a result of the content analysis. Accordingly, the implication matrix contains 43 x 43 rows and columns. In the fields of the matrix, we denoted how many interviewees showed a relation between two elements. Finally, we created the HVM to illustrate the hierarchical level of each element and mapped them with each other. For the mapping process, we chose a cut-off level of 6 relations because in our study this level brought about the most stable set of relations (Reynolds & Gutman 1988). The cut-off level determines the minimum number of interviewees illustrating the relations between the elements to be depicted in a HVM (Wagner 2007). With a cut-off level of 6, our HVM contains 28 elements.

In the second part of the interviews, we aimed to examine why the values prevail over the privacy risks. For this purpose, we used the semi-structured interview technique to collect data for in-depth investigation (Lacity & Janson 1994). The interviewees were first asked to describe their awareness of how their personal data were being used by the service provider. Afterwards, we asked them to describe the perceived privacy risks of wearable use. Then we asked why the perceived values outweighed the perceived risks and how this decision was made. As a final question, we asked the individuals whether there were any circumstances in which their opinion on the assessment of the privacy risks would change. Similarly to the first part of the interviews, the data from the semi-structured interviews were analysed through content analysis, which included a coding process (Bhattacherjee 2012). However, to analyse this data set, we followed a three-stage process of open, axial and selective coding (Bhattacherjee 2012). This analysis strategy helps researchers in "*classifying and categorising text data segments into a set of codes (concepts), categories (constructs) and relationships*" (Bhattacherjee 2012, p. 113) to create a chain of evidence and inferences. Each step of the coding process was conducted and discussed by different scholars to avoid subjective interpretation and enhance validity. First, two scholars analysed the interview transcripts line by line looking for privacy risks and salient factors influencing the decision-making process. Thereby, we identified codes such as financial disadvantage, unfair treatment, prior experiences, trust in the service provider, and personal interests. Second, the identified codes were assembled into the dimensions privacy risks (e.g., the code "financial disadvantage" was assigned to the dimension "privacy risks") and concepts from behavioural decision-making, i.e., heuristics and dispositional factors (e.g., the code "trust in service provider" was assigned to the dimension "dispositional factors"). Third, the core categories were built. After several iterations and discussions concerning the avoidance of overlaps, we subsumed the constructs under 6 meaningful core categories.

4. Results

Nearly all the respondents use their wearables in similar contexts. They stated that they wear them with the aim of tracking their daily activities. They monitor their step rate on the way to work, during work or while taking a walk. A respondent additionally stated that he evaluates his pulse frequency during important meetings or presentations. The device is also used by nearly all the respondents during the night to monitor their sleep. Additionally, the majority of the respondents use the wearables during fitness activities. They track their speed, distance, pulse frequency and calorie consumption while jogging, hiking, bicycling or skiing. The respondents also noted wearing the devices in unusual situations. One respondent, for example, wears the device while visiting nightclubs because she is interested in the distance that she covers during the night. Another stated that he wears the wearable to evening events because he is interested in his step rate while dancing. Most of the interviewees also wear the bracelet or watch during their holidays with the purpose of comparing the gathered information with information gathered during their daily activities. The majority of the respondents did not name a situation in which they are not willing to wear the device. On the contrary, the respondents explicitly emphasised their intent to wear wearables, regardless of the context, during all waking and sleeping hours.
Once we had observed the patterns of wearable use, in a first step, we proceeded to investigate the values that individuals perceive in the use of wearables. In a second step, we examined why these values prevail over the privacy risks.

4.1. Perceived Values

Analysing the laddering data, a total of 10 attributes of wearables were identified. For the next two hierarchical levels of the means-end chain, we identified 5 functional consequences and 6 psychological consequences. Finally, all of the elements were related to 8 values. For the sake of clarity, the cognitive structures captured in this study are shown in the HVM (Figure 1).

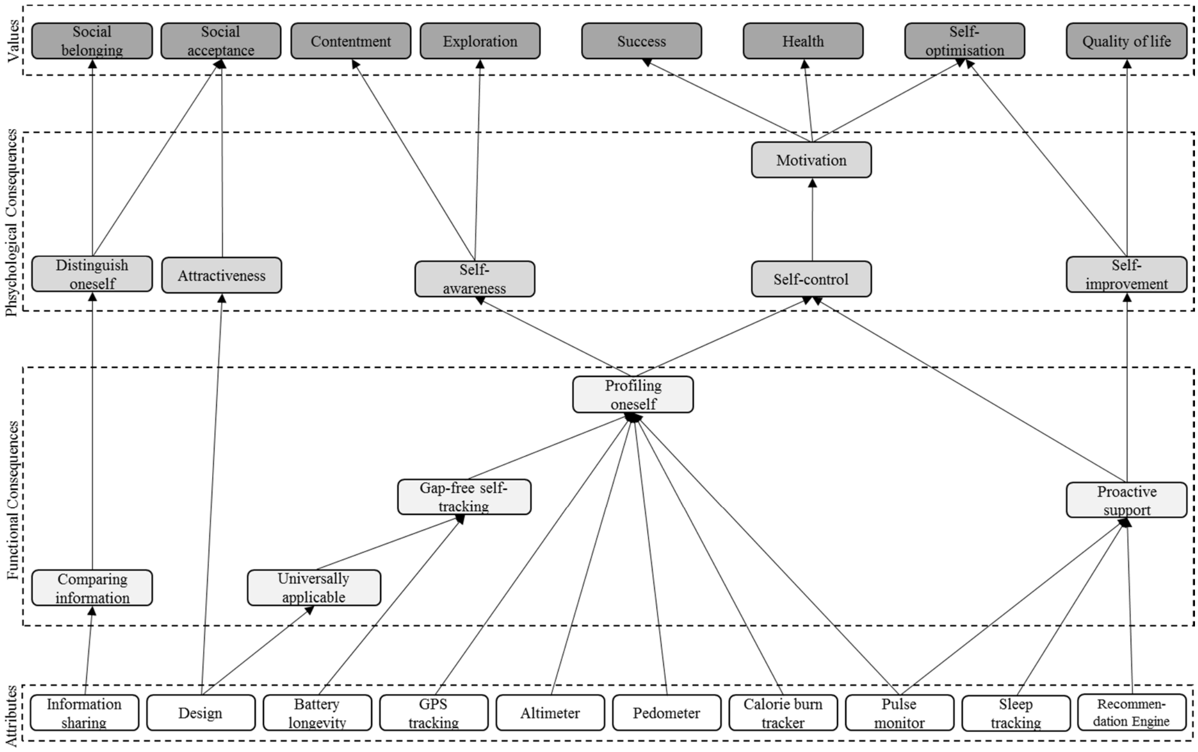

Figure 1: .Hierarchical value map of wearable use

Three major means-end chains of cognitive associations can be derived from the HVM.

The first chain of cognitive association is based on the attribute “information sharing”. It enables individuals to compare the gathered information (“comparing information”), for example, about their personal physical performance in the last week, with that of friends, family members or other people. This functional consequence provides individuals with the possibility of distinguishing themselves (“distinguishing oneself”) from others, which in turn derives the values “social belonging” and “social acceptance”.

The second chain of cognitive association is based on the “design” of the wearables, the “battery longevity” and the features that track individuals’ activities and physical conditions, i.e., “GPS tracking”, “altimeter”, “pedometer”, “calorie burn tracker” and “pulse monitor”. Wearables with an adequate design suit every occasion and situation (e.g., workplace, fitness, visiting nightclubs) and can be universally applied (“universally applicable”). This functional consequence and the attribute “battery longevity” are deemed important for individuals because they enable permanent and gap-free documentation of individuals’ activities (“gap-free self-tracking”). The consequence of “gap-free self-tracking” and the features “GPS tracking”, “altimeter”, “pedometer”, “calorie burn tracker” and “pulse monitor” are related to the desire for “profiling oneself” as accurately as possible. On the one hand, “profiling oneself” is valuable for individuals because it provides the ability to control oneself (“self-control”) in terms of the achievement of goals and plans that have been developed before. This, in turn, motivates (“motivation”) individuals to start, change or stop things with the aim of deriving the values “success”, “health” and “self-optimisation”. On the other hand, individuals profile themselves to generate “self-awareness”. Being aware of all the minutiae of everyday life provides the values “contentment” and “exploration”.

The third chain of cognitive association is based on the attributes “pulse monitor”, “sleep tracking” and “recommendation engine”. Based on these attributes, individuals receive “proactive support”, helping improve sleeping behaviour (e.g., by a recommended bed-time or sleep duration) or increase training efficiency (e.g., by recommended heart rate zones). The “proactive support” is used for “self-control” and for “self-improvement”, which is in turn associated with enhancing “quality of life”. This means, for example, that individuals feel rested and more agile when following the recommendations.

When employing an overall perspective on the derived values, it becomes obvious that the respondents clearly benefit from wearables in various ways. First, they can satisfy their desire for a healthier lifestyle. As explained by one respondent, the information provided by the wearable allows him to control himself. This, in turn, motivates him to change his behavioural patterns and increase or decrease several daily activities with the aim of improved health and quality of life. “*I always want to live healthier because very often, I felt tired and sick. But in the past, I was really lazy, undisciplined and not motivated to change anything. Since my wife bought me the wristband, I check my profile everyday, control my ‘activity level’ and read the recommendations, e.g., about the required hours of sleep. Now, I really pay attention to go to bed early, to take a walk or to eat less. Honestly, I feel much better now*” (Male, 57, butcher).

Furthermore, most of the interviewees explained that they derive an opportunity for self-fulfilment through the use of wearables. This means that they have an ideal image of whom they want to be. The continuous use of the wearables helps them identify their own weaknesses and become the best possible version of themselves. “*It sounds strange, but I have a concrete idea about my life, my body and my physical fitness. I defined many goals in order to reach this ideal picture. I am really successful in reaching these goals since starting to use the wearable because it helps me to control my everyday activities and make concrete changes*” (Male, 29, consultant). Additionally, nearly all the interviewees stated that they satisfy their epistemic interest through wearable use. The respondents are very curious to explore whether and to what extent daily activities affect their physical performance (e.g., step rate) or specific bodily functions (e.g., heart rate). One interviewee explained that he checks regularly whether the effects of several activities meet his expectations. “*For me, it is really fascinating to see how many kilometres I have actually hiked and how high my pulse frequency was. Often I realise that I did not hike that far or that my body did not even reach its limits*” (Male, 31, engineer). Additionally, the devices enable the individuals to explore hitherto-unknown relationships between performed activities and personal well-being. “*If I am tired, I check how high my physical strain was and how my sleep rhythm was. Often I realise that I have worked out a lot and slept little. That calms me down because I do not need to conclude that I am sick but rather that I need to take a break*” (Male, 29, financial analyst). Finally, the respondents stated that social values, such as social acceptance, are positive side-effects of wearable use. The possibility of sharing the information, e.g., about their fitness activities, with other wearable users, provides a positive feeling of being part of a community and differentiating oneself from others. One interviewee stated: *“I do not look very athletic. Some of my friends do not believe that I go running twice a week. Since I got the wearable, I have been able to show them my trails and they believe me. However, this function is nice to have. In the proper sense, I use the wearable for myself – not for others*” (Male, 24, student).

4.2. Value-risk assessment of wearables

After observing the perceived values of wearable use, we investigated why these values prevail over the privacy risks.

When asked about their awareness of how personal data is being used by the service provider, almost all of the interviewees stated that they had no idea how firms use the data generated from wearables. This circumstance was justified by two key arguments. On the one hand, the respondents expressed a lack of interest in gathering further information and a lack of time to do so. On the other hand, they argued that it is almost impossible to process all the information given by the firms or other sources. "*I've already tried to get an overview of the risks associated with the use of wearables. As a layman, you have no chance to get into it. I really have to say that, although I have tried to obtain information, I have no idea*" (Male, 29, project manager).

After this first question, we explicitly asked the interviewees about the perceived risks. Notably, most of the respondents needed some time to respond. "*I really have not thought about that so far. Therefore, I cannot give an answer right now*" (Female, 53, pharmaceutical assistant). Some respondents stated a concern that service providers could share their data with third parties, such as insurance companies. In this case, the interviewees were worried about suffering financial disadvantages or unfair treatment. "*For me it would be very strange if insurance companies used my data. Probably, based on this data, the firm would be able to analyse all my activities. Based on this information, it would be possible to adapt the policies because of a lower fitness level*" (Male, 38, department head). Additionally, several respondents saw a risk of unauthorised publication of the gathered data. One interviewee stated: "*Perhaps the service provider will start to publish all our profiles on his homepage. I wouldn't like this because I don't want everyone to know my health status or fitness level*" (Male, 40, human resources manager).

However, almost all of the respondents noted that these perceived risks do not influence their decision-making process in any way. It appears that the interviewees, under normal circumstances, do not base their decisions on a rational value-risk assessment. The respondents' statements suggest that risks are ignored and use is primarily value-driven. It seems that these individuals avoid effortful cognitive tasks and reduce the amount of processed information.

This assumption is based on our observation that many of the interviewees ignored the likelihood of negative consequences and focused on specific and personally important values. "*If I want to benefit from the advantages of self-tracking, I really don't worry about my privacy. I just don't care about that*" (Female, 57, secretary). Accordingly, we suggest that these individuals assessed wearable use based on a prominent dimension (Slovic 1995).

Additionally, in line with Kehr et al. (2015), we found indications of the use of the affect heuristic. Most of the interviewees stated that they used a wearable because it fits their interests or lifestyle perfectly. "*I just enjoy the use because it fits my lifestyle perfectly and I just use it without thinking about any risks*" (Male, 25, student). This finding indicates that the respondents' use decisions are driven by personal interests and the enjoyment of wearable use, i.e., hedonic values.

Furthermore, we observed that the respondents' judgements are evoked by easy-to-recall associations based on the previous use of wearables. In more detail, several interviewees stated that they rely on positive experiences associated with the use of wearables. For example, one interviewee stated: "*For me, there is no reason to be concerned about privacy risks or disadvantages. Neither I nor my friends have had bad experiences with the use of wearables*" (Male, 24, student). This statement indicates the use of the availability heuristic, which asserts that "*people assess the (…) likely causes of an event by* *the degree to which instances or occurrences of that event are readily 'available' in memory"* (Bazerman & Moore, 2008, p. 7).

The respondents do not only base their judgements on experienced characteristics of the object under investigation. They tend to focus on previously formed stereotypes resulting from the use of other digital devices. This strategy is known as the representativeness heuristic. It asserts that "*people tend to look for traits an individual may have that correspond with previously formed stereotypes*" (Bazerman & Moore, p. 8). Accordingly, the respondents emphasised basing their privacy assessments on prior experiences with smartphones or social networks: "*If I use my smartphone, I already give away many personal data. So far, nothing bad has happened by doing that, and I cannot imagine what bad things will happen to me. I do not see any reason why I should worry about that when using a wearable*" (Male, 23, student). Other interviewees indicated the use of the representativeness heuristic when generalising the value of their personal data. They attribute only a low level of relevance to their personal data in general and transfer this assessment to data gathered from wearables, which is why privacy risks are not mentioned: "*I don't think that the data gained from wearables are very interesting for companies. Honestly, if someone makes so much effort to collect the data, it is his own fault. There are certainly people whose data would be much more interesting than mine*" (Female, 28, social worker).

Finally, we observed the relevance of dispositional factors influencing individuals' decision-making. The key factor influencing the value-risk assessment was the provider of the wearable. If the provider was no longer one of the established brands (e.g., Fitbit or Jawbone) but rather a larger corporation, then the respondents stated that they would assess the risks in a more detailed way. The respondents thought primarily about insurance firms that could potentially offer the devices and retrieve the data. In this case, they would not be willing to wear the device all the time and in every situation. Due to a lack of trust, they do not want to share their private data, especially health data. The respondents assumed that insurance companies' primary goal is to maximise profit and not to offer added value to the consumer. When imagining an insurance company as the provider of wearables, the interviewees began to evaluate the values and risks in a more rational way. "*Of course, if my health insurance could use the data, I would be more cautious. For them, the data are relevant. If I had to worry that if I do not exercise enough then my premium increases, I would use the wearable more consciously and wear it only when I really need it*" (Male, 55, department head). Notably, we suggest that financial benefits do not have a positive influence on individuals' privacy-risk assessment. Most of the respondents stated explicitly the negative value of being paid, e.g., by insurance firms, for living a healthy lifestyle. One respondent describe it as an intervention in his daily life because it probably led to other-directed behaviour. "*Imagine, after having a busy but very successful day at work, you come home and instead of relaxing on the couch and being content with yourself, you have to go jogging to achieve the goals set by the insurance provider. Otherwise, you have to pay more the next month. This would be very stressful because you don't do it for yourself. You don't want to achieve your own goals. You are acting other-directed and solely focused on paying less*" (Male, 48, professor).

5. Discussion and Concluding remarks

The widespread use of wearables for self-tracking activities despite potential privacy risks is an intriguing phenomenon. For firms, the data collected from individuals' wearable use are highly valuable for generating in-depth customer insights (Zhang et al. 2011). Accordingly, firms have an increasing desire for individuals' data (Chen et al. 2012). However, in research, there is scarce knowledge about the perceived values of wearables that drive individuals' use and the reasons why these values prevail over the privacy risks (Markus & Topi 2015; Min & Kim 2015; Newell & Marabelli 2015). Additionally, there has been a call in IS research to revisit the assumption of rational decision-making and examine the influence of intuitive processes on privacy-related decision-making (Dinev et al. 2015; Newell & Marabelli 2015). Against this background, our research set out to better understand why people use wearables despite privacy risks by investigating the perceived values of wearables that drive individuals' use and data disclosure and the reasons why these values prevail over privacy risks of wearable use. Based on the concept of the privacy calculus (Dinev et al. 2006) and concepts from behavioural decision-making (Kahneman 2003), we conducted in-depth interviews with 22 wearable users from Switzerland.

The contribution of our research is threefold. First, grounded on empirical data, we provide insights into the perceived values of wearables that drive individuals' use and data disclosure. Thereby, we contribute to prior research in the IS field, which has primarily examined values of data disclosure in the contexts of e-commerce, social networks and LBS. We propose that individuals perceive the values "social belonging", "social acceptance", "contentment", "exploration", "success", "health", self-optimisation" and "quality of life". Interpreting the underlying meaning of the values shows that people pursue enjoyment, happiness and pleasure. Thus, it seems that they use wearables for activities that are intrinsically motivated and provide inherent satisfaction. Consequently, we assume that the values prevailing over privacy risks are distinctively hedonic in nature. This conclusion extends previous findings that emphasised the relevance of utilitarian values, such as financial rewards or personalisation, for sharing personal data with firms (Smith et al. 2011).

Second, our research contributes to the fundamental question of "*the overall awareness of individuals in terms of how their data are being used by businesses and whether people are happy with this*" (Newell & Marabelli 2015, p. 12). Based on in-depth interviews, we show the limited knowledge that individuals have about the consequences of using digital devices everywhere and anytime. Furthermore, our results suggest that many individuals do not want to invest time and cognitive effort to gather more information about how their personal data can be used by other stakeholders.

Third, our results provide a deeper understanding of the cognitive processes involved in privacy-related decision-making. Most research has described this process as a rational and effortful weighing of values and risks (e.g., Smith et al. 2011). Our results propose that individuals, under normal circumstances, do not base their decision on a rational value-risk assessment. Moreover, privacy risks appear to be ignored, and wearable use seems to be primarily value-driven. Few studies have investigated the impact of intuitive thinking, i.e., decision strategies, which reduce the amount of processed information and therefore the cognitive effort (e.g., Dinev et al. 2015; Kehr et al. 2015). Our study contributes to this research by emphasising the primary use of intuitive processes. Compared to Kehr et al. 2015, who focus on affect heuristics, our research suggests the use of further decision strategies. Based on our empirical study, we highlight the use of affective, availability and representativeness heuristics and the reliance on prominent dimensions.

Furthermore, our research can be used by practitioners to motivate their customers to use wearables and disclose personal data. The results give firms an idea of individuals' expectations regarding the perceived value of wearable use. Based on our results, they can configure their services to provide customers with the desired value. Additionally, our study provides firms with an in-depth understanding of the cognitive processes involved in consumers' decision-making. Using these findings, firms can adapt their communication or marketing strategies to motivate their customers to make use of heuristics or rely on prominent dimensions so that privacy risks do not influence their decision-making process.

Despite the careful design of our research approach, the findings are subject to some limitations that should be addressed by further research. First, the empirical data from the in-depth interviews do not allow us to make assumptions about the generalisability of our findings. Our findings refer to the use of bracelets and watches in the specific context of self-tracking. Researchers should be careful when transferring the results to other sorts of wearables or other digital devices in other use contexts. Furthermore, our sample only included actual wearable users and neglected non-adopters and discontinuers. Thus, our research solely discloses factors influencing the continued use of wearables. However, privacy risks may be regarded as more relevant by individuals who decided not to adopt wearables in the first place or who stopped using them. We encourage further research to investigate the generalisability of the findings by considering other technologies, use contexts and adoption phases. Second, our research focuses on individuals from Switzerland. A closer look at potential cultural differences may prove fruitful. Further research should focus on investigating the influence of cultural differences on the cognitive processes involved in privacy-related decision-making. Third, we focus on wearables offered by firms such as Fitbit, Jawbone, Samsung and Apple. The results illustrate the influence of customers' brand perception. We encourage scholars to investigate the relevant contextual factors of a firm that influence individuals' cognitive processes.

References

Acquisti, A., John, L. and Loewenstein, G. (2012). The impact of relative standards on the propensity to disclose. Journal of Marketing Research, 49 (2), 160-174.

Anderson, C.L. and Agarwal, R. (2011). The digitization of healthcare: Boundary risks, emotion, and consumer willingness to disclose personal health information. Information Systems Research, 22 (3), 469-490.

Bazerman, M.H. and Moore, D.A. (2008). Judgment in managerial decision making. 7th ed. John Wiley & Sons, New Jersey.

Bech-Larsen, T. and Nielsen, N.A. (1999). A comparison of five elicitation techniques for elicitation of attributes of low involvement products. Journal of Economic Psychology, 20, 315-341.

Belanger, F. and Crossler, R.E. (2011). Privacy in the digital age: A review of information privacy research in information systems. MIS Quarterly, 35 (4), 1017-1041.

Bhattacherjee, A. (2012). Social science research: Principles, methods, and practices. Florida.

Buchwald, A., Letner, A., Urbach, N. and von Entress-Fuerstenbeck, M. (2015). Towards explaining the use of self-tracking devices: Conceptual development of a continuance and discontinuance model. In proceedings of the Thirty Six International Conference on Information Systems (ICIS 2015), p. 1, Association for Information Systems, USA, Forth Worth.

Chen, H., Chiang, R.H.L. and Storey, V.C. (2012). Business intelligence and analytics: From big data to big impact. MIS Quarterly, 36 (4), 1165-1188.

Constantiou, I.D., Lehrer, C. and Hess, T. (2014). Changing information retrieval behaviours: An empirical investigation of users' cognitive processes in the choice of location-based services. European Journal of Information Systems, 23, 513-528.

Dinev, T., Bellotto, M., Hart, P., Russo, V., Serra, I. and Colautti, C. (2006). Privacy calculus model in e-commerce – a study of Italy and the United States. European Journal of Information Systems, 15 (4), 389-402.

Dinev, T. and Hart, P. (2004). Internet privacy concerns and their antecedents-measurement validity and a regression model. Behaviour & Information Technology, 23 (6), 413-422.

Dinev, T., McConnell, A.R. and Smith, H.J. (2015). Informing privacy research through information systems, psychology, and behavioral economics: Thinking outside the "APCO" box. Information Systems Research, 26 (4), 639-655.

Fitbit (2014). Fitbit official site for activity trackers more. https://www.fitbit.com/uk. Accessed 3 January 2016.

Gao, Y., Li, H. and Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. Industrial Management & Data Systems, 115 (9), 1704-1723.

Gutman, J. (1982). A means-end chain model based on consumer categorization processes. Journal of Marketing, 46 (2), 60-72.

IDC (2015). Worldwide wearables market forecast to reach 45.7 million units shipped in 2015 and 126.1 Million Units in 2019. http://www.idc.com/getdoc.jsp?containerId=prUS25519615. Accessed 3 January 2016.

Jawbone (2014). Jawbone UP: The path to better starts here. https://jawbone.com/. Accessed 3 January 2016.

Jung, Y. (2014). What a smartphone is to me: Understanding user values in using smartphones. Information Systems Journal, 24, 299-321.

Jung, Y. and Kang, H. (2010). User goals in social virtual worlds: A means-end chain approach. Computers in Human Bevaviour, 26, 218-225.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. American Economic Review, 93 (5), 1449-1475.

Kehr, F., Kowatsch, T., Wentzel, D. and Fleisch, E. (2015). Blissfully ignorant: The effects of general privacy concerns, general institutional trust, and affect in the privacy calculus. Information Systems Journal, 25, 607-635.

Kehr, F., Wenztel, D. and Mayer, P. (2013). Rethinking the privacy calculus: On the role of dispositional factors and affect. Proceedings of Thirty Fifth International Conference on Information Systems (ICIS 2013), p. 1, Association for Information Systems, Italy, Milan.

Lacity, M.C. and Janson, M.A. (1994). Understanding qualitative data: A framework of text analysis methods. Journal of Management Information Systems, 11 (2), 137-155.

Li, H. and Wu, J. (2014). The war in the wearable device market: The analysis from economic perspective. In Proceeding of the 19th Pacific Asia Conference on Information Systems (PACIS 2014), p. 1, Association for Information Systems, China, Chengdu.

Maddox, T. (2016). The dark side of wearables: How they're secretly jeopardizing your security and privacy. http://www.techrepublic.com/article/the-dark-side-of-wearables-how-theyre-secretly-jeopardizing-your-security-and-privacy/. Accessed 3 Janurary 2016.

Markus, M.L. (2015). New games, new rules, new scoreboards: The potential consequences of big data. Journal of Information Technology, 30, 58-59.

Markus, M.L. and Topi, H. (2015). Big Data, big decisions for science, society, and business. https://www.bentley.edu/files/2015/10/08/BigDataWorkshopFinalReport.pdf. Accessed 3 January 2016.

McAfee, A. and Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review*, October.

Motti, V.G. and Caine, K. (2015). Users' privacy concerns about wearables. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8976, 231-244.

Mills, D. (2015). Consumers like wearable technology but worry about data security. http://www.healthline.com/health-news/consumers-concerned-about-privacy-personal-health-data-wearables-mobile-apps-072815#1. Accessed 3 January 2016.

Min, J. and Kim, B. (2015). How are people enticed to disclose personal information despite privacy concerns in social network sites? The calculus between benefit and cost. Journal of the Association for Information Science and Technology, 66 (4), 839-857.

Newell, S. and Marabelli, M. (2014). The crowd and sensors era: Opportunities and challenges for individuals, organizations, society, and researchers. Proceedings of Thirty Fifth International Conference on Information Systems (ICIS 2014), p. 1, Association for Information Systems, New Zealand, Auckland.

Newell, S. and Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification'. Journal of Strategic Information Systems, 24 (1), 3-14.

Olson, J.C. and Reynolds, T.J. (2001). The means-end approach to understanding consumer decision making. In: Reynolds, T.J., Olson, J.C. (Eds.). Understanding consumer decision making: The means-end approach to marketing and advertising strategy. Lawrence Erlbaum, Associates, Mahwah.

Reynolds, T.J., Gengler, C.E. and Howard, D.J. (1995). A means-end analysis of brand persuasion through advertising. International Journal of Research in Marketing, 12, 257-266.

Reynolds, T.J. and Gutman, J. (1988). Laddering theory, method, analysis, and interpretation. Journal of Advertising Research – February/March, 11-24.

Reynolds, T.J. and Olson, J.C. (2001). Understanding consumer decision making: The means-end approach to marketing and advertising strategy. Erlbaum, Mahwah.

Rogers, E. (1995). Diffusion of innovations. Free Press, New York.

Schäfer, T. (2013). Exploring carsharing usage motives: A hierarchical means-end chain analysis. Transportation Research Part A, 47, 69-77.

Setia, P., Venkatesh, V. and Joglekar, S. (2013). Leveraging digital technologies: How information quality leads to localized capabilities and customer service performance. MIS Quarterly, 37 (2), 565-590.

Sjöklint, M., Constantiou, I. and Trier, M. (2015). The complexities of self-tracking - an inquiry into user reactions and goal attainment. In Proceedings of the European Conference on Information Systems, p. 1, European Research Centre for Information Systems, Germany, Münster.

Slovic, P. (1995). The construction of preferences. American Psychologist, 50 (5), 364-371.

Smith, H.J., Dinev, T. and Xu, H. (2011). Information privacy research: An interdisciplinary review. MIS Quarterly, 35 (4), 989-1015.

Statista (2016a). Welche der folgenden medien nutzen sie an einem normalen wochentag (montag bis freitag), egal wie häufig? http://de.statista.com/statistik/daten/studie/420271/umfrage/regelmaessige-nutzung-ausgewaehlter-medien-in-der-dach-region/. Accessed 3 January 2016.

Statista (2016b). Wie wahrscheinlich ist es, dass sie sich in den nächsten 12 monaten eine smartwatch kaufen? http://de.statista.com/statistik/daten/studie/422088/umfrage/marktpotenzial-der-smartwatch-in-der-schweiz-nach-alter-geschlecht-und-region/. Accessed 3 January 2016.

Sun, Y., Wanga, N., Shen X. and Zhang, J. X. (2015). Location information disclosure in location-based social network services: Privacy calculus, benefit structure, and gender differences. Computers in Human Behavior, 52, 278-292.

Sutanto, J., Palme, E., Tan, C.H. and Phang, C.W. (2013). Addressing the personalization-privacy paradox: An empirical assessment from a field experiment on smartphone users. MIS Quarterly, 37 (4), 114-1164.

Trickler, C. (2013). An overview of self-monitoring systems. In Proceedings of the Nineteenth Annual 16th Southern Association for Information Systems Conference (SAIS 2013), p. 197, Southern Association for Information Systems, USA, Georgia.

Wagner, T. (2007). Shopping motivation revised: A means-end chain analytical perspective. International Journal of Retail & Distribution Management, 35 (7), 569-582.

Wilson, D.W. and Valacich, J.S. (2012). Unpacking the privacy paradox: Irrational decision-making within the privacy calculus. In Proceedings of Thirty Third International Conference on Information Systems (ICIS 2012), p. 1, Association for Information Systems USA, Orlando.

Xu, H., Teo, H.H, Tan, B.C. and Agarwal, R. (2009). The role of push–pull technology in privacy calculus: The case of location-based services. Journal of Management Information Systems, 26 (3), 135-173.

Xu, H., Dinev, T., Smith, J. and Hart, P. (2011). Information privacy concerns: Linking individual perceptions with institutional privacy assurances. Journal of the Associations for Information Systems, 12 (12), 798-824.

Zhang, D., Guo, B. and Yu, Z. (2011). The emergence of social and community intelligence. Computer 44 (7), 21-28.

Zhao, L., Lu, Y. and Gupta, S. (2012). Disclosure intention of location-related information in location-based social network services. International Journal of Electronic Commerce, 16 (4), 53-90.

Alexander Wieneke
German citizen, born April 2, 1988

EDUCATION

04/14 – 10/17	**University of St.Gallen (HSG)**, Institute of Information Management, Chair of Business Engineering (Prof. Dr. Reinhard Jung), St.Gallen, Switzerland *Ph.D. Candidate in Business Innovation*
06/17 – 09/17	**National University of Singapore**, School of Computing, Singapore *Visiting Scholar*
04/12 – 03/14	**University of Bayreuth**, Bayreuth, Germany *Master of Science in Business Studies*
10/09 – 12/11	**University of Bayreuth**, Bayreuth, Germany *Bachelor of Science in Business Studies*
10/07 – 09/09	**Leibniz University of Hanove**r, Hanover, Germany *Bachelor of Science in Economics*
08/00 – 06/07	**Gymnasium Neustadt**, Neustadt am Rübenberge, Germany *Abitur (German university entrance diploma)*

WORK EXPERIENCE

Since 02/18	**Hilti Befestigungstechnik AG,** Buchs, Switzerland *CIO Office, Strategic Projects (Strategic Assistant to the CIO)*
04/14 – 10/17	**Competence Center Digital Service Innovation of the University of St.Gallen (HSG)**, St.Gallen, Switzerland *Project manager*
02/13 – 04/13	**Kienbaum Management Consultants GmbH**, Düsseldorf, Germany *Intern in the industrial department*
01/12 – 03/12	**KPMG Luxembourg S.à r.l.**, Luxembourg *Intern in the audit department*
09/11 – 11/11	**SAP AG**, Walldorf, Germany *Intern in the on-demand solution department*
02/11 – 04/11	**KPMG AG**, Nuremberg, Germany *Intern in the audit department*
02/10 – 04/10	**Volkswagen Commercial Vehicles**, Hanover, Germany Intern in the process design department
02/09 – 03/09	**Hanover State Opera**, Hanover, Germany *Intern in the controlling department*
07/07 – 08/07	**AOK Lower Saxony**, Sarstedt, Germany *Intern in the human resource department*