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Insights

Welcome to the October issue of the Technology Innovation Management Review. We invite your comments on the articles in this issue as well as suggestions for future article topics and issue themes.

Carleton University

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Overview
The Technology Innovation Management Review (TIM Review) provides insights about the issues and emerging trends relevant to launching and growing technology businesses. The TIM Review focuses on the theories, strategies, and tools that help small and large technology companies succeed.

Our readers are looking for practical ideas they can apply within their own organizations. The TIM Review brings together diverse viewpoints —from academics, entrepreneurs, companies of all sizes, the public sector, the community sector, and others —to bridge the gap between theory and practice. In particular, we focus on the topics of technology and global entrepreneurship in small and large companies.

We welcome input from readers into upcoming themes. Please visit timreview.ca to suggest themes and nominate authors and guest editors.

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About TIM

The TIM Review has international contributors and readers, and it is published in association with the Technology Innovation Management program (TIM; timprogram.ca), an international graduate program at Carleton University in Ottawa, Canada.

Editorial: Insights

Gregory Sandstrom, Managing Editor

Welcome to the October issue of the Technology Innovation Management Review. This month features two more invited papers from the 31st ISPIM Innovation Conference, with the theme "Innovating in Times of Crisis", held virtually on June 7-8th, 2020. Two other papers add further contributions rounding out an edition that explores AI for platform innovation, data-driven business logic, business models in disruptive industries, and sustainability communications patterns by companies spending on R&D.

Sergey A. Yablonsky's "AI-Driven Digital Platform Innovation" begins the issue by focusing on the business shift towards big data (BD) involved with emerging digital enterprise platforms. He highlights the potential of advanced analytics (AA) and artificial intelligence (AI) to enhance value chain growth and efficiency as companies grow their AI capacities. The paper "develops a multi-dimensional AI-driven platform innovation framework with AI/BD/AA innovation value chain and related levels of AI maturity improvement" (pg. 5). It addresses "new ways to reuse and extract value from BD assets through AI-driven platform innovation" (pgs. 14-15) and proposes that "today's leaders [also] need to more openly embrace AI and become involved in contributing to the discussion of AI ethics" (pg. 15).

Petra Kugler follows this with "Approaching a Data-Dominant Logic". Her paper also looks at data science, here in the context of developing a new type of "dominant logic" for business that makes better use of data. "[F]irms first need to establish a new mindset," says Kugler, "in which data plays a central role" (pg. 17). Researching the ways data can be used to impact businesses led her to propose a data-dominant logic (DDL) framework, which she applies in this paper based on an empirical study of the organizational and managerial requirements of SMEs. Through a survey and interviews with representatives from 16 SMEs in Austria, Germany, and Switzerland, she develops a list of DDL working hypotheses, noting that "many firms have no clear repertoire to act on a data strategy within the changing setting and therefore cannot fully exploit the potential inherent to data science practices" (pg. 26).

Alina Marie Herting and **Alexander Lennart Schmidt** partner on "A Systematic Analysis of how Practitioners Articulate Business Models across Disruptive Industries". They start with the problem that "[t]oo little is still known about how practitioners highlight different characteristics of business models across industries confronted with disruptive dynamics" (30). To explore the different characteristics and how business models are articulated in disruptive industries, they studied the business models of companies based on 1,095 press releases and company reports across 11 industries published between 1995 and 2019. From this, they identify various challenges and components of business models that differ across specific disruptive industries.

The final paper is by **Giacomo Liotta*, Stoyan Tanev, Andrea Gorra,** and **Alicja Izabela Pospieszala** focusing on "Sustainability-related Communication Patterns on the Websites of European Top R&D Spenders". Their research draws attention to sustainability patterns in corporate communication that could inform sustainable innovation business decision-making. The authors use a web-based data collection methodology and principal component analysis of frequencies of words in publicly available textual data to make the key observation that a "focus on sustainable operations serves as most companies' key communication pillar, which they complement with a focus on stakeholder benefits and sustainable innovation" (53). The findings show "a strong relationship between the communication of sustainable innovation aspects and sales, which offers a promising message to companies looking for evidence about the potential impact of their commitment to sustainable operations and innovation" (pg. 44).

The TIM Review currently has Calls for Papers on the website for Upcoming Themes with special editions on "*Digital Innovations in the Bioeconomy*" (Feb. 2021) and "*Aligning Multiple Stakeholder Value Propositions*" (March 2021). For future issues, we invite general submissions of articles on technology entrepreneurship, innovation management, and other topics relevant to launching and scaling technology companies, and for solving business practical problems in emerging domains such as artificial intelligence and blockchain applications in business. Please contact us with potential article ideas and submissions, or proposals for future special issues.

Gregory Sandstrom
Managing Editor

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Keywords: Artificial intelligence (AI), AI-driven platform innovation, big data, advanced analytics, enterprise platform, AI value chain, AI maturity. Data science, dominant logic, data-dominant logic, empirical study, organizational and managerial requirements, SMEs. Disruptive innovation, business models, industries, business model components, content analysis, secondary data. Sustainability, sustainable innovation, business decision-making, online communication, research and development, R&D, online data collection, principal component analysis.

AI-Driven Digital Platform Innovation

Sergey A. Yablonsky

> *"We're rapidly entering a world where everything can be monitored and measured. But the big problem is going to be the ability of humans to use, analyze and make sense of the data."*
>
> Erik Brynjolfsson
> Director of the Digital Economy Lab,
> Stanford Institute for Human-Centered AI (HAI)

Artificial Intelligence (AI) innovation becomes useful today when it enriches decision-making that is enhanced by applications of big data (BD), advanced analytics (AA), and some element of human interaction using digital platforms. This research aims to investigate the potential combination of AI, BD and AA for digital business platforms. In doing so, it develops a multi-dimensional AI-driven platform innovation framework with AI/BD/AA innovation value chain and related levels of AI maturity improvement. The framework can be used with a focus on the data-driven human-machine relationship and the application of AI at different levels of an AI-driven digital platform technology stack.

1. Introduction

The industry platform is a distinctive organizational form that has become significant over the past decades (Evans & Gawer, 2016). Nowadays, a new digital platform together with its related ecosystem (industrial, data or otherwise), is positioned to create and capture value in digital economies (Yablonsky, 2019a; 2020).

With digital platforms, data has become a kind of raw material and the basis for a new infrastructure used to generate revenue. In digital economies, with billions of consumers and providers connected through mobile online devices and engaging with other users almost continuously, platforms record and analyze enormous amounts of user-generated data, tracked via cookies and other services (Cusumano et al., 2020). Where there is data, there is value. Data and analytics are central to success in the platform business. But successful platform growth and scaling requires more data, more complex data, more variables, and more sophisticated analysis by more business people, beyond what can be done manually.

The vast array of available digital platform data together with the rapid emergence of Artificial Intelligence (AI) insights and services have given rise to a perception of technology abundance. However, while most platforms have enough data processing solutions, products, and vendors, they are typically lacking a single organizational view into 1) what AI transformation services they need to use, on 2) which digital assets, regarding 3) who, when, and why they should be provided, as well as 4) what services they should be integrating with, and 5) why they should be doing it.

Insights from the literature on platform enterprise architecture conceptualization are essential to understanding the relationship between platforms and AI innovation. In the era of Big Data (BD) and the privacy issues it raises, platform enterprises can ill afford to ignore runaway AI technology that may be collecting data outside the lines of industry and government regulations. Indeed, BD and AI present more than just a compliance risk. Understanding – and strategically planning – exactly what AI services are or should be in use across the platform as directed by the official business organization is critical to maintaining a sound BD and AI business platform strategy. It is not only

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about the technology when it comes to AI integration. It is also about what AI technology enables a platform to do. This involves understanding how the data is being collected, passed between technology platforms, stored, processed by AI, and ultimately used (or not used) to add value to business.

This paper addresses the following questions:

- What is AI-driven platform innovation?
- What is the potential value of multilayer business platform AI innovation through a descriptive framework that combines AI with a digital platform stack?

My aim in the paper is to investigate a step further work done already that combines AI and a "digital platform stack" (Yablonsky, 2018ab, 2019b, 2020). The term "digital platform stack" is defined in (Yablonsky, 2018a) and discussed in Section 3 of this paper. The reason I find the term "digital platform stack" important for discussing AI platform innovation is because it helps to combine and describe the main platform layers involved with emergent AI technology (Figure 1).

The remainder of this paper is structured as follows. Section 2 describes the methodology. Section 3 discusses the main definitions and conceptual background of AI and digital platform innovation based on a literature review. Section 4 confers the place of AI in digital platforms and presents a multidimensional AI-driven innovation framework that combines platform innovation value chains with AI innovation. Section 5 interprets the research results, provides discussion, and suggests implications of this study.

2. Research Methodology

This research aims to explore a multilayered AI-driven platform framework working together with a digital platform stack in order to facilitate understanding, analysis, and more concrete structure of the AI relationship in platform business model design and value creation. This approach proves particularly beneficial for the field due to the current lack of such systematic empirical analysis from management research. Likewise, it holds potential value for platform firms engaging with innovative AI technologies

The development of the AI-driven platform innovation framework used in this research was guided by the approach of Nickerson et al. (2012). It facilitates the iterative combination of conceptual-to-empirical as well as empirical-to-conceptual approaches. At this point, the research process consists of four distinct steps.

The process initiated through a conceptual-to-empirical approach by defining the primary platform value chains, their relations with AI and components/dimensions of an established AI-driven platform innovation conceptualization.

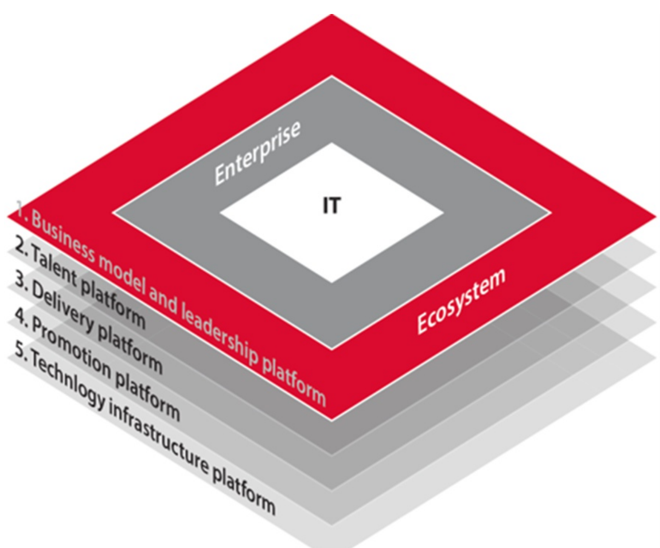

Figure 1. Digital Platform Stack (Yablonsky, 2018 ab)

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Subsequently, we collected qualitative data from secondary data sources and through 10 semi-structured expert interviews. The 15 min interviews were recorded and transcribed. Our interview partners were members of the technology-oriented groups, founders and CTOs of the Russian National Technology Initiative, and international AI-driven platform ventures.

To further improve data reliability and internal validity, the streamlined and codified interview outcomes were triangulated with a range of secondary data, consisting especially of publicly available government AI strategic documents and policies, venture's white papers and annual reports, research papers and cases. To identify the sub-dimensions and instantiations, ventures were screened for differences and commonalities, thus leading to a preliminary version of the BD/AI-driven platform framework presented here.

Finally, a second version of the framework was developed through an online survey consisting of 15 questions about BD/AI-driven digital platform stack enterprise innovation. Invitations were sent to 50 AI-driven platform ventures, specifically to Russian and international startup incubators. The list was chosen from the crunchbase.com database, plus several sites that publish ventures' annual reports. Out of the 50 contacted companies, we received 20 fully filled-out surveys. Based on this feedback, the final minor adjustments to the AI-driven platform framework were made, required modifications identified, and a refined framework proposed.

3. Current Understanding

Despite the growing research interest in AI innovation, most studies on AI innovation look at innovation from a technical, architectural, or information system-level perspective (Lyytinen et al., 2016; Jyoti et al., 2019), rather than from a managerial or business perspective. Let us then have a brief look at what is meant by AI.

Definition (Gartner, 2020)
"Artificial intelligence" applies advanced analysis and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions.

"Artificial Intelligence":

- Emulates human performance, typically by "learning"
- Comes to its own conclusions
- Understands complex content
- Engages in natural "dialogues" with people
- Helps enhance human cognitive performance
- Replaces people as workers in the execution of non-routine tasks.

The EU (2018) defines "artificial intelligence" as a digital innovation that offers solutions to transform enterprise products, services and businesses using AI, BD, and related AA.

In this article AI-driven platform innovation, data and analytics are approached in terms of platform enterprise digital business platforms and technological platforms. Thus they take on a more active and dynamic role in powering the activities of the entire digital platform and business organization.

Therefore, previous studies took an approach to AI innovation types by choosing BD and AA as its background context (Yablonsky, 2019b). This previous research aimed to investigate the potential value of BD and AA, together with AI within a multidimensional framework that combines AI maturity and AI/BD/AA value chains. In doing so, it developed a data-driven AI innovation taxonomy framework with related levels of AI/BD/AA maturity improvement across innovation value chains. This was done to see how strategy, products, and solutions transform into innovative data-driven AI business strategies, products, or solutions that subsequently impact traditional business operations, and can even lead to the creation of new businesses. Indeed, there is little argument that AI is right at the heart of digital disruption.

AI disruption itself has a goal to drive better customer engagement and lead to accelerated rates of innovation, higher competitiveness, higher margins, and more productive employees. AI innovation has been powered by BD and AA. BD involves collecting and active gathering from of a wide variety of inputs, including publicly available data, information, or knowledge, human intelligence, then processing the resulting inputs in a way that helps to better understand and predict competitor strategies and actions (Erickson & Rothberg, 2015; Marr, 2015).

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The AI value chain identifies the following key high-level AI/BD/AA activities, also described as "dimensions" (Yablonsky, 2019b):

- AI Awareness/Big Data Acquisition is the process of gathering, filtering, and cleaning data before it is put in a data warehouse, data lake, or any other storage solution on which data analysis can be carried out based on the availability of BD and access to BD sources. There are a variety of BD types and sources. Value for business purposes is created by acquiring data and combining data from different sources. BD pre-processing, validating, and augmenting, as well as ensuring its integrity and accuracy, adds value to the data.

- Adjusting AI/Big Data Analysis is concerned with making the raw data acquired amenable to use in decision-making, including that which is domain-specific. "Value" here refers to providing access to data with low latency, while ensuring data integrity, and preserving privacy. Evaluation, machine learning, information extraction, and data discovery of intangible AI/BD assets adds further value.

- Measuring AI/Big Data Curation is the active management of data over its life cycle for effective usage based on the measurement of AI/BD assets to ensure it meets the necessary BD quality requirements for its effective usage.

- AI Reporting and Interpreting/Big Data Storage denotes the persistence and management of data in a scalable way that satisfies the needs of applications that require fast access to the data.

- AI Decision Making/Big Data Usage covers data-driven business activities that need access to data, its analysis, and the tools to integrate data analysis as a business activity. It covers the main AI/BD assets usage in business decision-making that can improve competitiveness through reducing costs, increasing added value, or any other parameter that can be measured against existing performance criteria.

This paper uses and integrates into one framework:

- the current AI value chain to model high-level activities that comprise a digital platform enterprise.

- the five levels of AI maturity (Yablonsky, 2019b), from a completely ad hoc approach with limited awareness, to one in which AI innovation strategy is integrated into the organization's culture at every level, enable defining AI-driven platform innovation dimensions.

- the digital platform stack (Yablonsky, 2018ab, 2020).

AI maturity can be seen as a useful lens for understanding a company's AI-driven platform innovation logic because it explains what value is provided, how the value is created and delivered, and how profits can be generated from it. Thus, the main technological and platform type dimensions can be extended with various levels of AI maturity. This helps to understand how to capture AI-driven value from technological innovations and platforms, by taking into account the boundaries of a firm (Zott et al., 2010), and creating a direct connection between business strategy, business processes, and technological platforms.

Digital platform transformation of enterprises across industries is still an emerging phenomenon. At a high level, digital transformation covers the intense changes taking place in society and industries through using digital technologies (Khin, Ho, 2018; Vial, 2019). At the organizational level, it has been contended that firms must find means to innovate with new technologies by creating "strategies that embrace the implications of digital transformation and drive better operational performance" (Hess et al., 2016).

A "multi-sided business platform" is an enterprise organization that creates value primarily by enabling direct interactions between two (or more) distinct types of affiliated customers (Evans & Gawer, 2016; De Reuver et al., 2018). Researchers (Cusumano et al., 2020) have divided such platforms into three basic types:

- Innovation platforms enable third-party firms to add complementary products and services to a core product or technology (examples: Google Android, Apple iPhone operating systems or Amazon Web Services)

- Transaction platforms enable the exchange of information, goods, or services (examples: Amazon Marketplace, Airbnb, or Uber)

- Hybrid platforms (combination, emerging type).

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The six most valuable firms in the world are built around these three basic types of platforms (Cusumano et al., 2020). In their analysis of data going back 20 years, researchers have identified 43 publicly listed platform companies in the Forbes Global 2000. It has been asserted that "these platforms generated the same level of annual revenues (about $4.5 billion) as their non-platform counterparts, but used half the number of employees. They also had twice the operating profits and much higher market values and growth rates" (Cusumano et al., 2020). In order to provide managerial guidance for digital platform transformation, research needs to enhance our understanding of how firms can achieve a sustainable competitive advantage by building on specific AI-related platform resources. This includes identifying which strategies they should adopt to succeed digitally, and how a firm's internal organizational structure must change to support digitalization strategies.

Gartner defines "innovation management" as a business discipline that aims to drive a repeatable, sustainable innovation process or culture within an organization. Innovation management initiatives focus on disruptive or step-by-step changes that transform a business ecosystem in some significant way.

According to one definition (Burton & Basiliere, 2016), a "digital platform" is a business-driven framework that allows a community of partners, providers, and customers to share and enhance digital processes and capabilities, or to extend them for mutual benefit.

To design a digital business platform, organizations must lead their business to take a data-driven, outside-in approach (Evans & Gawer, 2016). Digital business platforms empower flexible and dynamic digital business transactions. Disruption through such platforms is a process that impacts multi-sided markets through digital capabilities, channels, and assets. Digital business innovation thus creates disruptive platform network effects or externalities.

Definition (Leiblein, 2018)
"Platform innovation" refers to changes in support structures that increase the effectiveness with which a group of activities may be performed on a platform. Product platform innovation entails changes to a common component or body of knowledge that may be redeployed across products. Industry platform innovation entails changes to infrastructure, standards, and rules that enable transactions between multiple firms. Digital technology platforms are described through the lens of applications and business capability components of the business platform technology stack they support (Yablonsky, 2018ab, 2020).

The author of this paper previously (Yablonsky 2018ab, 2020) distinguished the following main platform types related with the digital platform stack (Figure 1):

1. Business platforms
   - 1.1. Business Model and Leadership platform (B1).
   - 1.2. Talent platform (B2).
   - 1.3. Delivery platform (B3).
   - 1.4. Promotion platform (B4).
2. Technology platforms
   - 2.1. Information systems platform (T1): Supports the front and back office and operations, such as ERP and other core systems.
   - 2.2. Customer experience platform (T2): Contains the main customer-facing features, such as customer and citizen portals, omni-channel commerce, and customer apps.
   - 2.3. Data and analytics platform (T3): Includes information management and analytical capabilities. Data management programs and analytical applications fuel data-driven decision making, and algorithms automate discovery and recommended action.
   - 2.4. IoT platform (T4): Connects physical assets and smart machines (smart things) for monitoring, optimization, control, analytics, and monetization. Capabilities include connectivity, analytics, and integration to core and OT systems.
   - 2.5. Ecosystems platform (T5): Supports the creation of, and connection to, external ecosystems, marketplaces, and communities. API management, control, and security are its main elements.
   - 2.6. Trust platform (T6): Enables a higher sense of trust between participants in the ecosystem. A

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distributed ledger (for example, blockchain) technology used to foster community trust provides one emerging example.

2.7. Integration platform (T7): Supports the integration of all the above platforms, allowing the maximum flexibility to support business transformation demands.

4. AI-driven Platform Innovation

AI-driven platform innovation can be developed through the lens described above involving business capability components and applications of a digital business platform technology stack they support. It is intended to provide a high-level overview of the key capabilities necessary to assemble a AI-driven platform innovation in the digital business platform stack.

Business Platforms

The Business Model and Leadership platform, as well as the Talent platform, are related more with platform capabilities (Teece, 2017). Their goal is to facilitate knowledge exchange in Business Model and Leadership environments and to offer affiliates the opportunity to access large intra-ecosystem or ecosystem communities of actors, with experiential, educational, or professional knowledge in a company's diverse geographical and disciplinary fields (Boudreau, 2010; Boudreau et al., 2011; Colombo et al., 2013; Colombo et al., 2015; Evans & Gawer, 2016). The key roles of a Business Model and a Leadership platform are to collect dispersed sources of knowledge, to recombine the collected knowledge, to empower innovation and management, and to transfer it to new technological and organizational contexts. Delivering a digital platform business requires new capabilities to enable, support, and manage digital business (Burton & Basiliere, 2016).

The variance in a company's digital business performance can be a function of the differences in their platform's resources and capabilities compared with market competitors.

In contrast with the clear inside and outside distinction in traditional business, a digital platform provides a business with a foundation where resources can come together in various combinations to create value. Some resources may be inside, permanently owned by the company, while some may be shared by customers, and others can even come from an outside ecosystem. The combined value a company uses to scale comes largely from the dynamic connection of resources and actors, and the potential network effects that arise between them.

Platform design facilitates matching among providers ("producers") and consumers ("users") or, in other words, the creation or exchange of goods, services, and social currency, so that all participants in the market can capture value. Digital platforms offer unique opportunities to engage members of a business ecosystem in transactions to exchange value (Blosch & Burton, 2016).

Platform business model management is an important managerial function (Osterwalder and Pigneur, 2010; Hagiu, 2014). It involves the ongoing monitoring of activities that encompass the company's business model, as well as of incentives for stakeholders participating in the business model. Business model management thus considered could be viewed as part of a firm's ordinary capabilities (in terms of the day-to-day performance of activities), but it also requires dynamic adaptation and transformation in light of market conditions, and thus links to the dynamic capabilities framework. Identifying sustainable business models and ecosystems in and across sectors and platforms is an important challenge. Many SMEs that are now involved in highly specific or niche roles will need support to help align and adapt to new AI-driven value chain opportunities in the future.

New concepts for digital platform AI-driven BD collection, processing, storing, analyzing, handling, visualization and, most importantly, usage are emerging, and new AI-driven platform strategies and business models are being created around them. With AI-driven digital platform business models, platform assets may be added or combined in new and different ways to support the platform's strategy.

In platform business models, AI is good for scale acceleration to:

Automate sorting processes and actions.

- Automate predictions in detail.
- Address historical desires first.
- Address data with clear parameters.

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- Identify credible, good-quality data with sufficient scope to fully engage the problem.

- Pursue reasonable and possible goals.

AI provides the potential for generating the following economic benefits from platform data:

- Indirect data monetization

- Using data to improve platform efficiencies.

- Using data to develop new platform products and markets.

- Using data to build and solidify platform partner relationships.

- Branded indices.

- Direct data monetization

- Bartering/trading with platform data.

- Data-enhanced platform products or services.

- Selling platform raw data through brokers.

- Offering platform data/report subscriptions.

A Delivery business platform creates value primarily by enabling direct interactions between two (or more) distinct types of affiliated delivery consumers. Here AI-driven innovations can influence smart transport delivery business processes related with driverless transport, AA/BD predictive analytics, and supply chain management.

A Talent business platform creates value primarily by enabling direct interactions between two (or more) distinct types of affiliated talent consumers. The talent platform is at the center of the enterprise's relationship with talent. How can an enterprise acquire and keep its top talent in the age of digital business? In its relationships with top talent, enterprises can use marketing tools and analyses. Seeing talent through the eyes of a customer, based on an employment-by-talent platform as a kind of company brand promise fulfilled, can improve talent acquisition and retention. Persistent shortfalls in key talent areas show that enterprises have to act now to adapt their talent approaches in the digital world.

A Talent platform serves the need of multiple customer segments, including enterprise executives, managers, HR professionals and recruiters, potential or current employees, to create and maintain engagement and dynamic relationships between the enterprise and its contributors, internal and external (Hunter and Coleman, 2016). A key function of the talent platform is data capture and analysis related to talented individuals and talent pools; before, during and after their employment by the enterprise. Treating talent through the eyes of a customer whose relationship with the enterprise includes a mix of exploration, evaluation, and engagement over time is more realistic and fruitful for all involved than has been the former tradition of treating the acquisition of talent as a transaction.

AI influences and provides platform data literacy: the ability to read, write, and communicate data in context, including an understanding of data sources and constructs, analytical methods and techniques applied, and the ability to describe use-case applications and their resulting value.

A Promotion business platform creates value primarily by enabling direct promotional interactions between two (or more) distinct types of affiliated platform participants, including consumers, producers, and providers. It enables internally managed outbound messages and external inbound messages by platform participants themselves. A Promotion platform in uences platform participants to submit multimedia messages, provide footage, documentation, or reports about different types of activities and share them on social media and other platform ecosystems.

Technology Platforms

Each area of a platform can deliver insight that is descriptive, diagnostic, predictive, and/or prescriptive. BD, analytics, and algorithms are essential to digital business platforms and should be integrated with platform services to permit other platforms to use external and internal data and analytics. To democratize data processing and visualization, a Technology platform should include self-service features for increasingly wider enterprise constituencies. AI may infuse digital platforms in all mentioned above business and technology versions (Table 1).

Key stakeholders of AI-driven platform innovation include executives, IT leadership, line-of-business managers, employees, partners, and suppliers.

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Table 1. AI-driven digital platform technology stack innovations

Platform type	**AI-Driven Innovation**
	Business Platforms
Business Model and Leadership platform (B1)	B1 facilitates knowledge exchange in Business Model and Leadership environments and offers affiliated actors the opportunity to access large intra-ecosystem or ecosystem communities of actors with experiential, educational, or professional knowledge in company's diverse geographical and disciplinary fields.
Talent platform (B2)	B2 creates value primarily by enabling direct interactions between two (or more) distinct types of affiliated talent consumers.
	AI impacts and provides platform data literacy: the ability to read, write and communicate data in context, including an understanding of data sources and constructs, analytical methods and techniques applied, and the ability to describe the use-case application and resulting value.
Delivery platform (B3)	B3 creates value primarily by enabling direct interactions between two (or more) distinct types of affiliated delivery consumers.
	AI impacts smart transport delivery business processes related with driverless transport and AA/BD predictive analytics and supply chain management.
Promotion platform (B4)	B4 creates value primarily by enabling direct promotion interactions between two (or more) distinct types of affiliated platform participants: consumers, producers, and providers.
	AI influences – Creation of internally managed outbound messages and externally inbounded messages by platform participants themselves. – Exchange/sharing among platform participants - consumers, producers, and providers - multimedia messages. – Provision and promotion on social media and platform ecosystems different activity types.

AI-driven digital platform innovation incorporates multiple activities that are sometimes difficult to unravel, analyze, and predict. Such innovations on digital platforms are often rapidly changed. To maximize complementarity across the platform technology stack, it is important to identify the relationship between different business platforms (capabilities), technological platforms, performance, and innovation for enterprise-level digital platforms.

This paper uses a simple method of matrix mapping (Yablonsky, 2018ab, 2020) for the business model platform layer and platform's technology stack. As a synthesis of various views commonly held by technology analysts, researchers, and practitioners today, the paper analyses and designs AI-driven platform innovation dimensions through a minimalistic, object-oriented, and functional representation. This is based on seven key technology platforms and five levels of AI maturity (Table 2).

For example, the following sequence for companies to use in their self-assessment based on five key levels of AI platform maturity might be implemented as follows:

(1) List key five levels of AI-driven platform maturity.

(2) Use needed or assessed level of platform maturity

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Table 1. AI-driven digital platform technology stack innovations (cont'd)

Technological Platforms	
Information systems platform (T1)	T1 supports the front and back office and operations, such as ERP and other core systems (Employees & Suppliers).
	AI transforms – Business and Operational Analytics. – Core IT Systems. – Back-Office Systems. – Supplier Portal. – Supplier Apps.
Customer experience platform (T2)	T2 contains the main customer-facing counterparts, such as customer and citizen portals, omni-channel commerce, and customer apps.
	AI transforms – Customer Analytics. – Multichannel Commerce. – Social Networks. – Customer Portal. – Customer Apps. – Customer Facing and Public APIs.
Data and analytics platform (T3)	T3 includes information management and analytical capabilities. Data management programs and analytical applications fuel data-driven decision making, and algorithms automate discovery and action.
	AI transforms – Decision Models. – Algorithm and AI Engines.
IoT platform (T4)	T4 connects physical assets and smart machines (smart things) for monitoring, optimization, control, analytics, and monetization. Capabilities include connectivity, analytics and integration to core and OT systems.
	AI transforms – IoT Analytics. – Connected Things (Enterprise). – Connected Things (Partner). – Connected Things (Customer). – Endpoint Computing.
Ecosystems platform (T5)	T5 supports the creation of, and connection to, external ecosystems, marketplaces and communities. API management, control and security are its main elements.
	AI transforms – Partner and Supplier Analytics. – Partner Facing Public APIs. – API Marketplaces. – Enterprise Run Ecosystems. – Industry & Partner-Run Ecosystems.
Trust platform (T6)	T6 is used to foster trust.
	AI enhances blockchain security, risk, and compliance strategies.
Integration platform (T7)	AI influences integration of all above platforms that allows the maximum flexibility, security and trust to support business transformation demands.

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as a starting point for coming up with some initial ideas for AI-driven platform transformation analysis.

(3) Use a proposed framework (map of the digital platform technology stack), reflect on strategic intent, analyse business platform layers in the stack (Business model and Leadership platform, Talent platform, Delivery platform, etc.) using an idea design process, while streamlining the analysis with an eye for possible Technology platform synergies.

(4) Use value drivers for specific dimensions of platform innovation to clarify how technology is employed in implementing AI-driven digital platform innovation ideas. Value drivers related to specific digital dimensions of platform performance and innovation generation may be a consideration.

The framework proposed in this paper could be run through several iterations until all platform layers (Table 1) are analysed/classified, and all table cells are filled. This approach keeps the focus on the AI-driven digital platform transformation throughout the platform BM portfolio design/analysis process, while providing leeway to explore opportunities beyond digitalization. The level of granularity depends on the needed level of detailing.

Another example is to do a “checklist” exercise to determine what platform parts are missing, in need of improvement, or updating in an enterprise. The results of such a checklist can be foundational.

5. Conclusion

Organizations worldwide must evaluate their vision and transform their people, processes, technology, and data readiness to unleash the power of AI and thrive in the digital era (Jyoti et al., 2019). To help with strategic innovation planning and investment decisions related to AI-based automation, this paper developed a multi-dimensional data-driven AI platform innovation framework. The framework allows for evaluating the support by platforms in the human-machine relationship regarding applications at different levels of automation across any industry and functional use case.

The paper adds the following results to current understanding:

1. An AI-driven platform innovation framework is now available for the first time to use with related AI-driven platform innovation value chains. The new dimensions of AI-driven platform innovation maturity and value chains allow for repeating this analysis with different types of business components (technology, leadership, talent and skills, ecosystem, and new data-driven business models). The emergence of a new wave of platform data from innovative sources, such as the Internet of Things (IoT), sensor networks, open data on the Web, data from mobile applications, and social network data, together with the growth of datasets inside platform organizations, creates new

Table 2. Multi-dimensional AI-driven platform innovation framework, A_j, j ϵ {0,1} or other scale. Matrix integration of the AI maturity stages (Yablonsky, 2019b) and the business platform stack (Yablonsky, 2018a).

Stage of AI maturity	Business platforms				Technological platforms						
	B1	B2	B3	B4	T1	T2	T3	T4	T5	T6	T7
D1: Human Led	$A_{D1\,B1}$	$A_{D1\,B2}$	$A_{D1\,B3}$	$A_{D}\,{}_{1}^{B4}$	$A_{D}\,{}_{1}^{T1}$	$A_{D1\,T2}$	$A_{D1\,T3}$	$A_{D1\,T4}$	$A_{D1\,T5}$	$A_{D1\,T6}$	$A_{D1\,T7}$
D2: Human Led, Machine Supported	$A_{D2\,B1}$	$A_{D2\,B2}$	$A_{D2\,B3}$	$A_{D}\,{}_{2}^{B4}$	$A_{D}\,{}_{2}^{T1}$	$A_{D2\,T2}$	$A_{D2\,T3}$	$A_{D2\,T4}$	$A_{D2\,T5}$	$A_{D2\,T6}$	$A_{D2\,T7}$
D3: Machine Led, Human Supported	$A_{D3\,B1}$	$A_{D3\,B2}$	$A_{D3\,B3}$	$A_{D}\,{}_{3}^{B4}$	$A_{D}\,{}_{3}^{T1}$	$A_{D3\,T2}$	$A_{D3\,T3}$	$A_{D3\,T4}$	$A_{D3\,T5}$	$A_{D3\,T6}$	$A_{D3\,T7}$
D4: Machine Led, Human Governed	$A_{D4\,B1}$	$A_{D4\,B2}$	$A_{D4\,B3}$	$A_{D}\,{}_{4}^{B4}$	$A_{D}\,{}_{4}^{T1}$	$A_{D4\,T2}$	$A_{D4\,T3}$	$A_{D4\,T4}$	$A_{D4\,T5}$	$A_{D4\,T6}$	$A_{D4\,T7}$
D5: Machine (Machine Led &Machine Governed)	$A_{D5\,B1}$	$A_{D5\,B2}$	$A_{D5\,B3}$	$A_{D}\,{}_{5}^{B4}$	$A_{D}\,{}_{5}^{T1}$	$A_{D5\,T2}$	$A_{D5\,T3}$	$A_{D5\,T4}$	$A_{D5\,T5}$	$A_{D5\,T6}$	$A_{D5\,T7}$

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ways to reuse and extract value from BD assets through AI-driven platform innovation.

2. The AI-driven platform innovation framework outlined here can be used for better communicating the value of AI capabilities to clients through the lens of changing human-machine interactions, as well as in the context of legal, ethical, and societal norms. While business, IT, and analytics leaders need to recognize how AI is different from previous cycles of IT-based innovation, this paper shows that today's leaders also need to more openly embrace AI and become involved in contributing to the discussion of AI ethics. With the broad participation of a diverse, global population in conversations about the future of AI, we are more likely to advance safely through different levels of AI-driven platform automation, while accumulating benefits for the largest possible population of human beings. A clear and precise description and structuring of information in the AI-driven platform enterprise maturity framework are thus considered as prerequisites for developing a

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Approaching a Data-Dominant Logic

Petra Kugler

> *"The goal is to turn data into information, and information into insight."*
>
> Carly Fiorina
> Former CEO, Hewlett-Packard

This paper introduces the construct of "data-dominant logic". The findings of a multi-step exploratory study indicate that SME have an established mindset (dominant logic) that often hinders these firms from turning data in innovative products, services, and business models. The availability of large amounts of data and the use of this data through data science-driven practices has reached a stage when it now enables new and promising possibilities for firms to innovate. However, the actual use of data and data science insights has proven to be difficult for many companies. The firms under consideration in this paper recognize that the availability of data fundamentally changes their businesses. But also, they lack the appropriate culture, mindset, and business repertoire that would enable them to act by turning data into innovation. The paper concludes that firms first need to establish a new mindset in which data plays a central role. Here I term this mindset "data-dominant logic" (DDL). Future research is required to further concretize the construct beyond this introduction.

Introduction

This paper introduces the construct of "data-dominant logic" (DDL). SMEs that aim to use data and adopt data science insights within their company currently lack this way of thinking. DDL is a hurdle for (established) companies that use data in their value creation process.

Researchers agree that organizations and the prevailing rules of competition alike are fundamentally changing in the digital age (Brynjolfsson & McAffee, 2014; Iansiti & Lakhani, 2017; Parker et al., 2018; McAffee & Brynjolfsson, 2018). The recent spread of digital technology is enabling new and promising possibilities for many firms, such as efficiency increases (Kugler, 2019), new products and services, or innovative business models (Parker et al., 2018). Especially the use of insights from data and data science seems to be a key success factor in the digital economy. The fact that at least seven out of the ten most valuable companies today ground their business in data, platforms, and networks, demonstrates this.

However, generating new business and new value that is linked to data science, still proves to be difficult (Chin et al., 2017), especially for established companies. Little is known concretely about which organizational and managerial requirements (established) companies need to consider as ways of facilitating the efficient adoption of data science-driven approaches and practices. When compared to large firms, the situation seems to be even more difficult for SMEs. Small and young firms face specific challenges, such as the liability of smallness and market entry barriers (Gruber & Henkel, 2004). In comparison with large firms, SMEs lack resources, giving them a competitive disadvantage.

Against this background, the growing availability of data and data science seem to offer valuable opportunities for SMEs to build up competitive advantages, and thus to stay in business. At the same time, exploiting data-oriented opportunities can be a challenging task for these firms. This paper therefore asks about the organizational and managerial requirements that facilitate data- and data science-driven value creation, focusing especially on SMEs.

The findings of this manuscript emerged out of a literature review and an exploratory field study that aimed at gaining deeper knowledge of the current state of data and data science-related practices in SMEs. Empirical data was gathered through a series of

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interviews with 16 SMEs in Austria, Germany, and Switzerland that were condensed into a list of working hypotheses, as well as a survey with more than 100 fully completed replies.

The study's findings suggest that established organizational and managerial structures are the most critical factors that hinder firms from adopting data and data science-driven approaches for new business value creation. A firm's established business mindset or, "dominant logic", came out as being most critical for the companies studied. This is defined as "the dominant way in which managers think and act" (Bettis et al., 2003). Firms that wish to adopt data science-driven approaches, therefore first need to transfer their established dominant logic into a new DDL. At least, that is the main argument presented in this paper.

The remainder of the paper is structured as follows: The next section discusses the relevance of SMEs adapting data-science driven practices and the construct of a dominant logic in the realm of business. The section after gives a brief overview of the paper's research design. The section following discusses key findings of the study and introduces the concept of a data-dominant logic and the final section concludes the paper, setting the new construct up for further elaboration, exploration and testing.

Current Understanding

SMEs are adopting data science-driven practices

"Data science" refers to large data sets that require deep analysis for generating insights from these data (Gupta & George, 2016). Data science practices can be described by up to five characteristics: volume, variety, velocity, veracity, and value (Remane et al., 2011; Fosso Wamba et al., 2015, 2017). Researchers and practitioners alike agree that data science has the potential to fundamentally change the rules of competition and to enable immense possibilities for generating value, profit, innovation, and competitive advantages. Consequently, a firm's performance can be enhanced by using data analytics (Henke et al., 2016; Fosso Wamba et al., 2017). Data science, then, is responsible for the "new gold rush" (Tabesh et al., 2019), "the next frontier for innovation, competition, and productivity" (Manyika et al., 2011), a "new paradigm of knowledge assets" (Hagstrom, 2012), that which requires an "analytics revolution" (Chin et al., 2017).

One complaint has been that firms struggle to turn data into value and that the potential inherent to data science to a large degree cannot be exhausted (Henke et al., 2016; Chin et al., 2017). Large amounts of information by themselves do not make the ability to sense change and respond effectively to it easier. However, "What is seen instead, are information-rich, but interpretation-poor systems. In other words, systems that seem to confuse raw information or data with appropriate actionable knowledge" (Bettis & Prahalad, 1995), when it comes to changing a firm's dominant logic in situations of fundamental structural change.

Researchers have identified a variety of challenges that organizations face if they wish to adopt data science-driven practices. To date many studies have focused on large firms, without illustrating the situation of SMEs. Other work has identified a lack of data competence on all hierarchical levels of companies. This lack of competence has led to difficulties in identifying data science use cases involving organizational and technical issues (Bange et al., 2015; Wamba et al., 2015). Firms, thus, find it hard to identify and use value that is generated by data science-driven approaches and insights. These studies concluded that employees and management alike lack the appropriate competences and knowledge that could help them to understand how new insights can be generated through data science-driven practices (Barton & Court, 2012; Wamba et al., 2015).

Other research concluded that firms depend upon employees that are capable of linking technical knowledge with business knowledge for the purpose of applying data science insights within an organization. Through these linkages, data science can generate and transfer findings into business opportunities (Henke et al., 2016; Chin et al., 2017). Without these linkages, however, organizations might easily overlook the potential inherent in data science-driven practices. This result is also reflected in a lack of coherent data strategies or benchmarks for measuring success that can be traced back to insights generated by data science (Brown, et al., 2013; New Vantage Partners, 2017). In general, studies have found that firms to date have not been able to make use of a data-driven culture (New Vantage Partners, 2017), or so-called "analytics-culture" (Brown et al., 2013). Instead, organizations, seem to lack a basic and holistic understanding of how data and the adoption of data science-driven approaches may be able to fundamentally change the character of their business, and thus how the data and analytics gap can be filled. In

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the following chapter, the notion of a “dominant logic” will be introduced to conceptualize this challenge and to fill the gap that has been identified.

Dominant logic

The concept of a “dominant logic” deals with why a group of intelligent managers fails when thinking strategically about forthcoming structural changes to their core business (Prahalad & Bettis, 1986). Members of the top management team tend to “conceptualize the business and make critical resource allocation decisions - be it in technologies, product development, distribution, advertising, or in human resource management”, in a largely similar way, which is a consequence of their shared dominant logic (Prahalad & Bettis, 1986). More concretely, a “dominant logic represents the shared cognitive map (Prahalad & Bettis, 1986) and strategic mindset of the top management team or the dominant coalition, and it is closely associated with the process and tools used by top management” (Bettis et al., 2003).

A dominant logic in business can be traced back to the fact that a group of managers use similar tools, share implicit and explicit knowledge, and also interpret the tools and knowledge in a way that aligns. Established cognitive models of business have been used to serve as a simplifying filter mechanism, especially when confronted with complex or ambiguous situations. Cognitive models help individuals to focus on certain aspects they are familiar with, while other (unknown or unclear) factors remain largely ignored (Bettis & Prahalad, 1995). Some researchers have found that cognitive structures are not limited to only top management teams, as suggested by Prahalad and Bettis (1986; Bettis & Prahalad, 1995). These ways of thinking can also be found in other organizational groups, including software development teams (Espinosa et al., 2001, 2002) and airplane flight deck crews (Weick & Roberts, 1993), all of which find themselves in highly dynamic and uncertain settings. The characteristics of a dominant logic overlap with other cognitive approaches, such as “shared mental models” (Espinosa et al., 2001, 2002), “organizational cognition” (Smircich, 1983), “underlying assumptions” (Schein, 1995), and a “collective mind” (Weick & Roberts, 1993).

Bergman and colleagues (2015) indirectly proved the stated meaning of “dominant logic” in the context of innovation. Vargo and Lusch (2004; Lusch & Vargo, 2006a; Vargo et al., 2010) found it to prevail in the context of typical manufacturing-oriented firms in contrast with service-oriented firms. These two types of firms rely on different business logic, either a “goods-dominant logic” (GDL) or a “service-dominant logic” (SDL). While a GDL puts a physical product and tangible, inert resources in the center of value creation, the emphasis of a SDL rather lies in intangible, dynamic resources, co-creating the process of exchange. While GDL can be characterized as “exchange paradigm”, SDL serves rather as a “relationship paradigm” (Prahalad, 2004; Vargo & Lusch, 2006a).

Lusch and Vargo (2006b) conclude that applying SDL instead of GDL leads to numerous changes in how value creation and exchange take place within a company. In short, this shift requires a new set of “specialized competences (knowledge and skills), through deeds, processes, and performances for the benefit of another entity or the entity itself” (2006b). Generally speaking, SDL offers a new lens on how organizations function and how organizational members interpret their role in an organization. Therefore, SDL bears the potential to constitute a new paradigm for economic exchange and value creation (Vargo & Lusch, 2006).

Indicators of a dominant logic

Although the intangible concept of a “dominant logic” has been discussed in a vast body of literature, it is noteworthy that “the exact contents in the dominant logic are usually left unspecified” (Bettis et al., 2011). The construct itself does not refer to a single theme or discipline; rather it should be conceptualized as a set of “main themes” or “configurations” (Obloj et al., 2010). Although the concept is “intellectually appealing, the empirical support for its impact has been weak to date” (Obloj et al., 2010). Attempts to study and measure dominant logic are methodologically challenging because it is an intangible and cognitive concept (Lampel & Shamsie, 2000). Thus, when people have written of a dominant logic, it can only be captured indirectly, and the literature presents a variety of approaches to do so.

Some authors use analogies to circumscribe the construct, such as, for instance, likening it to a medical diagnosis (Bettis & Prahalad, 1995; Prahalad, 2004). Other authors have broadly compared how closely the empirical setting conforms to descriptions of dominant logic in the literature (for example, Lampel & Shamsie, 2000, in the case of Jack Welch and General Electric). Similarly, the literature has discussed a broad set of characteristics and typical settings that indicate the

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Table 1. Indicators of dominant logic on the individual and organizational level, based on a literature review

Level of Analysis	Tangible, directly observable, "acting"	Intangible, indirectly observable, "thinking"
Individual	Individual acting (7) Individual decision making, e.g. resource allocation (1, 3) Individual problem-solving behavior (2)	Beliefs, assumptions, expectations, interpretation, propositions (1, 3, 4, 7, 10) Cognitive schemas, mindset, world view, cognitive map (1, 2, 3, 6) Conceptualization of business (1, 2, 3, 10) Constraints to search spaces associated with problems (3) Criteria for choice, evaluation, decision making (10) Individual routines (5) Information filter (5, 9) Key features of acceptable solutions (3) Learning, unlearning, forgetting curve (1, 5) Reinforced behavior (1) Specific set of premises (6)
Organizational	Performance of the organization (2) Administrative tools, organizing and management principles, formal procedures, control (2, 3, 7, 8, 10) Culture (3) Use of technology (4) Goal setting, e.g. performance targets (5) Systems, structure, locus of decisions (1, 2, 3, 4) Processes, procedures (3, 4, 7, 9) Resource allocation (4, 5, 8) Strategy (1, 2, 3, 5, 7, 8) Products, brand (3, 4) Value exchange and creation (4, 11) Tasks critical to success, core activities (5, 10)	Cultural values and norms (1, 3, 5, 10) Organizational identity, image (7) Organizational Routines (5, 8) Procedural memory (7) Social architecture of the firm, socialization (7) Social control (3) Top management team thinking (7)

Literature Source	
1 Bettis & Prahalad, 1995	6 Lampel & Shamsie, 2000
2 Prahald & Bettis, 1986	7 Jarzabkowski, 2001
3 Bettis, Wong & Blettner, 2011	8 Grant, 1988
4 Prahalad, 2004	9 Pan, 2017
5 Obloj, Obloj & Pratt, 2010	10 Côté, Langley & Pasquerc, 1999
	11 Vargo & Lusch, 2004

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prevalence or absence of a certain dominant logic. However, these characteristics have often been presented in broad categories that only give an idea where to search for a dominant logic, instead of showing a clear list of indicators (see Table 1).

Dominant logic typically refers to thinking and acting in organizations (Jarzabkowski, 2001). It is a multi-level construct that relates to both the individual and the organizational levels of analysis. On an *individual level*, dominant logic refers to the thinking and of framing a specific situation or problem definition by an organizational member or the top management team. The indicators mentioned in the literature include, among others, cognitive schemas, mindset, and cognitive maps (Prahalad & Bettis, 1986; Bettis & Prahalad, 1995; Bettis et al., 2003; Vargo & Lusch, 2004) that serve as information filter (Obloj et al., 2010), criteria for choice, evaluation, decision making (Côté et al., 1999), business conceptualization (Prahalad & Bettis, 1986; Bettis & Prahalad, 1995; Côté et al., 1999; Bettis et al., 2003), and beliefs, assumptions, expectations, and interpretations (Bettis & Prahalad, 1995; Côté et al., 1999; Jarzabkowski, 2001; Bettis et al., 2003; Prahalad, 2004). These indicators are admittedly intangible and hard to observe in a direct way.

"Thinking" on an individual level only turns into "acting" on an *organizational level*, where intangible cognition turns into tangible activities or structures. On an organizational level, dominant logic becomes visible through management principles, formal procedures, and control actions (Prahalad & Bettis, 1986; Grant, 1988; Côté et al., 1999; Jarzabkowski, 2001; Bettis et al., 2003; Prahalad, 2004), culture, processes, and procedures (Jarzabkowski, 2001; Bettis et al., 2003; Prahalad, 2004), resource allocation (Grant, 1988; Prahalad, 2004; Obloj et al., 2010), and strategies (Prahalad & Bettis 1986; Grant, 1988; Bettis & Prahalad, 1995; Jarzabkowski, 2001; Bettis et al., 2003; Obloj et al., 2010).

A company's dominant logic that is anchored in individual and organizational thinking and acting provides an organization with a specific *repertoire to act* that fits certain situations. a A dominant logic under stable conditions of exploitation (March, 1991) leads to efficiently and informally coordinating a company. Instead, when operating under conditions of fundamental change ("exploration", March, 1991) or disruption (Christensen, 1997; Christensen & Raynor, 2003), a certain dominant logic can be a hurdle to organizational adaptation.

When confronted with *fundamental structural changes in their environment*, firms therefore also need to change or adapt their respective dominant logic (Bettis & Prahalad, 1995; Bettis et al., 2003). In situations in which firms are unable to adapt to environmental changes, in which they are unable to turn information into actionable knowledge (Bettis & Prahalad, 1995), or in which they use inappropriate (cognitive) schemas (Côté et al., 1999), one of the main problems may be that organizations have not (yet) developed a new, appropriate dominant logic. Consequently, these organizations lack the appropriate *repertoire to act*.

This discussion reveals that a dominant logic can be recognized by a vast array of indicators across organizations. This finding indicates that dominant logic permeates entire organizations, because many of the indicators and characteristics of a dominant logic are interrelated. Consequently, a holistic perspective or integrative framework is required to study the concept of dominant logic (Obloj et al., 2010), while also accepting the concept's limitations. This requirement will be mirrored in the empirical study below, which approaches the field from a set of four different perspectives.

While the concept of "dominant logic" has been studied in the context of analog firms, to date little to nothing in the literature addresses, first, if digital firms actually need a different, data-related (digital) dominant logic, second, what exactly is different between these two types of dominant logic (analog and digital), and third, how firms can develop a data-dominant logic for their business. The remainder of this paper will focus on the first question to lay a foundation for future research. It discusses the situation of many established SMEs that today lack a data-dominant logic (DDL). The manuscript does not discuss in detail empirical findings of how DDL can be characterized, or what firms should do to build up DDL for their own organization. The paper thus takes only a first introductory step towards a detailed characterization of why a DDL is necessary for firms, how it can be characterized, and what it takes to foster one in organizations.

Method

The paper's findings emerged from a two-year (2018-2019) rather open exploratory field study that aimed at gaining deeper knowledge of the current state of data and data science-related practices in SMEs. The study focused on the so-called DACH-region (Austria, Germany, Switzerland) and explored opportunities and threats related to data science practices. The study went through several methodical steps, based upon each other (see Table 2 and succeeding paragraphs). Throughout these steps, the study focused on four specific core themes, namely: (1) strategy and business model, (2) organizational culture, (3) processes and services, and (4) leadership and human resources management (HRM). These groups of core themes were chosen to get a broad picture of the role data science practices play in firms, and also to pre-structure and pre-define the problem space in question.

A dominant logic, or, business mindset, was not explicitly thought to be a focal aspect of the study. Rather, the construct emerged during the course of the exploratory study. Nevertheless, according to Schein (1985), how the members of an organization interpret their situation (so-called "underlying assumptions") constitutes one out of three critical components of organization and organizational culture (next to artifacts and an organization's values and norms), which was one of the core themes that guided the empirical work.

Step 1: Literature analysis

The first methodological step was to perform a literature analysis. About 150 sources in total on the topics "data", "data science", "data analytics", and related terms, as well as on the four core themes that guided the study were compiled. The sources of literature were then analyzed to identify research gaps and gain an overview of the current state of the field. The literature covered studies, scientific articles, and practitioner articles, which delivered mutually complementary insights. The analysis revealed that in recent years data science-related topics have been attracting increased interest within the scientific community and among practitioners. However, the way firms adopt data science-related practices and how all types of

Table 2. Methodological steps, including input and output (own depiction)

Step	Method	Input	Output
1	Literature analysis	Literature on data, data science, data analytics and related topics, as well as on the selected core themes: (1) strategy and business model, (2) organizational culture, (3) processes and services, (4) leadership and HRM.	Insights into opportunities, threats, applications, causalities, research gaps in the context of data and data science Interview guide that covers questions in the fields of all four core themes
2	Qualitative interviews	Interview guide that covers questions in the fields of all four core themes (from step 1) Knowledge of all interviewees	Catalogue of working hypotheses
3	Condensation of working hypotheses	Catalogue of working hypotheses (from step 2) Comparison and evaluation of the hypotheses	Selection of the strongest hypotheses and questions Formulation of questions for the quantitative survey
4	Quantitative survey	Selection of the strongest hypotheses and questions (from step 3)	Quantitative testing and strengthening of selected hypotheses

organizations turn data into value, remains largely nebulous. Also, only a few empirical sources in the literature were found that explicitly discuss the situation of SMEs. The literature review's output was an interview guide structured along the four core themes, which helped to prepare the qualitative interviews in step 2.

Step 2: Qualitative interviews

In a second step, 23 interviews were conducted with 28 individuals (some group-interviews) from 16 firms. All interviews were semi-structured, with guidelines defining the overall structure and broad categories of interest (Table 3). Interviewees were, first, representatives of SMEs in the manufacturing and service industries who have (some) experience with data science-driven approaches (8 firms), or second, IT/data science consultants (8 firms). These two groups of interviewees were chosen to gain insights into the topic in question from inside and outside of SMEs. The perspectives of both groups of interviewees helped to better understand and interpret the SMEs' situations, because SMEs might not totally be aware of the role of data and data science insights in their respective current business situation. Data science for many firms is a rather unfamiliar topic, and firms do not completely know what they do not know about data science-driven approaches. The interviews typically lasted about one hour in length and were led in person and on-site at the respective companies. The interviews were either recorded and transcribed, or notes were taken during the interview in the minority cases that an interviewee refused the recording.

Step 3: Condensation of working hypotheses

In the third step, the interviews were analyzed using content analysis (Mayring, 2015). For this purpose, categories and hypotheses on possible causalities and

Table 3. Interview guide: Overview of core themes and subtopics (summary, abridged)

Question block #	Core theme	Subthemes
1	General initial questions	▪ general situation of the interviewee and the company ▪ understanding of data science and current state of data science practices in the company ▪ opportunities and threats, goals and expectations that relate to data science
2	Strategy and business model	▪ data science and formal / informal company strategy ▪ role of data science on the market, competition, rules of competition ▪ role of data science in business models, types of business models
3	Organization and Organizational culture	▪ role, meaning and awareness of data, data science practices in the firm ▪ relationship between data, data science practices and actionable knowledge, opportunities in the company ▪ artefacts, norms and values, underlying assumptions regarding data and data science (practices)
4	Processes and services	▪ data and (smart) products, services, smart service design processes ▪ value of data and data science practices ▪ infrastructure, workflow, tools, data security
5	Leadership and HRM	▪ roles, tasks, challenges of a data scientist in the company ▪ required skills, competences, knowledge ▪ distribution of data-related tasks within the firm / across firm boundaries
6	Closing questions and remarks	▪ various closing questions

relationships between the categories were compiled. Categories and causalities were established within and between the four core topics that guided the interviews. Each category was filled with quotes from the interviews that addressed or justified the working hypotheses.

A selection of 20 hypotheses on all four core themes formed the basis for the formulation of a quantitative survey (step 4). In comparison to the hypotheses that were not selected for the survey, the selected hypotheses could be classified as 'strong' in the sense that more quotes from the interviews are attributable to them. However, it was not possible to clearly determine the strength of all hypotheses. This is because some topics were touched on in most of the interviews, while other topics were addressed only in one or a few, or the topics were mentioned only by one or few interviewees.

Step 4: Quantitative survey
In a fourth step, based on insights gained from the interviews, a quantitative online survey was designed that primarily included 42 closed questions. The goal of the survey was to gain a deeper understanding of selected issues and hypotheses from the proceeding steps. It was distributed over a variety of channels (multiple university-owned databases, social media, newsletters), so a response rate cannot clearly be defined. 280 respondents replied to the survey, of which 110 individuals answered all questions. This constitutes the sample that was analyzed for the purpose of this paper.

Some respondents did not answer all sub-questions. For some variables, the sample size is therefore smaller than 110. Representatives of SMEs (<250 employees) from all industries make up 75% of the answers. The situation of large firms as compared to SMEs was compared for the purpose of analysis. The survey covered all core topics that also guided the interviews, as well as some general questions about the firms. The survey results were primarily analyzed using descriptive statistics.

This paper's focus on organizational and managerial aspects of DDL in SMEs is only one of several insights generated from the field study. The following section summarizes some of the key findings that emerged from the empirical data.

Findings: Approaching Data-Dominant Logic

The analysis of the qualitative and quantitative data both directly and indirectly indicate that in the SMEs under consideration, first, the expectation of *fundamental structural changes in firms' competitive environments* can often be traced to the growing use of data science-related practices. Second, the collected data reveals that many of the firms under study have been *unable to yet develop an appropriate organizational repertoire to act* with a data science strategy under the current circumstances. These observations, third, lead to the hypothesis that many of these firms have not yet been able to adapt their dominant logic to the changing situation, by putting data and data science-related practices at the center of their thinking and acting. One conclusion to be drawn is that up until now they are *missing data-dominant logic*.

Firms expect fundamental structural changes
The respondents to the quantitative study expect fundamental structural changes in their respective industries. This situation requires a shift in managers' dominant logic (Bettis & Prahalad, 1995). Today, data science-driven approaches can have the biggest benefit for SMEs in creating customer proximity and optimizing processes or products (in roughly 55% of the cases), while new products and services have less relevance (in roughly 35% of the cases). Generating new business models does not have a significant impact on most SMEs today (only in roughly 15% of the cases). However, the respondents expect the situation to fundamentally change within five years, to a situation in which more new business models will be required. Almost 50% of respondents from companies expect products that build on data science insights to be important for their future business.

SMEs are usually well aware of the general strategic consequences to which the expected changes might lead. While today data science-driven practices are of great or very large importance for 15% of firms, in five years almost 60% of firms expect this to be the case. Also, only about 25% of the respondents stated that the use of data science insights today changes the competitive situation of their industries. In five years, this is projected to be the case for more than 55% of the represented firms.

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These findings were also mirrored in the interviews. One interviewee claimed, "There is still a point that indicates a paradigm shift. I can summarize this fact in one sentence. Formerly, producing firms could influence the market. Today it's completely different. Completely" (J.E., IT and data science consultant).

However, the incoming changes suggested above are often not (yet) mirrored in firms' strategic behavior. SMEs largely use data science insights to improve their cost situation and to become more efficient players (see above, in approx. 55% of the cases). In doing so, they rather focus on staying in business today, than on coming up with innovative solutions for the future.

One may conclude that for SMEs, data science-driven approaches today are a set of tools that are more often used for operational rather than strategic purposes. But also, that data science insights will gain importance for more strategic and innovation-related issues in the near and foreseeable future. These insights might lead to, and at the same time are a consequence of, fundamental structural changes in how business is conducted digitally.

Firms have no repertoire to act

Many SME's have not yet developed a clear repertoire of what they could concretely do with data and data sciences-driven practices. In the interviews, the respondents claimed that using data science insights is related to a high degree of uncertainty, and today many crucial questions still lack a clear answer. These questions comprise, for instance, "Where does data come from?", "Which data is relevant?", "Is an inductive or rather a deductive approach for analyzing and using data adequate for a specific situation?", "(How) can we use data, at all?", etc. Some of the interviewed individuals reported that their firms approach data science-related practices through a process of trial-and-error. The firms test and compare stepwise different data-based products or services that could help them to design data-based business models.

The respondents to the quantitative survey claimed that both C-level and other managers (55%), as well as employees (70%), strongly or very strongly lack knowledge and competences that could help them to cope with data and data science insights. One interviewee claimed that, "The companies have a big problem. I always call this a 'knowledge problem 4.0'. The knowledge does not exist. […] They don't have the know-how at the C-level, they don't have the potential to change and they don't even know what they want to develop." (J.E., IT and data science consultant).

Instead, the interviewees reported a lot of fear from employees on all hierarchical levels, as job descriptions that refer to data-oriented positions are still lacking. Many people wonder if their jobs will still exist in the future, and if or how their job might change. The fear rather leads to inertia instead of actively changing today's situation by learning more about what data and data science can do for business. Mentally, the people interviewed seem to displace the expected situation that data science-driven approaches might bring for their company's future.

Lack of an appropriate culture and mindset; missing a data-dominant logic

The survey revealed that the biggest hurdles for using data science-driven practices are related to the so-called "soft factors" that lie inside of organizations. Soft factors include a lack of knowledge (40%), unsolved organizational issues (39%), no urgency to use the data (37%), or an unclear vision of how to use data for company business (34%). 70% of the firms claimed that their employees very strongly or strongly lack skills for dealing with data and data science insights. This finding was also reflected in the interviews, in which the interviewees referred to the need for change in the firms' mindset or organizational culture (both terms have been used by the interviewees).

The interviewees also referred to the need for one or several data-oriented change agents in their firms. Managers and employees alike seem to have difficulties including data-related aspects into their established mindset, or into their prevailing dominant logic (Prahalad & Bettis, 1986). This research concludes that the way companies function today is not (yet) designed to make fundamental use of data science-driven approaches for business.

According to the study's findings, for respondents' businesses, "soft factors" are a higher hurdle than the so-called "hard factors". Hard factors refer to security concerns (28%), costs (24%), other technologies (24%), or firm size (too small, 22%). Perhaps surprisingly, "inadequate data" (SMEs: 4%, large firms: 17%) is the least important hurdle for the use of data. One interpretation of this finding is that companies often do not even know what they don't know, or, stated differently, they are lacking sensitivity regarding their insufficient use of business-relevant data sets.

It can be concluded that firms require a holistic approach that covers adapting their culture and mindset, knowledge and capabilities, as well as their business model and services, in a way that is grounded together in the use of data and data science insights. All of these are reflected and stored in a firm's dominant logic (Prahalad & Bettis, 1986; Bettis & Prahalad, 1995). Thus, a new type of dominant logic seems to be required to cope with situations for firms that deal with data and data science-driven practices. I term this new dominant logic as data-dominant logic (DDL), which is the guiding way in which the members of a data-driven company think, act, and design their value creation process within and across the boundaries of their organization.

Discussion and Conclusions

This paper asked for organizational and managerial requirements that facilitate data and data science-driven value creation, focusing especially on the situation faced by SMEs. A literature review and multi-step field study was conducted in the DACH-region. The study's findings suggest, first, that the firms under consideration expect incoming fundamental structural changes caused by the application of data-driven practices. Also, the study revealed that many firms have no clear repertoire to act on a data strategy within the changing setting and therefore cannot fully exploit the potential inherent to data science practices. These findings indicate that SME organizations often lack an appropriate dominant logic for coping with data science-driven approaches. Therefore, second, the paper concludes that to facilitate a data-driven business, firms need to transform their traditional dominant business logic into a data-dominant logic (DDL), thus a new construct was introduced through this work. DDL proposes to add value to both the scientific community and market practitioners, because it helps to clarify and remove hurdles that hinder (established) organizations from more deeply making use of data science principles and practices for their value creation process.

The findings of this research suggest the importance of learning for firms that seek to ground their business in data and data science insights. First, the research shows that firms, especially SMEs, should take some initial steps to become digital, even though to date it is not yet clear what it takes for firms to be a "digital player". To sensitize their management team and build up DDL, firms need to learn how to cope with both the opportunities and also the constraints of data science-driven approaches. It might be that firms will have to learn from mistakes, which sometimes can be costly, but necessary.

Second, firms can also recruit data science experts or develop the data science competencies of their own employees. This study indicates that individuals who are familiar with data science-driven principles, practices, and digital technologies can take over the role of a "digital change agent", who serves as a translator and facilitator between the established analog and the new digital paradigms.

Third, a digital change agent might help with a company's change processes. This may be because dominant logic is not restricted to a certain individual's cognition, but is also closely related to a firm's organizational structure, management methods, business model, and value creation processes (Prahalad & Bettis, 1986). To link a firm's business with data science insights, it thus might be necessary to also change organizational structures, as shown by the field study in question.

Fourth, in the case of organizational changes, DDL might not only be helpful for members of the top management team, as suggested by Bettis and Prahalad (1995, Prahalad & Bettis, 1986), but also for other members of the organization, employees, and stakeholders. The notion of DDL in this way becomes a broader concept than originally introduced by these authors.

Research on the requirements and challenges of data science-driven approaches in strategy and management is still at an infant stage. We have only begun to understand what it takes for firms to efficiently use data for their businesses, for example, with new products, services, or business models. This work thus can only be considered as a starting point for discussion and research on data-dominant logic, and other organizational and managerial requirements of digital firms. However, this situation leaves room for future research.

First, this paper primarily focused on the construct of data-dominant logic. However, the empirical study did not aim explicitly at studying (data) dominant logic. The construct of DDL rather emerged during the process of conducting the empirical study, as an effective way of targeting a current business need. The paper was therefore not able to explore and clarify in detail, how exactly the dimensions and features of DDL can be characterized, or what firms should do in order to establish or enhance it in their organizations. Both questions are open issues that should be clarified through future research.

Future studies could compare the similarities and differences of the dominant logic of organizations that can be characterized as analog or digital and focus on both how and how much firms are making use of data-driven approaches. To do so, it might be helpful to explicitly compare the situation of firms that already clearly take a DDL approach (firms in which data science is at their very core), with those that do not have such an approach (firms that do not focus on working with data science). Such research would respond to the conclusion and challenge of Bettis et al. (2003) that “there is considerable potential for exploring the emergence of a dominant logic based on the competition of multiple logics”.

Finally, it would be interesting to learn which kinds of firms can adopt a data-dominant logic and if it is easier for some types of organizations than others (for example, small vs. large firms, young vs. established, or certain industries)? If so, (how) can the transformation process towards DDL be designed to give more SMEs a data-driven development roadmap? DDL in sum might therefore bear the potential to open a new organizational paradigm for the digital economy.

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A Systematic Analysis of how Practitioners Articulate Business Models across Disruptive Industries

Alina Marie Herting & Alexander Lennart Schmidt

" *A powerful idea communicates some of its strength to him [or her] who challenges it.* "

Marcel Proust
French novelist, critic, and essayist

Ongoing debates surround the role of business models in understanding the dynamics related to disruptive innovation. Too little is still known about how practitioners highlight different characteristics of business models across industries confronted with disruptive dynamics. This shortcoming in current debates hampers a better understanding of the context-dependent phenomenon of "disruption", ultimately limiting the development of adequate business strategies for incumbents and entrepreneurs alike. Consequently, we generated a systematic database of communicated business models from 1,095 relevant press releases and company reports published between 1995 and 2019. The business models from the retrieved articles were assigned to their corresponding industry using the Global Industry Categorization Standard (GICS) to allow for diverse categorization. Subsequently, we performed a deductive coding procedure, building on accepted business model component classifications. Our study contributes insights about relevant business model components, drawing on practitioner experiences in the face of disruptive dynamics.

Introduction

The phenomenon of "disruptive innovation" is frequently discussed amongst scholars and business practitioners alike. Recent discussions especially have acknowledged the crucial role of business models for spurring disruptive dynamics (Christensen et al., 2018; Cozzolino et al., 2018). Anchored in conceptual statements from Christensen (2006) and Markides (2006), the essential inducer of disruptive processes is argued to lie in business model innovation.

Simultaneously, scholars from the business model domain have discussed similarities and differences between business models (Baden-Fuller & Morgan, 2010; Teece, 2010). The "business model" concept has indeed been utilized to comprehensively understand how companies do business and perform processes of value creation, capture, and delivery (Schneider & Spieth, 2013; Foss & Saebi, 2017). With a continuous increase in researcher and practitioner interest in the phenomenon of disruptive innovation (Christensen et al., 2018), the traditional technological view of disruptive innovation was challenged, ultimately highlighting the relevance of dynamic and flexible business model innovation (Christensen & Raynor, 2003; Cozzolino et al., 2018; Si & Chen, 2020).

Whereas existent debates increasingly discuss case-specificities of disruptive business models in particular industries, what we miss is a consolidation of these findings to advance discussions of disruption and account for the circumstance-contingency inherent in the phenomenon (Christensen, 2006; Hopp et al., 2018). Consequently, we follow Schiavi and Behr's (2018, p. 349) call "to identify similarities and differences between the cases of different sectors". Further, since business models can be conceived "as a performative representation" (Perkmann & Spicer, 2010) operationalized by articulating narratives (Ibid), for the purposes of this paper, we excerpted several disruptive business model characteristics from the communication of practitioners and managers of corresponding companies.

In other words, little is known about how disruptive business models potentially differ across diverse industries in practice, or how practitioners within these industries highlight the particular characteristics of underlying disruptive dynamics. To enhance ongoing discussions with insights from practical communication about disruptive developments, our aim in this paper is to answer the research question: How do practitioners communicate business model characteristics across disruptive industries?

To answer this, we systematically searched for press releases and company reports about business models, published between 1995 and 2019. Subsequently, we assigned the retrieved business models to their respective industry by applying a developed classification scheme before performing a deductive coding procedure. Thereby, we built on accepted business model component classifications (Wirtz et al., 2016) to uncover which business model components are highlighted by managers across eleven industries. Besides delivering insights regarding the quantification of highlighted business model components among industries, we further present inside views into the particular ways practitioners communicate characteristics of business model components, and how they are linked to their respective disruptive market dynamics.

Theoretical Background

From disruptive innovation to disruptive business models

Following Christensen et al. (2018), disruptive innovation describes a process in which an entrant with an innovative business model is able to challenge established industry incumbents, ultimately taking over large parts of the mainstream market. In this regard, the increasing pace of technological advance enables a myriad of disruptive technologies, each of which bear potential for respective new disruptive business models (Cozzolino et al., 2018; Kumaraswamy et al., 2018).

According to the specificities of disruptive business processes, new entrants emerge, targeting the bottom of the market, which is widely neglected by incumbents because of limited profit potential. Departing from this market foothold in the niche, entrants develop their business models, increasingly aligning with mainstream customers' demands, ultimately attracting larger shares of the market. These dynamics challenge incumbents to a different degree compared to companies attempting to sustain their innovations, which depart from profitable mainstream market segments (Christensen et al., 2015).

Disruptive innovation was initially attributed to a technology-focused view. This was revised in 2006 as researchers acknowledged that disruptive dynamics are rooted in the respective business model, which is built on individual disruptive technologies (Christensen, 2006; Markides, 2006). In other words, disruptive dynamics arise from the strategic choices performed by positioning a new business model in a disruptive way relative to existing mainstream alternatives (Christensen et al., 2018). This underlines that disruptive technology and disruptive business models are disparate phenomena (Cozzolino et al., 2018). Consistently, Chesbrough and Rosenbloom (2002) stated that the failure or success of a company in a competitive environment depends on integrating technology into an applied business model. The concept of "business models" has thereby proven itself as a critical concept in understanding the dynamics related to the complex phenomenon of disruptive innovation (Chesbrough & Rosenbloom, 2002; Christensen, 2006; Markides, 2006; Kumaraswamy et al., 2018).

Business models and the role of underlying components

Despite the early divergent understanding of business models, recent discussions and debates have agreed on the key dimensions of a business model; namely, value creation, value delivery, and value capture (Zott & Amit, 2010; Wirtz et al., 2016). Referring to the decisive role of a business model in inducing disruptive dynamics, current research is increasingly interested in the characteristics of disruptive business models (Amshoff et al., 2015; Teece, 2018; Trabucchi et al., 2019). Fielt (2014) identified three main areas of business model research that enable researchers to gain a complete understanding of the concept: definitions, components, and archetypes. Hence, research already has engaged in investigating definitions and archetypes of business models in the context of disruptive innovation (Amshoff et al., 2015; Trabucchi et al., 2019).

However, still little is known regarding the business model components (also known as "elements") which, as we argue here, along with others, are needed to provide a detailed view of the overall business model

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(Wirtz et al., 2016). More precisely, these components describe "what a business model is made of" (Fielt, 2014). Further approaches describe the underlying elements of a business model as "activity system" (Zott & Amit, 2010), as well as a more details about a company's activities to create and capture value (Chesbrough & Crowther, 2006). Concerning business model components, researchers have started to offer various approaches in terms of their corresponding structure. The hitherto most prominent presented structure is the Business Model Canvas by Osterwalder et al. (2010).

Additionally, Johnson et al. (2008) propose to define a "business model" based on four components for value creation and value delivery; namely, customer value proposition, profit formula, key resources, and key processes. Motivated by the variety of interpretations regarding business model components, Wirtz et al. (2016) contributed to the debates by presenting a systematic review of business model components. The authors proposed nine components to grasp the modularity of the business model concept: strategy, resources, network, customer, market offering, revenue, manufacturing, procurement, and finances (Wirtz et al., 2016).

Since a business model component can be observed in a non-static form, research has also provided insights in the development of industry-specific business models once competitive changes in the environment occur (Zott et al., 2011). Based on this, competitive advantages can be realized through continuously innovating the components of a business model (Markides & Charitou, 2004). Consistently, Foss and Saebi (2017) recently defined the related concept of business model innovation as "designed, novel, nontrivial changes to the key elements of a firm's business model and/or the architecture linking these elements".

As mentioned above, many researchers contributing to the business model research have focused on detecting underlying structures and shared characteristics of components. In this regard, Teece (2010) stated that "successful business models very often become, to some degree, 'shared' by multiple competitors". Following this, business models can be used as recipes for how to do business in a specific industry (Baden-Fuller & Morgan, 2010), or describe respective archetypes (Bocken et al., 2014; Fielt, 2014; Gassmann et al., 2014; Ritter & Lettl, 2018). While the notion of business models as recipes serves to instruct the involved actors, Perkmann and Spicer (2010) go further to classify "business models" as narratives that construct "a representation of how business might succeed or thrive in a particular environment". Functioning in a narrative manner closely links the characteristics of business models to how they are communicated and highlighted by market practitioners, making the detailed communication of individual business models a relevant and required competence for managers (Sousa & Rocha, 2019).

Methodology

To deepen our understanding of how the highlighted business model components differ among industries, we conducted a qualitative content analysis. We based our analysis on secondary data in the form of press releases and company reports. Our aim was to receive holistic information about companies' actions, motives, and outcomes (Dahlin et al., 2016).

Step 01: Data collection and selection
In the first step, we collected data using the database LexisNexis. As we particularly aimed to investigate differences among business models in a disruptive context, we operationalized the domains by identifying keywords based on previous reviews in the research area of disruptive innovation (e.g. Hopp et al., 2018; Petzold et al., 2019). By combining two keyword-clouds (see Table 1), articles must at least contain one keyword from each cloud. To ensure a contextual fit of selected articles with the concepts of interest, we further adjusted the subjects of publication as selection criteria and just allowed the subjects business, company activities and management, reports, reviews and sections, science and technology, presses, and reports to be part of the analysis. Additionally, because the concept of "disruptive innovation" was introduced in 1995 (Bower & Christensen, 1995), only material that was published after 1995 was considered.

We identified 1,404 articles. After removing duplicates (289) and resume lists (20), a set of 1,095 relevant articles was carried forward to the analysis phase.

Step 02: Industry-classification scheme
Before analyzing the identified articles, we specified the corresponding industries to allow for comparisons. We therefore built on the categorization scheme consisting of eleven industries as defined by the Global Industry Classification Standard and including selected sub-industries (GICS). Following Bhojraj et al. (2003), we assigned each article to one of the following industries:

Table 1. Keywords of data collection

Keyword (OR)	AND	*Keyword (OR)*
"disruptive innovation*"		"business model*"
"disruptive technolog*"		"business idea*"
		"business concept*"

Source: Self-provided

- Energy: Energy equipment and services, oil, gas, consumable fuels.
- Utilities: Electric utilities, gas utilities, multi-utilities, water utilities.
- Real estate: Equity real estate investment trusts, real estate management and development.
- Financials: Banks, insurance.
- Information technology: Software and services, hardware.
- Communication services: Communication, media, entertainment.
- Consumer discretionary: Automobiles and components, consumer durables and apparel, retailing, education.
- Consumer Staples: Food, food and staples retailing, household and personal products.
- Health Care: Equipment and services, pharmaceuticals, biotechnology, life science.
- Materials: Chemicals, metals, mining, containers, packaging, construction materials.
- Industrials: Capital goods, transportation, commercial and professional services.

We used the software tool MAXQDA for classifying the relevant articles into their respective industries. The dictionary tool allowed for categorizing words and phrases with similar meanings into equal categorical groups. In particular, the GICS classification scheme offers 158 sub-industries which were partly used as keywords for the classification process. We further refer to an industry-specific classification of the collected data to ensure an understanding of the disruptive innovation theory within each case. In particular, we solely allowed keywords of sub-industries to be part of the analysis whose industry context has been formerly discussed by scholars in relation to disruption, thereby acknowledging the particular role of contexts in the interpretation of disruptive dynamics (Si & Chen, 2020). Table 3 presents examples of disruptive business models from our collected data for each industry, accompanied by anchor references discussing disruptive dynamics in respective industries, as well as corresponding business models.

Step 03: Coding scheme
Subsequently, we developed the deductive coding scheme based on the aforementioned integrated business model components proposed by Wirtz et al. (2016) that served as theoretical grounding. By introducing nine business model components, this approach was appropriate as we aimed to generate an overview regarding practical communication about the various characteristics of disruptive business models. To utilize these nine components as a coding scheme, we created a set of keywords for each of the business model components based on Wirtz et al.'s "overview of selected business model components" (2016) and "components of the integrated business model" (2016). Additionally, we extended the list of keywords based on recent reviews of the business model concept (for example, Schneider & Spieth, 2013; Foss & Saebi, 2017).

Table 2 presents these nine sets of keywords, which constitute a basis for the following deductive coding process.

Step 04: Deductive content analysis
Two independent researchers conducted the qualitative content analysis, assisted by the software program MAXQDA18 for coding textual data. By applying the depicted sets of keywords, we used standard content analysis techniques (Lincoln & Guba, 1985).

We controlled for inter-coder reliability by using the dictionary-tool of MAXQDA, while additionally performing the coding process of all relevant articles independently of each other. We used upcoming coding divergence for discussions to come to a consensus (Lincoln & Guba, 1990), thereby further enhancing the reliability of the analysis and aiming for reproducibility (Krippendorff, 2004).

The primary purpose of the textual coding was to identify the quantitative distribution of coded keywords and thus, to transform keywords into numbers. That way, the quantitative display of data helps in organizing the information by compiling them into matrices,

Table 2. Set of keywords

Business model component	*Set of respective keywords*
Strategy:	strategy model; core strategy(ies); managerial process(es); organizational process(es); company's strategy; firm's strategy; business' strategy; strategy of the firm; strategy of the company; strategy of the business; positioning, company position.
Resource:	resources model; core asset(s); core competency(ies); core resource(s); key resources; human resources; physical resources; capital resources; financial resources; company('s) resource(s); firm('s) resource(s); business('s) resource(s); resources of the company; resources of the firm; resources of the business; company('s) asset(s); firm('s) asset(s); business('s) asset(s); asset(s) of the company; asset(s) the firm; asset(s) of the business.
Network:	logistic stream; network model; key partners; partner model; value distribution; partners network; company('s) distribution; firm('s) distribution; business('s) distribution; distribution of the company; distribution of the firm; distribution of the business; company('s) network; firm('s) network; business('s) network; network of the company; network of the firm; network of the business.
Customer:	target costumer(s); market segmentation; customer models; channels; channel configuration; customer segmentation; customer segment(s) distribution channel(s); company('s) customer(s); firm('s) customer(s); business('s) customer(s); customers of the firm; customers of the company; customers of the business
Market Offering:	market offering model; value proposition; value stream; value architecture; customer value; market offer(s); market offering(s); company('s) offering(s); firm('s) offering(s); business('s) offering(s); offering(s) of the company; offering(s) of the firm; offering(s) of the business; company('s) product(s); firm('s) product(s); business('s) product(s); product(s) of the company; product(s) of the firm; product(s) of the business; company('s) service(s); firm('s) service(s); business('s) service(s); service(s) of the company; service(s) of the firm; service(s) of the business.
Revenue:	revenue model; profit formula revenue form; revenue stream; company('s) revenue(s); firm('s) revenue(s); business('s) revenue(s); revenue(s) of the company; revenue(s) of the firm; revenue(s) of the business; company('s) profit(s); firm('s) profit(s); business('s) profit(s); profit(s) of the company; profit(s) of the firm; profit(s) of the business.
Manufacturing:	manufacturing model; key activity(ies); combination of goods; core activity(ies); value configuration; value generation; core operation(s); core processes(s); service provision(s); company('s) activitiy(ies); firm('s) activitiy(ies); business('s) activitiy(ies); activitiy(ies) of the company; activitiy(ies) of the firm; activitiy(ies) of the business; company('s) process(es); firm's process(es); business' process(es); process(es) of the firm; process(es) of the company; process(es) of the business. company('s) operation(s); firm's operation(s); business' operation(s); operation(s) of the firm; operation(s) of the company; operation(s) of the business.
Procurement:	procurement model; resource(s) acquisition; production factors; procurement
Finance:	accounting model; accounting system; cost(s) structure; financial model; financial arrangement(s); company('s) cost(s); firm('s) cost(s); business('s) cost(s); cost(s) of the company; cost(s) of the firm; cost(s) of the business

networks, graphs, or charts (Neale, 2016). Consequently, the distribution of keywords in the industry-assigned articles provides us with information about the importance of a specific business model component-keyword in the corresponding industry (Krippendorff, 2004). The code distribution constituted a proxy to evaluate the highlighted relevance of business model components per industry. This detected keyword-frequency in terms of code distribution within each industry was mutually compared with all other GICS-industries to detect differences as well as discrepancies across industries.

Ultimately, the coded keywords were utilized as orientation, eventually extracting text passages from practitioners to give examples and insights into their individual business model component-communication across industries. The extraction-phase is a further step

Table 3. Overview of assigned press releases and examples of observed business models

Industry	*Number of press releases & company reports*	*Exemplary disruptive business models*	*Exemplary references from literature*
Financials	255	· Peer-to-peer platforms for credits & trading · Micro credit solutions	Markides & Oyon, 2010; Zhang et al., 2018
Information technology	206	· On-demand software-as-a-service solutions · Subscription-based cloud services	Kaltenecker et al., 2015; Cohen & Gans, 2017
Health Care	146	· Supply of good enough medical instruments · Digital diagnostics	Heikkilä et al., 2015; Winterhalter et al., 2017
Communication services	130	· online supply of IP-based communication · Freemium/on-demand video streaming services	Hynes & Elwell, 2016; D'Ippolito et al., 2019
Consumer discretionary	96	· Platforms for car- and/or ridesharing · No-frill, digital universities	Laurell & Sandström, 2016; Osiyevskyy & Dewald, 2018
Industrials	84	· No-frill airlines · E-mobility products and transportation services	Habtay, 2012; Woo & Grandy, 2019
Utilities	73	· Decentralized packaged water systems · Demand response services for utility suppliers	Reficco & Gutiérrez, 2016; Tayal, 2016
Energy	42	· Peer-to-peer power grid · Energy trading based on blockchain technology	Mahama, 2012; Doomernik et al., 2019
Materials	26	· Micro mines & mills · Cloud based building information modeling	Koen et al., 2011; Nellippallil et al., 2019
Consumer staples	20	· Services enabling connected cleaning (IoT) · Supply of good enough household products	Rajala et al., 2018; Brown & Anthony, 2011
Real estate	17	· Low-cost brokerage · Automation of customer service (robo-advisors)	Dewald & Bowen, 2010; Osiyevskyy & Dewald, 2015

Source: Self-provided

towards controlling for whether the retrieved data relate to the communication of business models in a disruptive context. By following Anthony et al.'s (2008) simple fit assessment, which provides "a quick check as to whether a team is following a disruptive approach", we compared extracted passages from the sources with examples of how managers actually communicate in disruptive situations.

Findings

We started our analysis by applying a classification scheme and assigning each relevant article to a corresponding industry. Table 3 presents how many articles were assigned to each specific industry, with an overall number of 1,095 articles integrated into the analysis. The numbers are presented in descending order. This indicates in which industry managers communicate more frequently about their business models in the context of disruption.

The content analysis' deductive approach provides insights into how the coded keywords of each business model component are distributed across the eleven industries. Across the whole sample, we generated 1,113 business model component related codes.

In general, with 231 coded component-keywords, the component customer reflects the highest number of codes. Opposed to that, the business model component financial with 29 codes indicates having limited relevance for practitioners operating in industries which face disruptiveness. Besides indicating the number of assigned press releases and reports, we additionally outline how often specific components were found across the 11 industries. The following list illustrates the quantity of exclusively observed components per industry.

- Financials (256): Network (58), Customer (53), Strategy (34), Market offering (33), Resources (23), Revenue (21), Procurement (15) Financials (12), Manufacturing (7).
- Information Technology (208): Customer (60), Network (44), Market offering (32), Procurement (23), Revenue, (16), Strategy (14), Resources (11), Manufacturing (6), Financial (2).
- Health Care (189): Procurement (46), Customer (30), Network (30), Strategy (27), Market offering (21), Resources (14), Manufacturing (8), Revenue (7), Financial (6).
- Communication Services (119): Customer (27), Strategy (19), Revenue (16), Market offering (15), Network (14), Procurement (11), Manufacturing (7), Financials (6), Resources (4).
- Consumer Discretionary (68): Customer (29), Network (10), Strategy (7), Market offering (6), Procurement (6), Resources (5), Revenue (3), Manufacturing (2).
- Industrials (138): Network (42), Procurement (24), Strategy (23), Customer (15), Market offer (12), Manufacturing (11), Resources (8), Financials (2) Revenue (1).
- Utilities (26): Strategy (6), Market offering (6), Manufacturing (4), Revenue (3), Procurement (3), Network (2), Resources (1), Customer (1).
- Energy (28): Revenue (12), Market offering (5), Customer (5), Strategy (3), Resources (2), Financials (1).
- Materials (45): Procurement (11), Network (7), Strategy (7), Revenue (6), Customer (6), Resource (4), Manufacturing (2), Market offer (2).
- Consumer Staples (31): Network (13), Revenue (10), Customer (3), Strategy (3), Market offer (1), Manufacturing (1).
- Real Estate (5): Resource (5), Customer (2), Strategy (1).

Discussion and Contribution

In this paper, we provide an overview of the most pertinent business model components according to practitioners communicating what is to be confronted with disruptive developments across several industries. Although many researchers have previously contributed in detecting patterns of disruptive settings across industries (Amshoff et al., 2015; Garbuio & Lin, 2019), our approach suggests that the importance of the business model components for disruptive business models in practice is communicated differently amongst the studied industries. Our findings deliver a quantification of distributed business model components across industries confronted with disruptive dynamics by taking a 'bird's-eye view' of how practitioners highlight the respective components. Hence, findings reflect the relevance of these components based on practitioners' statements per industry on a meta level, thereby allowing for a more comprehensive orientation.

We contribute through this research to ongoing debates in the disruptive innovation domain by discussing the different roles of business model components across industries and demonstrating how managers interpret the influence of business model components when being confronted with disruptive dynamics.

In the following, we discuss a selection of the most relevant business model components across industries, conclusively illustrated and enriched with statements from practitioners. Table 4 provides a comprehensive overview of the business model components, industries, and the identified intensity of code distribution. Empty boxes represent business model components for which our data did not suggest any codings in the respective industry, or just a minimal number of codings that did not indicate commonalities in the corresponding industry.

Our empirical results suggest that the business model component customer is the most communicated across industries. Following Wirtz et al. (2016), companies that state to focus on the customer-component concentrate on value towards target groups, including "products and services for specific customer segments of the business model". This component is especially highlighted by practitioners in the industries of Real estate, Consumer discretionary, Communication services, Information technology, and the Financial industry.

Within our data, practitioner statements about integrating and targeting customers can be distinguished across industries. From the perspective of Real estate and Communication services, managing the customer-component has the objective to "expand distribution channels" [CM090_RE], with practitioners taking over the role as "head of Emerging Channels responsible for the development and support of new distribution channels" [CM027_CM]. These findings are in line with Christensen et al. (2018), as well as Govindarajan et al. (2011) disclosing disruptive dynamics in targeting overlooked or unserved markets. However, we also detected a large focus in manager statements, especially in the industries of Information technology and Consumer discretionary, striving "to learn how to develop and nurture lasting customer relationships" [CM113_IT] in existing segments. According to this, practitioners from an offshore IT and software development company revealed that their "unique kind of disruptive innovation in its business model focusing on value centricity [...] has resulted in deepening customer relationships" [CM088_IT]. An articulated lever to manage customer relationships for practitioners is thereby a simultaneous integration of different on- and offline channels, whereas managers "increasingly seek to strengthen with their customers directly through online channels" [CM161_IT] and also by use of "extended omni-channels solutions" [CM073_CD]. As a result, the data provided insight of practitioners in the Information technology and Consumer discretionary industries formulating strategies in a way that customers are "more and more integrated across all channels" [CM101_CD].

We additionally find statements giving evidence for the customer-component being highlighted in the Financial industry. In detail, practitioners operating in this industry are found out to regularly combine both previously described strategies, with "banks that have made market changes or improvements within the distribution network to either existing channels [...] or have introduced a new channel or distribution strategy that has benefited customers" [CM025_FI]. This strategy was found to be further applied by a bank investing in startups to transform the financial industry:

> "This transformation is already taking place with the development of new digital channels and means of payment that are generating new customer relationship models" [CM025_FI].

To conclude the role of the customer-component in industries confronted with disruptive dynamics, practitioners from different industries effectively apply diverse channel- and distribution-strategies, all of them which deal with targeting new customer segments or strengthening the relationship to existing segments.

Another business model component that gained momentum across practitioners in different industries is based on a network-oriented view, with networks and partnerships considered as having "a great influence on the value creation of a company" (Wirtz et al., 2016). This component is found to be highlighted by practitioners operating in the industries Information technology, Financials, Industrials, and Consumer staples. It is not surprising that this component is of decisive importance for managing business models in disruptive industries. Notably, in systemic industries, where industry stakeholders are dependent on each other, the network component appears to be relevant (Ansari et al., 2016). By comparing how practitioners weigh and implement the network-component, we discover two highlighted functions of networks that foster disruptive dynamics in their business models.

First, in the industries of Information technology and Financials, networks play an essential part in formulating business model innovation. Thereby, "the value of strong partnerships to create and promote innovative solutions is central to the business"

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[NM042_IT]. This sort of co-creation activity involves diverse parties, as managers aim to operate on "formulating strategies with new business partners" [NM038_FI], as well as for "working closely with our global customers" [NM153_FI]. Accordingly, several practitioners also expressly use networks as an explicit source for their disruptive business models. This is illustrated by an international hard- and software company architect and builder:

> "Working with major international corporate and technology partners [...] and leading universities, [the company] first identifies global unmet market needs and then targets and exploits these by the systematic creation of successful, disruptive technology businesses" [NM153_FI].

Another example of the crucial role of networks in the Information technology sector is presented by a supplier of multi-party digital platforms, stating:

> "With a vast number of retailers, distributors, manufacturers, carriers and third-party logistics onboarded, [the company] offers a disruptive technology and business model that enables our community to slash inventory, improve service levels, and speed up the supply chain in order to outpace the competition" [NM083_IT].

Second, in Industrials and Consumer staples, the network-component is highlighted to be used for reshaping practitioners' existing processes and offerings. Thereby, companies from the industrial industry leverage their "core competencies with those of the outsourcers and build solid long-term relationships" [NM052_IN]. Additionally, managers from the industry of Consumer staples expressed themselves to have "signed warehouse relationships with [a company], which gives us capabilities to inventory products with improved logistics" [NM158_CS], and thus, to form networks that improve their actual offer.

The next business model component found to be in discussion amongst practitioners was revenue, which is communicated to be shared as the center of the business models of the industries Consumer staples and Energy. Following Wirtz et al.'s (2016) declaration of the component, it is characterized by a large number of potential indirect and direct revenue streams with an overlying goal to generally maximize revenues.

Concerning the analyzed statements, we again observe the revenue-component to be highlighted by practitioners confronted with disruptive dynamics in their industries in a twofold way. On the one hand, this allows a company "to convert new technologies into revenue streams" [RM012_CS]. On the other, it is "capable of supporting additional revenue streams (zones) unrelated to its core operations" [RM032_CS].

By giving attention to monetize new technologies, especially companies of the Energy sector emphasize the need to design revenue models around a new technology. An example of this constitutes a company that provides energy from natural resources and reveals having "identified two potential applications for the technology which could present very significant revenue streams in the future" [RM013_EN]. Further, a supplier in the oil-industry focusing on technical innovations to create value assumes that their "relatively low-cost and environmentally benign disruptive technology has the potential to unlock [...] the opportunity for the group to develop additional revenue streams" [RM075_EN]. Besides this, we also find evidence in both Consumer staples and Energy industries that different revenue strategies are applied to "generate more predictable and profitable revenue streams within the product line" [RM013_EN], and thus enable new ways to monetize existing offerings.

An additional example of a business model component with differing importance across industries according to practitioners is procurement. This component has been found to play an essential role in company business models within the Health care and Material industries. Following Wirtz et al. (2016), the Procurement component has the potential to evoke "far-reaching consequences for other components".

Both industries face challenges concerning a high degree of dependence on external parties within their supply chain, making the intermediation of Procurement a relevant step in managing disruptive innovation (Edler & Yeow, 2016). This especially holds for the Health care industry as decision-making authorities concerning procurement are in general governmentally steered. Managers within this industry are aware of those contingent hampering challenges and acknowledge that "procurement is power. It is extremely difficult for social entrepreneurs to break into government funding sources because the procurement system is set up to favour traditional approaches rather than disruptive technologies" [PM005_HC]. Consequently, practitioners from both industries

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Table 4. Exemplary characteristics of respective business model components per industry.

Business model elements (Wirtz et al., 2016)	Industry Classification (Standard & Poor's & Morgan Stanley Capital International, 2018)											
	Real Estate	Consumer Staples	Materials	Energy	Utilities	Industrials	Consumer Discretionar	Communication Service	Health Care	Information Technology	Financials	Intensity of Component distribution
Customer	· Expansion of distribution channels · Targeting of emerging markets		· Expansion of distribution channels to world market	· Building of lasting customer relationships · Customized offer to B2B		· Transformation towards customer-centricity	· Building of lasting customer relationships	· Expansion of distribution channels · Targeting of emerging markets	· Expansion of distribution channels mainly with online channels	· Building of lasting customer relationships	· Building of lasting customer relationships · Targeting of emerging markets	◕
Network		· Networks to improve existing offer				· Networks to improve existing offer	· Networks as source of innovation	· Networks to utilize other firms' assets	· Parnerships with logistic services	· Networks as source of innovation	· Networks as source of innovation	◕
Strategy			· Elimination of intermediaries		· Positioning-efforts to enter new markets	· Focus on positioning of innovative products for diversification	· Innovation as core strategy · Efforts to enter new markets	· Focus on technology enabling business models	· Focus on shift to e-Business	· Flexible Business model due to fast changes in the market	· Elemination of intermediaries · high investments in start-ups	◑
Market offer				· Efforts to offer new technologies to mass market	· Long-term contracts with B2B customers	· Modular offer & multi-modal services			· New technology to enhance services · low-cost models	· New technology to enhance services · Open source solutions	· Low-cost models	◑
Revenue		· Transforming new technologies into revenue streams	· Revenue from core business across (emerging) markets	· Transforming new technologies into revenue streams				· Generate new revenue streams from existing offer		· Transforming new technologies into revenue streams	· Multifolded revenue streams	◔
Resources	· Focus on pioneering skills through human resources					· Focus on pioneering skills through human resources			· Investments in new technological resources (e.g. robotics)	· Focus on pioneering skills through human resources	· Reduction of human resources by digital transformation	◔
Manufacturing					· Product improvement by manufacturing innovation	· Digital transformation						◔
Procurement			· Strong dioalog with regulators			· Integration of new technologies (e.g. AI) in supply chains	· Aggregation of demand	· Challenge of high competition due to missing diversification	· Challenge to overcome governmental decision power	· After-sales procurement as a service	· Extension of supply-chain with international players	◑
Financial											· Aggressive scaling activities	○
Intensity of Industry distribution	○	○	◔	○	○	◑	◔	◔	◕	◕	◕	1113

Source: Self-provided based on Wirtz et al. (2016)

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underline that "particular attention should be given to dialogue with regulators and compliance with safety and regulatory requirements" [PM072_MA]. Therefore, innovating companies need to overcome external interfering forces and ensure for "new or improved services in which public procurement approaches for innovative solutions are successfully applied" [PM061_HC].

Within our analysis, we identified and highlighted the relevant differences in business model components across industries. Still, we additionally detected similarities in how managers communicate characteristics of the described components, thereby also agreeing with previous arguments which have stated that business models are to a certain degree shared by multiple competitors across industries (Teece, 2010).

Thus, our approach enriches the current understanding by adding an industry-specific view on the communication of single components in practice. Likewise, it gives insight on how single components potentially create opportunities or even challenges in the disruptive dynamics of practitioners.

Furthermore, our classification-scheme presented a number of assigned articles to each industry, thus demonstrating an industry-disruptiveness "spectrum of maturity" (Christensen, 2006). In detail, our analysis allows us to draw a conclusion about how frequently practitioners communicate disruptive dynamics in industries. With 255 identified secondary sources of disruptive business models within the Finance industry, for example, it is apparent that this industry is highly confronted with disruptive dynamics. The Real estate industry (17) and Materials industry (26), on the other hand, present a very limited number of articles, suggesting that disruption is attributed less importance in this market so far.

Ultimately, through analyzing secondary data in the form of press releases and company reports, our industry-specific contribution was generated from effectively applied business models, ensuring the practicability of results.

Conclusion, Limitations and Future Research

By using a deductive coding procedure, we analyzed differences in highlighted business model components as stated by practitioners across industries confronted with disruptive dynamics. We thus systematically searched for press releases and company reports in this regard that were published between 1995 and 2019.

In a twofold contribution, we first provided information about how frequently practitioners highlight and express relevant business model components across industries with disruptive dynamics. Second, we aimed to enrich the current state of research with a practical overview of opportunities and challenges of business model components communicated by managers taking an industry-specific view.

Our approach nonetheless also comes with limitations, which at the same time open new opportunities for future research. The quantitative distribution of our qualitative analysis presents a comprehensive overview of the highlighted business model components per industry by taking a 'bird's-eye view'. This approach provides guidance for scholars and practitioners to better understand the articulated differences in disruptive dynamics across industries. To extend these insights, future research should further take an in-depth view to investigate the particular business model components and their underlying structures in various disruptive contexts. Although a few results of particular components are already prevalent (for example, Hahn et al.'s 2014 study on value propositions based on 3D technologies), a more complete analysis of individual business model components would allow a consolidation of the results, ultimately contributing to a synthesis of existing research on disruptive innovation (e.g. Hopp et al., 2018).

Further, although we described the advantages of secondary data for content analysis, the included press releases and company reports potentially hold a limited degree of accuracy and sufficient detail for profound insights into the disruptive dynamics of entire industries. Prospective studies should, therefore, consider applying a detailed and longitudinal study design to shed light on the characteristics of different industries and how they change during the disruptive process.

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Sustainability-related Communication Patterns on the Websites of European Top R&D Spenders

Giacomo Liotta, Stoyan Tanev, Andrea Gorra, and Alicja Izabela Pospieszala

> *" Sustainability communications can bring your business many benefits, and help you stand out from your competitors. "*
>
> Amfori
> A guide to effective sustainability communications

Many firms struggle to incorporate "sustainability" into their operations in a way that can capture economic value and deliver social and environmental benefits. This article aims to answer two questions in this regard: (i) How do companies articulate the sustainability aspects of their businesses online, and (ii) In what ways does the degree of articulation of specific sustainability aspects relate to company performance metrics, such as sales and R&D expenditure. The research method measures the occurrences of a set of sustainability-related keywords on the websites of a sample of 387 firms that were ranked as top R&D spenders in Europe for 2013. We processed the keyword occurrences in a simplified version of latent semantic analysis based on the application of principal component analysis to identify the specific combinations of words used by companies to communicate sustainability issues on their websites. The results show that "sustainable innovation" and "sustainable operations" based on partnerships and cooperation represent a dominant part of companies' online communication strategies. One of the findings suggests a strong relationship between the communication of sustainable innovation aspects and sales, which offers a promising message to companies looking for evidence about the potential impact of their commitment to sustainable operations and innovation.

1. Introduction

Sustainability concerns have become a major driver of business change (Seebode et al., 2012) and innovation (Nidumolu et al., 2009). The quest for sustainability is now transforming the competitive business landscape, which forces companies to reconsider the ways they think about products, services, processes, and business models (Nidumolu et al., 2009). The importance of making a shift from adopting traditional business models focused exclusively on process optimization and economic return, to business models that integrate sustainability concerns into a firm's strategy and business operations has been increasingly emphasized (Matos & Silvestre, 2013; Boons et al., 2013). Sustainable business model innovation involves changing the very ways firms do business (Bocken et al., 2014). Unfortunately, there little research has been done on how exactly companies can most effectively embed sustainability issues into their businesses and revenue models (Seebode et al., 2012). There is even less research on how companies communicate the focus of their sustainability efforts as well as the potential value of these efforts for their customers and stakeholders in general.

The present article contributes to answering two specific questions: (i) How do companies articulate the sustainability aspects of their businesses on their websites?, and (ii) In what ways does the degree of articulating specific sustainability aspects relate to a company's performance metrics, such as sales and R&D expenditure? We focus on top R&D spenders in Europe, that is, a type of company that is highly inclined to pursuing sustainable innovation, such that they consider R&D spending not only as an engine of economic growth, but also as a driver of sustainable development (Fernández et al., 2018).

The article is organized as follows. The next section describes key insights gained from the literature review we conducted focusing on sustainable innovation, sustainable business models, the benefits of sustainability, and the analytical method that was applied to develop research insights. The third section describes the method used. The fourth section summarizes the results. The fifth section offers an analysis of the results, followed by the final section, which focuses on the study's main contributions and its relevance for scholars and practitioners.

2. Key Insights from Literature

Sustainability and Innovation

"Sustainable innovation" has been described in the literature with different terms and embedded in conversations using several related concepts. The term is used somewhat interchangeably with eco-innovation, green innovation (Boons & Lüdeke-Freund, 2013), and sustainability-oriented innovation (Hansen et al., 2009; Klewitz & Hansen, 2014; Neutzling et al., 2018). It is grounded in wider notions such as environmental sustainability (Boons & Lüdeke-Freund, 2013) and sustainable development (Nidumolu et al., 2009). According to Hansen et al. (2009), integrating sustainability and innovation activities carries importance both from normative and business perspectives. The normative perspective relates to solving societal and environmental challenges and problems. It can be seen through the development of new areas of innovation such as, for example, new technologies supporting the elimination of waste. The business perspective relates to the interplay between sustainable innovation management and business opportunities. Innovation pressure comes often from regulations and policies regarding environmental and social matters. Furthermore, the challenges associated with adopting a sustainability paradigm can be a valuable source for generating new business ideas.

The quest for sustainability has therefore put a normative demand on innovation to become more environmentally and socially friendly (Hansen et al., 2009). At the same time, seeking sustainability can provide a new source of innovation and competitive advantage. By treating sustainability as a priority today, early movers can develop competencies that rivals will be hard-pressed to match (Nidumolu et al., 2009). Sustainable innovation, however, requires organizations to rethink their businesses, reshape their value chains and use resources in innovative ways (Lampikoski et al., 2014). More specifically, Claudy, Peterson and Pagell (2016) argue that firms with an explicit sustainability orientation are more likely to find innovative solutions to ecological and social problems. Taking a sustainability orientation can result in operational efficiencies, higher quality products, greater value for customers, and in new product development success. In order to solve the trade-offs between sustainability goals and profitability aims, firms must engage in intensified learning and market knowledge development to identify and develop solutions that satisfy economic, environmental, and social objectives (Claudy et al., 2016).

Sustainable Business Models and Innovation

According to Charter & Clark (2007), "Sustainable innovation is a process where sustainability considerations (environmental, social, financial) are integrated into company systems from idea generation to research and development (R&D), and commercialisation. This applies to products, services and technologies, as well as new business and organisation models". Sustainable innovation thus widens the previous concept of eco-innovation, which emphasizes the need for environmental performance improvement (Carrillo-Hermosilla et al., 2010), because it also includes the social dimension and a more holistic, long-term perspective involving sustainable development (Boons et al., 2013).Impactful sustainable innovation opens new global market opportunities, fosters smart specialization of regions, and spurs long-term policy actions by governments (Boons et al., 2013). At the same time, it tends to be included at the end of the development process, making it difficult to achieve more than incremental improvements (Vandaele, Decouttere, 2013). Operations striving for sustainability need to be properly integrated into business model frameworks in order to enable the delivery of the expected benefits for all relevant stakeholders. A lack of concrete frameworks exists, however, that can help turn sustainable innovations into business model innovations. Researchers have already discussed the relationship between sustainable innovation and business models by considering the sustainability aspects of the interplay between business model components, the potential for value creation in the supply chain, and revenue models (Boons & Lüdeke-Freund, 2013; Boons et al., 2013). At the same time, the question of how business models should adopt a more comprehensive view regarding sustainability has not been systematically addressed in the literature (Bocken et al., 2014).

The Benefits of Sustainability

Multiple benefits of sustainability have already been discussed in the literature. Some of the examples are summarized as follows:

- Eco-design and eco-efficiency improvements have helped in reducing energy, resource intensity, emissions, and waste per unit of production (Bocken et al., 2014).

- By managing the material side of the product, a company can reduce its pollution effects, increase its eco-efficiency, or optimize its resource characteristics, to make a product easier to recycle, reuse, and decompose (Klewitz & Hansen, 2014).

- Reducing a company’s carbon footprint through supply chain improvements or switching to less energy or resource intensive products and services that deliver equivalent value can generate signi cant savings (Seebode et al., 2012).

- Becoming environmentally friendly tends to lower costs because companies end up reducing the inputs they use. In addition, the process generates added revenues from better products, improves operational efficiency, or enables companies to create new businesses (Nidumolu et al., 2009; Amini & Bienstock, 2014).

- Improving operational efficiency, along with other sustainability initiatives, can give rise to innovations that inspire new business opportunities (Amini & Bienstock, 2014).

Analytical Methods using Web Search Techniques and Online Information

Several examples of methods and techniques have been used to analyze and interpret online information in a way that could support decision making about the content of online marketing communications. Examples of such applications include: using news articles or social media, forums and blogs to predict market trends (Nassirtoussi et al., 2014), extracting business intelligence factors (Chung, 2014), predicting stock price movements (Schumaker et al., 2012) and foreign exchange markets (Nassirtoussi et al., 2015), using online user reviews to improve the helpfulness of voting mechanisms of online review systems (Cao et al., 2011), engaging online consumer comments to improve the service level and rating of online merchants (Qu et al., 2008), and using online consumer reviews to evaluate readership and helpfulness (Salehan & Kim, 2016).

3. Research Method

Research Approach

We based the research approach on using existing sustainable business models and innovation frameworks in order to develop a set of keywords related to the sustainability aspects companies usually deal with. We then used a web search and text analytics tools to measure the frequency of use (web counts) of these sets of keywords on the websites of a sample of firms (di Tollo et al., 2015).

The research sample includes 387 product-driven firms from various sectors, such as: household goods and home construction, industrial engineering, oil equipment, services and distribution, industrial metals and mining, food production, automobiles and automotive parts, pharmaceuticals and biotechnology, and electronic and electrical equipment. The firms were selected from a list of the top 1000 EU R&D spenders for 2013 (provided by the EU Industrial R&D Investment Scoreboard, http://iri.jrc.ec.europa.eu/scoreboard.html) by choosing the firms that have a product-dedicated webpage. Purely service companies were not included in the sample. The focus on firms with a higher degree of R&D spending was used as an indicator for firms’ orientation towards innovativeness and growth.

The dataset includes company data for R&D spending, R&D growth for 2012 and for the previous 3 years, sales, sales growth for 2012 and for the previous 3 years, R&D intensity (R&D spending vs sales), profit, profit growth for 2012 and for previous 3 years, profitability (income vs sales), number of employees, employee growth for 2012 and for the previous 3 years, capital expenditures (Capex), Capex growth for 2012 and for the previous 3 years. The nature of the data allows for quantitative examination of the relationship between online articulation of sustainability aspects and more typical performance metrics such as sales and R&D spending.

Research Steps

The key steps in the research process are summarized as follows. The research started with a detailed study of the literature on sustainability to identify frameworks describing its core components, aspects, or activities. The search for relevant articles used the Web of Science research database, focusing on the fields of environmental engineering, business and management, and searching for the keywords “sustainability” and “sustainable” in the titles of articles published before Dec. 31, 2014.

An additional search for the terms “innovation”, “framework”, and “model” within the corpus identified 9 relevant articles, including frameworks or models focusing on corporate sustainability (Amini & Bienstock, 2014), business models (Boons & Lüdeke-Freund, 2013; Bocken et al., 2014), sustainable innovation (Nidumolu et al., 2009; Haanaes et al., 2011; Seebode et al., 2012; Klewitz & Hansen, 2014;), sustainable value-creation strategies (Lampikoski et al., 2014), and sustainable supply chain networks (van Bommel, 2011).

The sustainability frameworks described in the selected 9 articles were used to develop a set of 46 composite keywords related to different sustainability and sustainable innovation aspects. The data was collected by searching for the keywords on the 387 company websites using a web search tool that measured the frequency (web count) of the keywords on each of the websites. The keyword frequencies on a website were normalized by the number of sub-pages under the main company url. This was a way to account for the fact that larger companies tend to have a larger number of sub-pages and could be expected to have larger total keyword web counts (Libaers et al., 2010). The search process supplied a data matrix including the normalized frequencies of the keywords on each company’s website (387 companies X 46 keywords).

A Principal Component Analysis (PCA) was applied to the above data matrix to identify four sustainability components or themes (independent groups of co-occurring keywords addressing different aspects of sustainability). The initial interpretation of the four components was based on the loading values of the specific keywords within a given PCA component. Four quantitative variables (corresponding to each PCA component) were constructed by adding all (normalized) keyword web counts corresponding to every PCA component weighted by the specific keyword loading. The firms were ranked in terms of a total sustainability communication metric —the sum of the four PCA variables. The most highly ranked firms were then characterized by the combinations of sustainability themes (sustainability communication patterns) discussed by them on their websites.

The last step in the process was to perform a correlation analysis of the four sustainability components, the R&D spending, and sales of the firms, which provided an answer to the second research question.

4. Summary of Results

4.1 Principal component analysis of the sustainability issues articulated online

The application of the PCA lead to the identification (extraction) of four principal components that explained 72.31% of the total variance of the data we collected. The four components include 16 keywords out of the first set of 46 keywords. This is because some of the keywords had a relatively low representation on firms’ websites or did not contribute significantly to the composition of the principal components (keywords with a loading value lower than 0.4 were removed from the analysis). The criterion to affirm the existence of a specific principal component was twofold: to have an eigenvalue higher or equal to 1, as well as to have minimum 2 keywords (items) in the component with a loading value larger than 0.4 (Reinard, 2006).

Component 1 consists of seven keywords (Table 1). Except for “kw39”, all of them are related to sustainable innovation focusing on organization, process, technology, and service. Interestingly, the keyword corresponding to product innovation (kw9) was not included in this component as its loading value was less than the 0.40 threshold. The sustainability aspect that has the lowest loading value refers to environmental policies, regulation, and legislation standards (kw39).

Component 2 includes six strong keywords with loading values higher than 0.6 (Table 2). Two of the keywords (kw37 and kw38) refer to customer benefits such as trust, loyalty, and satisfaction. Two other keywords (kw34, kw12) focus on financial, economic, and social benefits, and new customer market niches. In addition, Component 2 (kw35, kw16) includes a focus on asset optimization, better material and energy efficiencies, and improved resource utilization. Finally, kw38 refers to better customer relationships. All the above could be considered as benefits for customers, companies, or other key stakeholders.

Component 3 includes three keywords (Table 3) referring to several issues related to sustainable operations based on partnerships and cooperation: production, manufacturing, and technology development that aim at maximizing material, energy, and resource efficiencies. More specifically, kw14 (with the highest loading of 0.814) includes the terms

Table 1. Keyword composition of Component 1

Keyword	Component 1 composition	Loading
kw8	sustainable OR sustainability AND innovation OR innovativeness AND organizational OR organisational OR corporate OR employee	0.828
kw6	sustainable OR sustainability AND innovation OR innovativeness AND technical OR technology OR technological	0.815
kw11	sustainable OR sustainability AND innovation OR innovativeness OR innovative OR new OR improve OR improvement OR improved AND service	0.744
kw7	sustainable OR sustainability AND innovation OR innovativeness AND societal OR social OR ethic OR ethical OR responsible OR responsibility OR equity OR CSR	0.741
kw13	sustainable OR eco OR green OR environment OR environmental OR ecological OR ecologic OR clean OR cleaner AND innovation OR innovativeness	0.728
kw10	sustainable OR sustainability AND innovation OR innovativeness OR innovative OR new OR improve OR improvement OR improved AND process	0.662
kw39	sustainability OR sustainable OR environmental AND policy OR regulation OR legislation OR engagement OR procedure OR standard OR management system	0.521

‘environmental’, ‘production’ and ‘manufacturing’, while kw46 (second highest loading of 0.602) includes the terms ‘sustainable’, ‘partnership’, ‘alliance’, and ‘cooperation’. Interestingly, kw16 (material, energy, and resource efficiencies) is cross-loaded with Component 2, which focuses on benefits. Its presence in Component 3 could be considered as an expression of the focus of companies’ sustainable operations.

Component 4 is composed of two keywords (Table 4), one of which has a much stronger loading —0.793 (kw40), as compared to 0.418 (kw7). The stronger keyword (kw40) emphasizes the challenges of meeting the requirements of environmental policies and regulations. The second keyword (kw7) expresses companies’ commitment to societal, ethical, and responsible innovation. It is cross-loaded with Component 1, which focuses on sustainable innovation. Its presence in Component 4 could be considered as an expression of corporate innovation efforts that focus on meeting environmental policies and regulations.

4.2 Interpretation of the principal components

The keyword composition of the four PCA components supplies a basis for their interpretation as specific sustainability aspects, issues, or priorities. The interpretation should be based on keywords with the highest loading values (Reinard, 2006). The PCA analysis allowed us to construct four quantitative variables: C1, C2, C3 and C4. These correspond to each of the four principal components by adding the normalized web counts of each keyword included in a component, weighted by specific keyword loading. We can also define a total sustainability metric as follows: C_T = C1 + C2 + C3 + C4. The total sustainability metric (C_T) offers the possibility of ranking the firms in terms of the degree of their online articulation of sustainability aspects corresponding to all four components. A search on the websites of companies selected from the most highly ranked firms was used to supply additional insights that could be applied in interpreting the four components, which is done in the next sections.

4.2.1 Interpretation of Component 1: Sustainable innovation

The keyword composition of Component 1 (Table 1) refers to sustainable innovation focusing on organization, process, technology, and services. Our textual examination of the websites of highly ranked firms suggested that Component 1 can be labelled ‘Sustainable innovation’ and interpreted as: Sustainability aspects related to innovative design,

Table 2. Keyword composition of Component 2

Keyword	Component 2 composition	Loading
kw37	sustainability OR sustainable AND improve AND customer AND trust OR loyalty OR fidelity OR allegiance OR satisfaction OR contentment	0.807
kw35	sustainability OR sustainable AND minimize OR optimize OR assets	0.785
kw34	sustainability OR sustainable AND raise OR enhance AND finance OR economic OR environmental OR social AND benefits OR return OR revenue	0.785
kw12	sustainable OR sustainability AND innovation OR innovativeness OR new OR improve OR improvement OR improved AND larger AND market OR niche OR customer	0.721
kw38	sustainability OR sustainable AND lengthen OR sustain OR strengthen OR improve OR enhance AND customer AND relationships OR interaction OR communication	0.678
kw16	maximize OR maximize OR increase OR improve AND efficiency OR use OR effectiveness OR effectivity AND material OR energy OR resource	0.636

organizational, technological, service, process and social innovation enabled by cooperation with external partners and informed by existing environmental policies, regulations, standards and management systems. (This and the three italicized sentences in the following paragraphs mark our key findings from this research.)

What is notable in the interpretation of Component 1 is its broad perspective on the relationship between sustainability and innovation, which goes beyond the typical concerns related to sustainable product design and innovation.

4.2.2 Interpretation of Component 2: Stakeholder benefits

The keyword composition of Component 2 (Table 2) refers to sustainability-related benefits for customers, companies, or other key stakeholders. The textual examination of the websites of highly ranked firms suggests that Component 2 could be labelled 'Stakeholder benefits' and interpreted as: Sustainability-related stakeholder benefits including a balance between sustainable business risks and rewards, and alignment with government policy, legislation and industrial practice.

4.2.3 Interpretation of Component 3: Sustainable operations

The keyword composition of Component 3 (Table 3) refers to sustainable operations enabled by valuable partnerships and cooperation. The textual examination of the websites of highly ranked firms suggests that Component 3 could be labelled 'Sustainable operations' and interpreted as: Sustainable operations enabled by valuable partnerships and cooperation with suppliers and contractors focusing on delivering sustainable production solutions, implementing sustainable environmental policies, driving efficiency in resource use and implementing waste reduction systems.

It is worth noting that the cross loading of kw16 (material, energy, and resource efficiency) with Component 2 (Stakeholder benefits) suggests that companies' online communications discuss stakeholder benefits that are rooted in and emerge from their sustainable operations.

4.2.4 Interpretation of Component 4: Dealing with environmental policy and regulation challenges

The keyword composition of Component 4 (Table 4) refers to the challenges of meeting the requirements of environmental policies and regulations, along with companies' commitment to societal, ethical, and responsible innovation. Textual examination of the websites of highly ranked firms suggested that Component 4 can labelled 'Dealing with environmental policy and regulation challenges' and interpreted as: Dealing with the challenges of meeting the requirements of environmental policies and regulations by adopting governance principles driven by social responsibility and environmental concerns.

Interestingly, kw7 (ethical or responsible innovation) of Component 4 appears also in Component 1 (Sustainable

Table 3. Keyword composition of Component 3

Keyword	Component 3 composition	Loading	Comp. 2 cross loading
kw14	sustainable OR eco OR green OR environment OR environmental OR ecological OR ecologic OR clean OR cleaner AND production OR manufacturing OR manufacture OR development OR technology	0.814	
kw46	sustainability OR sustainable OR eco OR green OR environmental OR ecological OR ecologic OR clean AND partner OR partnership OR cooperation OR collaboration OR collaborative OR cooperative OR alliance	0.602	
kw16	maximize OR maximize OR increase OR improve AND efficiency OR use OR effectiveness OR effectivity AND material OR energy OR resource	0.543	0.636

innovation) with a higher loading value (0.741 as compared to 0.418 in Component 4). Such a link between Components 1 and 4 suggests that some of the key aspects of companies' sustainable innovation efforts are driven by the need to address the requirements of environmental policies and regulations.

4.3 Examining firms' online communication patterns of sustainability aspects

Our analysis of the emerging combinations of sustainability aspects that are most frequently articulated by firms on their websites provided insights about their most typical online communication patterns. The emerging combinations of sustainability components we analyzed will need a criterion to identify a minimum threshold level of online articulation below which a specific component will be considered as negligible. To do that, we normalized each component variable by its maximum value, for example C1' = C1/max(C1). Thus, the maximum value of the four normalized variables is 1 and their minimum value is zero. After several trials, a threshold value of 0.2 was chosen since it allowed us to identify a suitable subset of firms that manifest distinguishable communication patterns. In this way, the four component variables of each of the 387 firms was transformed into a binary form, as "zeros" (for the companies that have a component value below 0.2) and "ones" (for the companies that have a component value above 0.2).

We used an intuitive labelling scheme for the online communication patterns comprised of "zeros" and "ones". For example, a 1110 pattern corresponds to companies with C1, C2, and C3 values higher than 0.2 (hence, the first three "ones" in the label), and a C4 value lower than 0.2 (hence, the last "zero" in the label). Table 5 shows the most dominant communication patterns. Interestingly, the 0000 pattern corresponds to 54% of the companies. This means that the choice of a 0.2 threshold allowed us to identify almost 50% of the firms as not very active in articulating their sustainability concerns online. Reducing the threshold value would have decreased the number of "0000" firms, but would still have left many of them as non-active. We thus believe,

Table 4. Keyword composition of Component 4

Keyword	Component 4 composition	Loading	Comp. 1 cross loading
kw40	sustainability OR sustainable OR environmental AND policy OR regulation OR legislation issue OR problem OR challenge	0.793	
kw7	sustainable OR sustainability innovation OR innovativeness AND societal OR social OR ethic OR ethical OR responsible OR responsibility OR equity OR CSR	0.418	0.741

by working with the study's parameters, that the 0.2 value was a suitable choice since it both demonstrated the methodology used in the search and also allowed us to examine firms' dominant communication patterns.

Five communication patterns were used by at least 3.0% of companies: 0010, 0110, 1010, 1110, and 1111 (see Table 11). The companies that intensively communicated issues related to all four components accounted for only 3.62% (14 firms). The most dominant communication pattern (20.16%, 78 firms) included only Component 3 (0010) - Sustainable operations. The second dominant pattern was 0110 (8,01%, 31 firms) - Sustainable operations and Stakeholder benefits, followed by 1010 (4,65%, 18 firms) - Sustainable operations and Stakeholder innovation. The 1110 communication pattern - Sustainable operations, Stakeholder benefits, and Sustainable Innovation, is manifested by 4.39% (17) of the firms.

4.4 Correlation between sustainability and company performance metrics

The present section describes the results gathered from a correlation analysis we did that focused on examining the relationships between sustainability components and two of a company's key performance indicators - R&D spending and Sales (Table 6). The correlation coefficients, along with the rest of the performance metrics described in the Research method section, were found to be not statistically significant. We should emphasize the fact that the type of correlated variables used (online articulation of sustainability vs. performance metrics) was quite different. The variables C1 to C4 refer to the frequency of articulating online specific sustainability aspects, while the R&D and Sales variables were based on numerical data about annual R&D company spending and sales, provided by the companies themselves. This is an important point since it suggests that the degree of correlation between the variables used should be interpreted in relative rather than absolute terms.

The total sustainability variable (C_T) manifests a high degree of correlation with Sales (0.445). We found that the distinction between high and medium degrees of correlation follows the classification suggested by Cohen (1988), where correlation coefficients larger than 0.371 refer to high correlation, and ones between 0.243 and 0.371 to medium correlation.

The highest correlation coefficient is between Component 1 (Sustainable innovation) and Sales (0.463). The second highest correlation coefficient (0.416) is the one between Component 4 (Dealing with environmental policy and regulation challenges) and Sales. The other two sustainability components (C2 - Stakeholder

Table 5. Emerging combinations of sustainability components (online communication patterns). The light grey coloured rows highlight the most dominant patterns.

Online communication patterns					
Label	**C1** Sustainable innovation	**C2** Stakeholder benefits	**C3** Sustainable operations	**C4** 'Env. policy & regulation challenges'	**Total % (# firms)**
0010	0	0	1	0	20.16% (78)
0110	0	1	1	0	8.01% (31)
1010	1	0	1	0	4.65% (18)
1110	1	1	1	0	4.39% (17)
1111	1	1	1	1	3.62% (14)
1011	1	0	1	1	2.58% (10)
0100	0	1	0	0	1.29% (5)
1000	1	0	0	0	1.03% (4)
0001	0	0	0	1	0.26% (1)
0000	0	0	0	0	54.01% (209)
Total	**5**	**4**	**6**	**3**	**100.00% (387)**

Table 6. Correlation between sustainability components and performance metrics

	Sales 2012 (€M)	R&D 2012 (€M)
C1: Sustainable innovation	0.463	0.343
C2: Stakeholder benefits	0.365	0.323
C3: Sustainable operations	0.340	0.275
C4: Dealing with environmental policy and regulation challenges	0.416	0.304
C_T: Total sustainability component	0.445	0.352

benefits, and C3 - Sustainable operations) manifest a medium correlation with Sales - 0.365 and 0.340, respectively. In addition, a medium degree of correlation (0.352) was found between the total sustainability component (C_T) and R&D spending. The correlation between sustainability and R&D spending was seen as being driven by Sustainable innovation (0.343) and Stakeholder benefits (0.323). The lowest correlation (0.275) was identifiable between Sustainable operations and R&D spending.

5. Discussion of Results

There are two main sets of results. The first set of results showed the online communication patterns represented by specific combinations of sustainability themes articulated by companies on their websites. These patterns gave us an answer to the first research question: How do companies articulate the sustainability aspects of their businesses on their websites? The dominant communication patterns we found were: 0010 (20.16%), 0110 (8.01%), 1010 (4.65%), 1110 (4.39%), and 1111 (3.62%) (see first five rows in Table 11).

The most noticeable observation in these patterns is that Component 3 (Sustainable operations) appears in all of them. In addition, the most dominant pattern consists of Component 3 alone. This suggests that companies build their online communication of sustainability concerns around issues related to sustainable operations, partnerships and cooperation with suppliers and contractors. They focus on delivering sustainable production solutions, implementing sustainable environmental policies and effective environmental management systems, gaining efficiency in resource use, and constantly working on waste reduction systems (see section 4.2.3).

The second most dominant communication pattern is 0110 which corresponds to 8.01% of the firms and includes two themes: Sustainable operations and Stakeholder benefits. This finding supports insights formulated by Sarkis, Gonzalez-Torre, and Adenso-Diaz (2010), who indicated a relationship between stakeholder concerns and firms' environmental practices. According to Peloza et al., (2012), many firms engage in sustainability initiatives with the expectation of financial returns based on valuable relationships with stakeholders. Firms that meet stakeholder expectations for corporate environmental performance "show less unsystematic risk, compared to firms with low environmental legitimacy" (Kumar & Christodoulopoulou, 2014).

The other dominant communication patterns were 1010 (4.65% of the firms focus on Sustainable operations and innovation), 1110 (4.39% of the firms focus on the first three sustainability components), and 1111 (3.62% of the firms focus on all four components). This finding shows a tendency for companies to claim innovativeness in the context of their sustainable operations and stakeholder relationships. What is interesting is that the fourth component (Innovation and Dealing with environmental policy and regulation challenges) appears only in the most dominant pattern when all of the other components are also included. The cross-loading of one of its keywords (kw7) with Sustainable innovation suggests a strong link between regulations, policy, and innovation.

The second set of results answers the second research question: In what ways does the degree of articulating specific sustainability aspects relate to a company's performance metrics, such as sales and R&D expenditure? Our findings (see Table 6) show that the online communication about sustainability issues by companies has a high degree of correlation with sales and a medium (lower) degree of correlation with R&D. We believe the higher correlation between communicating sustainability aspects and sales marks an interesting finding. It is inline with existing theoretical and empirical research on the relationship

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between sustainability, customer satisfaction, stronger stakeholder relationships, and superior financial performance (Peloza et al., 2012). In addition, according to Baron (2001), as well as McWilliams and Siegel (2001), firms predominantly tend to engage in sustainable profit maximizing practices.

These results suggest that customers should more closely examine a company's sustainability activities when making their purchase decisions. Our research joins others in indicating that customers will favour firms with good sustainability performance (Gong et al., 2019). Our results reveal that sustainability plays an important role in companies' sales arguments and communications to customers in new market niches (Klink et al., 2014). Companies tend to refer to good sustainability practices in marketing their customer value propositions by claiming the material, energy, and resource efficiency of their products as a distinct dimension of value (Patala et al., 2016).

We find it interesting that the highest correlation between sustainability and sales appears to be driven by: a) Sustainable innovation, and b) Dealing with the challenges of environmental policy and regulations. We find the considerable impact of companies making sustainable innovation claims in their online communications as understandable, since a firm's innovativeness is an important factor in developing its corporate public image.

The lower degree of correlation between the total sustainability variable and R&D spending can be explained by the less frequent references to R&D activities on company websites, in large part due to their longer-term potential impact on business operations. On the other hand, the link between R&D spending and Sustainable innovation seems to make sense to us, since R&D activities have a direct impact on companies' innovation outcomes.

6. Conclusion

Our study makes two main contributions. The first contribution is methodological. We adopted a web-based data collection methodology, which was based on publicly available textual data, and used textual analytics tools to examine the online communication patterns of sustainability issues by top EU R&D spenders, focusing on the relationship between degree of articulating specific sustainability issues, corporate sales, and R&D spending. The method used can easily be replicated through adopting open source web search and text analytics resources that can be used by data analysts.

The second contribution is theoretical. The results offer what we believe to be valuable insights about the communication patterns top EU R&D spenders use to articulate the sustainability aspects of their businesses, providing a basis for comparison with other organizations. The focus on sustainable operations serves as most companies' key communication pillar, which they complement with a focus on stakeholder benefits and sustainable innovation. One of the most interesting findings suggests a strong relationship between communicating sustainable innovation aspects and sales, which is a promising message to companies looking for evidence about the potential positive impact of their commitment to sustainable operations and innovation on their market position. We believe that the results will be of interest to both researchers, company decision makers, and marketing communication experts who can both learn from and replicate the method used here in similar other contexts.

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Stoyan Tanev, PhD, MSc, MEng, MA, is Associate Professor of Technology Entrepreneurship and Innovation Management associated with the Technology Innovation Management (TIM) Program, Sprott School of Business, Carleton University. Before re-joining Carleton University, Dr. Tanev was part of the Innovation and Design Engineering Section, Faculty of Engineering, University of Southern Denmark (SDU), Odense, Denmark. Dr. Tanev has a multidisciplinary background including MSc in Physics (Sofia University, Bulgaria), PhD in Physics (1995, University Pierre and Marie Curie, Paris, France, co-awarded by Sofia University, Bulgaria), MEng in Technology Management (2005, Carleton University, Ottawa, Canada), MA in Orthodox Theology (2009, University of Sherbrooke, Montreal Campus, QC, Canada) and PhD in Theology (2012, Sofia University, Bulgaria). Dr. Stoyan Tanev has published multiple articles in several research domains. His current research interests are in the fields of technology entrepreneurship and innovation management, design principles and scaling of technology start-ups, business analytics, topic modeling and text mining. He has also an interest in interdisciplinary issues on the interface of the natural and social sciences, and philosophy of religion. Dr. Tanev is the Editor-in-Chief of the Technology Innovation Management Review.

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Alicja Pospieszala (Schroll Nielsen) has a Management and Manufacturing Engineering degree from the Technical University of Wroclaw in Poland with a focus on quality management systems in production. Alicja has also completed a Masters degree in Product Development and Innovation at the University of Southern Denmark. She is currently working in the LEGO Group being responsible for activities related to problem solving and quality improvement in Mould Design. Before joining the LEGO group Alicja has worked for around 3 years at EWII Mobility A/S focusing on the quality management support of the production of 3-wheel electric vehicles.

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