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Conceptualization, Operationalization and Validation of the Digital Data Stream Readiness Index

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Abstract

In their search for value creation, companies are investing considerable resources in so-called "Big Data" initiatives. One peculiar aspect of these initiatives is the increasing availability of real-time streams of digital data. Successfully leveraging these streams to extract value is emerging as a critical competence for the modern firm. Despite the significant attention devoted to "Big Data," scholarly research on real-time Digital Data Stream (DDS) remains insufficient. More importantly, we have no specialized definitions and measurement instruments that can move the field forward by initiating a cumulative research tradition. In this paper, we provide clarification on key definitions, differentiating DDS from the broader "Big Data" concept. Drawing on the organizational readiness concept, we then develop the DDS readiness index as a measure of organizational readiness to exploit real-time digital data. In this article we conceptualize, define, operationalize and validate the index. We identify the four dimensions of mindset, skillset, dataset and toolset as the elements of the DDS readiness index and we discuss its managerial and research implications.

Keywords: Digital Data Stream Readiness Index; Multiple-item scale; Big Data.

1 Introduction

Every day, people generate digital data through tweets, clicks, videos and the plethora of sensors that are embedded in their devices. Instruments and machines such as smart meters, manufacturing sensors, equipment logs, and vehicle tracking systems, automatically and continuously, generate digital data. Big data is "a holistic approach to manage, process and analyze 5 Vs (i.e., volume, variety, velocity, veracity and value) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantage (Fosso Wamba et al., 2015, p. 6). It is the umbrella term for this evolving trend. Recent research suggests that Big Data is a driver of business success across a wide range of industries (McAfee & Brynjolfsson, 2012). Organizations are investing considerable resources in Big Data initiatives in search of value creation opportunities (Chen, Chiang, & Storey, 2012),

in driving their digital business strategy (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013) and in making better informed business decisions (Eastburn & Boland, 2015).

Despite the expected impacts of Big Data and their organizational outcomes, there has been only limited research focusing on investigating the adoption and usage of Big Data in firms (Baesens, Bapna, Marsden, Vanthienen, & Zhao, 2016), or framing the organizational transformational outcomes (George, Haas, & Pentland, 2014). While the body of literature on Big Data is constantly increasing, little is known about the factors determining or moderating their adoption and, in particular, on the preconditions leading to their successful outcome.

Part of the problem resides in the intrinsic polysemy of the term Big Data not representing a single technology, technique or initiative, but rather a trend across many areas of business and technology. We observe that most definitions of big data (e.g., Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015) stress the dimension of volume - the size of the managed data sets. Such focus implies the development of new data management techniques (e.g., non-relational databases), increased and scalable data processing infrastructures and software (e.g., distributed and parallel tools, data visualization tools). Big data, is then a term that refers, at the same time, to initiatives related to data management, processing, analysis and visualization. This "all encompassing" definition makes it difficult to develop a cumulative tradition of research in the area (Chen et al., 2012). Thus, it is critical for academics to also explore specific aspects of the general Big Data trend.

In this article, we refer to the related, but more focused, concept of Digital Data Streams (DDSs). DDSs, defined as the flows of digitally encoded data, available in real time and describing a related class of events (Piccoli & Pigni, 2013; Piccoli, Rodriguez, & Watson, 2015), fit in the historical evolution of computing, from batch processing, to online transactions processing, to the continuous processing of streaming data (Watson, Wixom, Hoffer, Anderson-Lehman, & Reynolds, 2006). We focus on DDSs for three reasons. First, DDSs are a key organization resource that firms can leverage for competitive advantage. A world characterized by vast amounts of real-time digital data flows, beyond the historical data that companies have typically leveraged (Davenport, 2014; Watson et al., 2006). The emerging world of the Internet-of-Things, for example, is replete with DDSs (French & Shim, 2016). Second, the DDS concept has the appropriate level of focus and precision, thus enabling precise definition and rigorous academic inquiry. Third, DDSs are a promising level of analysis for understanding the organizational impacts of real-time digital data, thereby allowing managers to dissect events in real-time, to shorten the decision cycle, and deepen their understanding of customers at the same time (Piccoli et al., 2015).

In the general area of digital data streaming, we focus this article on organizational readiness – theorized as a multidimensional construct for assessing the extent to which resources and implementation conditions favor an initiative's success (Shahrasbi & Paré, 2015). In previous studies, the concept of organizational readiness was successfully used to predict and explain organizations' adoption, use and institutionalization of Information Technology (IT) related initiatives (Shahrasbi & Paré, 2014).

As pre-condition for organizational change, the readiness is a relevant measure in adoption studies and it has proven to be a valuable conceptual tool for organizational researchers interested in understanding the level of compatibility and consistency of IT change and firms' business (Nikolaeva, 2006), the effects of a positive culture towards the adoption of IT (Motwani, Subramanian, & Gopalakrishna, 2005), and firms' capabilities for executing IT change (Molla, Cooper, & Pittayachawan, 2011).

Despite the long established tradition of organizational readiness as a foundational concept, the extant literature relies on two distinct views of readiness: a structural view - focusing on firms' access to resources and capabilities favoring change - and a psychological view - emphasizing

organizational members' attitudes, beliefs, and intentions. These contrasting views founded two distinct and rarely integrated bodies of knowledge, limiting the understanding of the complementarities between the two (Shahrasbi & Paré, 2014, 2015). Additionally, organizational readiness has been studied considering different level of analysis either at the individual or the organizational level (Holt, Armenakis, Harris, & Feild, 2007).

The lack of a unitary, even if multifaceted view of organizational readiness, limits the applicability of existing organizational readiness measures and constructs to Big Data initiatives (Marchand & Peppard, 2013; Shahrasbi & Paré, 2014) that require a blend of technical resources and cultural mindsets to succeed (Marchand & Peppard, 2013).

Motivated by these challenges, with this study we provide two main contributions. We further the organizational readiness literature by advancing and validating an integrative measure embodying both the structural and the psychological views established in previous studies. In the context of DDS studies, we develop specific constructs to facilitates progress in theory building (Subramanian & Nilakanta, 1994, p13).

Methodologically, we qualify the determinants of DDS readiness, based on a survey of 302 organizations, and we conceptualize, operationalize and validate the DDS readiness index. The proposed index is a multidimensional construct that is composed of four dimensions - mindset, skillset, dataset and toolset - measured through a 12-item scale.

The paper is organized as follows. First, we provide the definition of DDSs and its theoretical underpinnings. Then, drawing from the organizational readiness literature, we develop and validate the DDS readiness index. We conclude the paper with an extended discussion, summary of our results, and suggestions for future research.

2 Digital Data Streams

A DDS is the result of the continuous digital encoding and transmission of data describing a related class of events, which may be human-generated (e.g., a tweet, an instagram) or machine-generated (e.g., a CO2 reading, a GPS location). DDS builds on the idea of Digital Data Genesis (DGG), the digital representation of a discrete event, or of a continuous event at a particular point in time (Piccoli & Watson, 2008). It is the transmission, or flow, of these digital representations of events that engenders the digital data stream (Piccoli & Pigni, 2013). For example, Uber, the world's largest 'taxi' company, bases its value proposition on optimally matching the real-time digital data stream of its affiliated drivers with that of transportation demand.

The DDS provides a novel lens for understanding new value creation opportunities and mechanisms in the current sensorized and interconnected world (Lawrence et al., 2016; Llewellyn & Leiponen, 2016; Ives et al., 2016). The DDS framework advances a typology for value extraction that can guide managerial decisions in profiting from the increasing availability of digital representations of events. Recent studies discuss the impact of DDSs on decision making and operational processes (Anand, Sharma, & Coltman, 2016b; Matthias, Fouweather, Gregory, & Vernon, 2017), on DDSs investments realization (Anand, Sharma, & Coltman, 2016a), and on customer service (Ives, Palese, & Rodriguez, 2016).

To clarify the terminology of the key terms used in this study, Table 1 reports their definitions.

Term	Definition	Reference
Big Data	The term denotes an approach to manage, process and analyze 5 Vs (i.e., volume, variety, velocity, veracity and value) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantages.	(Fosso Wamba et al., 2015)
DDG	The digital representation of a discrete event or of a continuous event at a particular point in time.	(Piccoli & Watson, 2008)

DDS	The continuous digital encoding and transmission of data describing a related class of events, which may be human-generated or machine-generated	(Piccoli et al., 2015)

Table 1 Key terms definition

In the context of DDSs studies, particular attention is given to the cultural, technical and managerial challenges confronting organizations deploying DDSs related strategic initiatives (Anand et al., 2016a; Herterich, Brenner, & Uebernickel, 2016). DDS strategic initiatives are a specific case of IT-dependent strategic initiatives (Piccoli & Ives, 2005). Thus, they consist of identifiable competitive moves that depend on the use of DDS to be enacted. In this sense, DDS initiatives are:

IT dependent. IT is a foundational element of the initiative without which it would not be possible (Piccoli & Ives, 2005).

Strategic. The initiative consists in specific competitive moves designed to improve firms' competitive position (Brandenburger & Stuart, 1996).

Real time. The initiative is based on the real-time or semi real-time capture, stream, and harvest of the data stream and of the events it contains (Pigni et al., 2016).

Data centric. It relates to the opportunities for value creation made possible by the increasing digitalization of physical occurrences (Piccoli & Watson, 2008).

While the notion of DDS has gained significant attention in both academic literature and managerial practice, no study to date has investigated the antecedents of a firm's ability to exploit opportunities offered by DDS. In the remainder of this section we review the organizational readiness literature to support our development of a DDS readiness index.

3 Organizational Readiness and Information Systems

Two views dominate the organizational readiness literature (Shahrasbi & Paré, 2014): a structural view (e.g., Weiner, Amick, & Lee, 2008) and a psychological view (e.g., Armenakis, Harris, & Mossholder, 1993). The structural view describes organizational readiness as a firm's access to the attributes that are required for change to occur (e.g., Collins, Phields, Duncan, & others, 2007), an internal capacity to change (Shahrasbi & Paré, 2015). Structural attributes are institutional resources, human resources, technical resources and capabilities, knowledge and skills (Shahrasbi & Paré, 2014). This view highlights the importance of an organization's capacity to adopt and implement a change initiative, as also discussed in the change management literature (e.g., Rao, 2015). By contrast, the psychological view emphasizes organizational members' attitudes, beliefs, and intentions for change. In this sense the psychological readiness embed the collective commitment to change, and the confidence in succeeding (Shahrasbi & Paré, 2015).

The readiness concept is widely applied in the literature. For example, organizational readiness is simultaneously regarded not only as an emotional inclination to accept, embrace and implement a change (Holt et al., 2007) but also as the representation of a collective commitment (Rusly, Corner, & Sun, 2012).

To date, limited efforts have been made to advance an integrative view of organizational readiness that comprises both the structural and psychological views , calling for further effort in this sense (Holt et al., 2007). Despite the rich literature on and recognized importance of organizational readiness (Iacovou, Benbasat, & Dexter, 1995), the results have remained only theoretical (Shahrasbi & Paré, 2014). Past Information Systems (IS) studies used the concept of organizational readiness in various settings but primarily adopted a single view. For example, Iacovou et al. (1995) and Mehrtens et al. (2001) describe organizational readiness for IS adoption and implementation as the interplay between financial and technological resources. In particular, Mehrtens et al. (2001) identify three forms of organizational readiness as being

highly relevant to the adoption of the Internet: the level of IT knowledge among IT professionals; the level of IT knowledge among non-IT professionals; and the level of IT use within the organization. In other studies, organizational readiness refers to whether an organization has made the necessary preparations for the effective deployment of IT solutions, such as an ERP system. Zhu et al. (2010) describe organizational readiness as building a favorable atmosphere for ERP usage, aligning the organization and the ERP system, and gathering sufficient resources for the system's operation.

The IS literature on readiness has often operationalized readiness at an organizational level mainly focusing on its structural nature, partially disregarding the psychological dimension. An integrative view is set to foster our understanding of readiness shedding light on the nature of the construct, and fostering the understanding of readiness outcomes (Shahrasbi & Paré, 2014). Furthermore, the lack of a perspective on organizational readiness comprising both the structural and psychological views calls for further theorization of the construct.

In the next section, we describe our development of a readiness index that is consistent with both views.

4 Conceptualizing the DDS Readiness Index

Real-time DDSs are becoming even more important given the emerging world of the Internet-of-Things that produce a huge amount of real-time digital data (Jernigan, Ransbotham, & Kiron, 2016). They can be of particular importance in developing a digital business strategy (Bharadwaj et al., 2013; Tan, Pan, Lu, & Huang, 2015).

The lack of theorization on DDSs (Piccoli, Pigni, & Watson, 2016) and the value creation opportunities that can derive from these new IT resources call for a rigorous development of the related constructs. Because advances in theory building and empirical investigation are required, we conceptualized our index components based on the change management and organizational readiness literatures. Specifically, the proposed DDS readiness index integrates these literatures, considering both the structural and psychological views in building an organizational readiness index along the four distinctive characteristics of DDS initiatives (Table 2). As previously discussed DDS initiative are distinctively IT based, strategic, data centric, and real-time.

In defining readiness dimensions, we followed a four-step process. First, we considered the factors that are necessary to develop broad organizational capabilities for transforming transactional data into knowledge and profiting from them (Davenport, Thomas H., Harris, Jeanne G., Long, David W., & Jacobson, Alvin L., 2001).

After having analyzed the definitions of all the constructs, we observed that the authors consider both the structural and psychological views in a single dimension, the "Technology and data" construct. Therefore, this dimension had the limitation of referring to two separate domains within a single construct. The other constructs, "strategy", "skills and experience", and "organization and culture", refer to distinguished psychological or structural views (see Table 2). Thus, with the aim of overcoming the limitations of the "Technology and data" construct, the index proposed in this study considers the four dimensions discussed by (Davenport, Thomas H. et al., 2001).

Second, we considered the dimensions described by Shahrasbi & Paré (2014). These dimensions refer to both the structural and the psychological views of the organizational readiness literature. We identified that all of them fit well with the purpose of our study, with the exception of "financial readiness" and "business readiness". The former did not fit because the readiness of companies to exploit DDSs is related to their ability to create value from DDSs, which is not necessarily related to their financial availability. The latter was not a good fit because it is an exogenous dimension of readiness, instead of being endogenous, as the

proposed index dimensions should be. Thus, with the aim of considering the dimensions that were well suited to the purpose of this study, we did not consider these two dimensions when constructing the DDS readiness index (see Table 2).

Third, we considered the change management literature, as it contends that embracing change effectively, as happens when firms exploit DDSs, requires a new mindset, toolset and skillset (Rao, 2015). The author in his study discusses these three dimensions, each of which fits well with a psychological or structural view (see Table 2). Thus, we considered these three dimensions when constructing the DDS readiness index.

Fourth, based on the definitions of the dimensions proposed in the three previous studies, we integrated them, eliminating those falling beyond the scope of this study (financial readiness and the business readiness) and dividing the construct that referred simultaneously to both the structural and psychological views (the "Technology and data" construct). In our analysis, we considered further evidence from practitioners (Weigend, former Chief Scientist at Amazon.com, and Zubin Dowlaty, Head of Innovation and Development at Mu-Sigma Inc.), who suggest that data-driven companies follow an evolutionary path from "data set to tool set to skill set to mindset". We thus developed four new measures on the basis of the definitions in the three cited studies and practitioners' references. We then defined four new dimensions, mindset, skillset, dataset and toolset, as detailed in the next sections. Accordingly, the DDS readiness index is a reflective measure composed of these four dimensions.

Table 2 clarifies the correspondences between the dimensions considered in previous works and the dimensions of the DDS readiness index proposed in this study.

Key Study	**Dimensions explored**	**View of the dimension**	**DDS readiness dimensions**			
			Mindset	**Skillset**	**Dataset**	**Toolset**
(Davenport, Harris, De Long, & Jacobson, 2011)	Strategy	Psychological	X			
	Skills and experience	Structural		X		
	Organization and culture	Psychological	X			
	Technology and data	Psychological			X	X
(Shahrasbi & Paré, 2014)	Technological readiness	Structural				X
	Staff readiness	Structural		X		
	Processes and operations readiness	Structural				X
	Cultural readiness	Psychological	X			
(Rao, 2015)	Mindset	Psychological	X			
	Skillset	Structural		X		
	Toolset	Structural				X
(Iacovou et al., 2011)	Financial resources	Structural				
	Technological resources	Structural		X		X
(Mehrtens et al., 2001)	the level of IT knowledge among IT professionals;	Structural		X		
	the level of IT knowledge among non-IT professionals;	Structural		X		
	the level of IT use within the organization.	Structural	X			
(Zhu et al., 2010)	Leadership involvement	Structural		X		
	Organizational fit	Structural		X		
View that the DDS readiness indicator refers to			Psychological	Structural	Structural	Structural

Table 2 Correspondences between constructs considered for developing the index and the DDS readiness index dimensions

4.1 Mindset

The concept of mindset has its roots in the fields of cognitive psychology and organization theory, where researchers have investigated how people and organizations make sense of the world with which they interact (Gupta & Govindarajan, 2002). Mindset is a key component that plays an important part in successful change (Rao, 2015). Mindset consists of the cognitive filters that a firm applies when selecting and interpreting the information environment, which guides decision-making and, ultimately, success or failure (Davenport et al., 2011). In this strict sense, mindset refers to employees' opinions, beliefs, and intentions (for example, whether an organization's leadership and employees perceive the benefits of using DDSs) (Aydin, de Groot, & van Hillegersberg, 2010). Furthermore, the concept of mindset refers to an organization's willingness to both invest in data-driven initiatives and assume the associated risks (Shahrasbi & Paré, 2014). Thus, mindset represents both an appreciation for the value potential of DDSs and the organization's interest in pursuing specific DDS initiatives.

4.2 Skillset

Skillset denotes an organization's ability to manage DDS initiatives. A firm needs to acquire and orchestrate all of its resources, both technical and complementary (Piccoli & Ives, 2005). This constitutes the managerial process of assembling unique configurations of resources (Wade & Hulland, 2004) to deliver value with a DDS in the form of new products, processes and decision-making routines (Sharma & Shanks, 2011). Successful technological adoption and implementation is possible thanks to skilled and knowledgeable staff (Rao, 2015; Shahrasbi & Paré, 2014). The extraction of value from a DDS requires the coordination of both business and technological capabilities. Events must be detected, measured, and interpreted before they can create value. This requires strong coordination mechanisms among business functions and the ability to create and institutionalize new practices underpinning a specific coordination capability (Davenport et al., 2011) both within and across organizational boundaries (Helfat et al., 2009; Sharma & Shanks, 2011).

4.3 Dataset

Dataset describes the ability to effectively identify, intercept, and access real-time data streams that match organizational needs for value creation. In turn, effective access and use implies a sound understanding of DDS characteristics and how they relate to business needs (Shah, Horne, & Capellá, 2012). For example, the decision to use a particular DDS to create a new service must account for the specific characteristics of both the event and the resulting stream, including their intrinsic quality (Davenport et al., 2011). Social media DDSs capture a multitude of events; they are very "noisy" data sources that require proper assessment and cleansing before they are analyzed and integrated. Conversely, earning calls and letters to shareholders are text DDSs of much higher quality, with no (or minimal) sarcasm, irony, grammatical errors, or implied references to pop culture. Data from sensor networks readings or RFID systems are intrinsically less "noisy" but may, for example, not measure all desired events or state attributes. These aspects of a dataset are generally reflected in a specific data and information governance configuration (Tallon, Ramirez, & Short, 2013; Weber, Otto, & Österle, 2009).

4.4 Toolset

Toolset is the ability to dispone and use appropriate software and hardware (Davenport et al., 2011) both to intercept a DDS and to harvest its content. Therefore, it refers to the availability

of architecture and software for data processing (Shahrasbi & Paré, 2014). It encompasses both technical competencies and resources that are necessary to tap into streaming data and manages an infrastructure to manage all of the dimensions of emerging information management environments (Beyer, Lapkin, Gall, Feinberg, & Sribar, 2011). The toolset dimension directly influences a firm's ability to profit from the increasing digital availability of events, when changes occur in the organization (Rao, 2015). To operate a DDS, four main elements are required at the technical and architectural levels (Dowlaty, 2012): 1) message-oriented middleware supporting standardized communication among heterogeneous systems; 2) an advanced analytics engine to extract value from DDSs; 3) a business process modelling engine that enables flexible and deep integration into an organization's human workflow, which significantly assists DDS value consumption and dissemination; and 4) a rules engine that is capable of executing business logic in real-time and a related rules repository, separating the business and application components.
As a summary, Table 3 shows the definitions of the four dimensions of the readiness index proposed in this study.

Index element	Description
Mindset	It concerns employees' opinions, beliefs, and intentions.
Skillset	It represents an organization's ability to manage DDS initiatives.
Toolset	It denotes the ability to use appropriate software and hardware to intercept a DDS and harvest its content, encompassing both technical competencies and resources that are necessary to tap into streaming data.
Dataset	It represents the capacity to effectively identify, intercept, and access real-time data streams that match organizational needs for value creation opportunities.

Table 3 Definitions of the elements of the readiness index

5 Building the DDS Readiness Index

5.1 Data collection

To develop the index, we followed a four-steps procedure. First, after assessing the purpose of the index, we generated an item pool (DeVellis, 2003) based on the literature review and the opinions of two IT experts and one academic, all of the Information Systems field and therefore knowledgeable about Information Systems, DDS and big data issues more in general. The experts helped us refine the initial measurement model, validating the items that were candidates for inclusion in the scale and formatting the items for measurement.
Second, we pilot tested the full measurement instrument to ensure that the wording was understandable and the length was appropriate. Specifically, the list of questions and underlying items was then tested through a pilot test for content adequacy by asking a sample of 52 participants (Master's-level business students) to attribute each item to the main dimensions of the model (Hinkin & Tracey, 1999). The objective was to identify cognitive difficulties and to rule out errors in the interpretation of questions, thus achieving a higher degree of confidence in determining item integrity and scale content validity. The sample size and composition are considered adequate for this type of analysis (Hinkin & Tracey, 1999). The respondents rated each of the 46 readiness items on the extent to which they believed the items were consistent with each of the four defined readiness dimensions (mindset, skillset, dataset and toolset). The response choices ranged from 1 (not at all) to 5 (completely). A definition of each dimension was provided after the respondent guessed the definition from several alternatives. We took this additional step to verify the coincidence of the meanings that the respondent attributed to the proposed construct. We then calculated the mean score for each item on each of the four readiness dimensions, and we used a one-way analysis of variance and Duncan's multiple range tests to compare item means across the four dimensions. Specifically, this test provides

significance levels for the difference between any pair of means, regardless of whether a significant F resulted from an initial analysis of variance. We retained only the items that were statistically significantly higher on the appropriate construct ($p<0.05$) and therefore correctly attributed to the proposed theoretical construct. We retained 19 of the initially generated 46 items.

Third, we empirically confirmed the theoretical framework by administering a first survey to a development sample in August 2013. According to recent studies (Tambe, 2014) we used the LinkedIn skills database to select and contact survey participants who have IS-related skills. From this database, we selected 1,066 European IT/IS professionals and contacted them by email to assess their interest in participating in the study. Three hundred forty-nine (32.7%) responded that they were qualified to participate in the study and began to complete the online survey; 138 surveys were fully completed (40%). We then controlled for the quality of the responses (time and coherence), obtaining a final sample of 101 organizations. Specifically, we considered those respondents that took a reasonable length of time to complete the survey. The excluded respondents took less than 7 minutes to complete the survey, possibly because they did not pay sufficient attention to the questions asked. In order to verify instead the coherence, we included in the questionnaire some items that were a rephrasing of the items that constitute the readiness index, in order to verify the correctness of the responses. With the collected data, we verify the psychometric properties of the variables involved in the study.

Fourth, following this first survey, in order to provide further validation of the variables involved in the study, we constructed a second panel with the support of Qualtrics (http://www.qualtrics.com), a company that specializes in data collection and analysis. We expressly targeted CIOs, CTOs, and senior IT managers of North American companies with more than 10 employees and annual revenues higher than 1 million dollars. Of the 732 responses received, 320 (43.7%) qualified based on those criteria. We further tightened our quality requirements (time to complete the survey, coherence and variance in the answers, use of DDSs, absence of missing values) and retained 302 (41.3%) respondents (see Table 4 for the sample composition). Through this second survey, we were able to further validate the psychometric properties of the variables involved in the readiness index.

Characteristics	Frequency	Percentage
Title of the respondent		
IS/IT Senior Management	223	73.84%
CIO/CTO	79	26.16%
Firm size (employees)		
Small: 10-50 employees	18	5.96%
Medium: 51-500 employees	81	26.82%
Large: > 500 employees	203	67.22%
Annual revenues (US dollars)		
1-10 million	18	5.96%
11-50 million	24	7.95%
51-100 million	57	18.87%
101 million - 1 billion	54	17.88%
1-10 billion	72	23.84%
0-50 billion	31	10.26%
More than 50 billion	46	15.23%
Sector		
Industrials	77	25.50%
Technology	74	24.50%
Telecommunications	28	9.27%
Financials	23	7.62%
Health care	22	7.28%
Consumer services	16	5.30%
Other	62	20.53%

Table 4 Respondent characteristics

5.2 Operationalization of the constructs

We operationalized the readiness index constructs and developed multi-item reflective scales based on the procedure described in section 5.1. We consequently infer that the indicators are caused by the latent construct, interchangeable, covariant, and share a common theme (Jarvis et al., 2003). In Table 5, for each construct, we summarize the items included in the survey and the literature considered when defining them. We asked the respondents to agree or disagree to a list of 19 items using a five-point Likert scale. However, the final constructs were composed of the items included in Table 5 because we progressively excluded items with low loading (cut off <0.707) on the intended factor (Chin, 1998) and items with an inter-construct cross-loading of less than 0.20.

Construct	Item	Reference
Mindset		
M1	Our organization has a data-oriented culture.	(McAfee & Brynjolfsson, 2012)
M2	We believe in experimenting and testing innovative IT initiatives.	(Chandrasekaran, Levin, Patel, & Roberts, 2013)
M3	We use real-time DDS to envision and pursue new competitive strategies.	(Aydin, de Groot, & Jos, 2010)
Skillset		
S1	We are good at designing new initiatives that exploit real-time DDS.	(Shanks, Bekmamedov, & Sharma, 2011)
S2	Once we envision an application of real-time DDS, we know how to assemble the needed organizational, financial, and technological resources.	(Wang, Liang, Zhong, Xue, & Xiao, 2012)
S3	Once we envision an application of real-time DDS, we know how to exploit the data to deliver the benefits of the initiative.	(Helfat et al., 2009) (Piccoli & Ives, 2005)
Dataset		
D1	We have a clear data governance policy.	(Tallon et al., 2013)
D2	We monitor the sources of the real-time DDS that we utilize.	(Beyer et al., 2011)
D3	We evaluate the quality of our internal DDS (e.g., timeliness, completeness, accuracy).	(Shah et al., 2012)
Toolset		
T1	We have the appropriate tools to integrate real-time DDS with current workflows.	(Dowlaty, 2012)
T2	Our system architecture allows for real-time DDS to be dispatched to existing systems.	(Beyer et al., 2011)
T3	We have the tools and the technical talent to create our own real-time DDS.	

Table 5 Item pool for the DDS readiness index

5.3 Measurement model

The dimensions composing the readiness index were measured through multiple items. Thus, we began by assessing their psychometric proprieties. We removed all responses containing missing values from the analysis. Thus, only complete observations were used.

The psychometric properties of the constructs were tested using SmartPLS 2.0 (Ringle, Wende, & Will, 2005). SmartPLS is similar to PLS-Graph and is a component-based path modelling program that is based on partial least squares (PLS). We chose PLS path modelling because PLS makes fewer demands on the underlying data distribution than does covariance-based structural equation modelling (Kuechler, McLeod, & Simkin, 2009). Indeed, the PLS method seems more suitable for the analysis because it does not require the data to be normally distributed (Hair, Ringle, & Sarstedt, 2011). Furthermore, PLS can be a valuable tool in explorative research and for theory development and hence is suitable for this study (Henseler & Sarstedt, 2013).

5.4 Measurement index assessment

We applied PLS modelling to validate the model constructs. To measure the model, we assessed indicator reliability, construct reliability, convergent validity, and discriminant validity.

First, the indicator reliability was evaluated based on the criteria that the loadings should be greater than 0.70 (Henseler, Ringle, & Sinkovics, 2009). As shown in Table 6 this criterion was met. Second, the construct reliability was tested using the composite reliability. All constructs have these values above 0.7, which suggests that constructs are reliable (Henseler et al., 2009), fulfilling this criterion. Third, the convergent validity was tested using the average variance extracted (AVE). If coefficient is above 0.5 the latent variable explains more than half of the variance of its indicators (Fornell & Larcker, 1981). Based on Table 6, we can conclude that all constructs have an AVE above 0.5, fulfilling this criterion.

Items	Mindset	Skillset	Dataset	Toolset	t-values of the associated items
M1	**0.77**	0.50	0.44	0.43	21.50
M2	**0.81**	0.49	0.51	0.45	29.25
M3	**0.79**	0.58	0.55	0.51	25.67
S1	0.55	**0.86**	0.58	0.62	43.54
S2	0.54	**0.82**	0.55	0.51	27.57
S3	0.58	**0.84**	0.56	0.57	38.75
D1	0.46	0.54	**0.75**	0.48	22.49
D2	0.50	0.50	**0.77**	0.57	23.79
D3	0.53	0.55	**0.85**	0.57	42.00
T1	0.53	0.58	0.58	**0.83**	33.58
T2	0.45	0.55	0.52	**0.79**	30.18
T3	0.44	0.51	0.56	**0.80**	30.81
Psychometric properties					
Composite Reliability	0.84	0.88	0.83	0.85	
AVE of the associated items	0.63	0.71	0.63	0.65	

Table 6 Psychometric table of the measurements

Finally, discriminant validity of the constructs was assessed using Fornell-Larcker (1981) criteria, widely used in literature when PLS is used. We computed the square root of AVE for constructs (diagonal elements of Table 7) and we found that are greater than the correlation between each pair of constructs (off-diagonal elements of Table 7). Thus, discriminant validity was met.
In our case, the construct reliability, indicator reliability, convergent validity and discriminant validity of the constructs are satisfactory.

	Mindset	Skillset	Dataset	Toolset
Mindset	**0.79**			
Skillset	0.67	**0.84**		
Dataset	0.63	0.67	**0.79**	
Toolset	0.59	0.68	0.69	**0.81**

Table 7 Discriminant validity (diagonal elements are square roots of the average variance extracted)

In assessing the measurement of the proposed readiness index, we first evaluated the overall model using the coefficients of determination (R^2) and the significance levels of each path coefficient (Chin, 1998). The R^2 of the four latent constructs ranged between 0.691 and 0.783, and each path coefficient of the model was significant (see the t-values of the associated items in Table 6). We also evaluated our model by calculating the Goodness of Fit (GoF) score as a global fit measure for PLS path modelling, bounded between 0 and 1 (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005). The GoF was 0.737. The GoF cut-off value for a model with large effect sizes should be 0.36 (Wetzels, Odekerken-Schröder, & Van Oppen, 2009). Because our value exceeded this recommendation, we conclude that our model fits well.

6 Applying the DDS readiness index

As a follow up analysis[1] designed to showcase the practical implications of the DDS readiness index, we computed a single factor-based score (Molla et al., 2011) estimated from the averages of both the items and the constructs. This approach is appropriate when scales are introduced and still untested, and in cases where factors have similar loadings (DiStefano, Zhu, & Mindrila, 2009). While with this process we emphasize the uni-dimensionality of the measure, the results are immediately calculable and easily interpretable, enabling a broader application of the index. In particular, both academic and practitioners may adopt the DDS readiness index across studies and settings developing a benchmarking practice.

We calculated the index and the component scores for each organization. Based on the 302 valid responses, the DDS readiness index score was 3.88 ($\sigma = 0.68$) which represents the average of the items response and the baseline set in current analysis. Figure 1a and Figure 1b provide further details about the DDS readiness index at a component and aggregate level. The current sample shows a generalized confidence of managers along the four dimensions and particularly concerning mindset and dataset.

We further analyzed the data considering both the size and the industry of each organization to observe how these sample companies fared in the DDS readiness index (see Table 8).

Measure	Size	N	$\bar{x}$	σ	Industry	N	$\bar{x}$	σ
Mindset	*small*	17	3.98	1.05	*Consumer service*	15	4.27	0.47
	medium	78	3.82	0.78	*Financials*	22	4.18	0.61
	large	198	4.12	0.76	*Health care*	22	3.98	0.99
					Industrials	75	4.14	0.68
					Technology	74	3.94	0.81
					Telecommunications	27	4.20	0.65
Skillset	*small*	18	3.55	1.29	*Consumer service*	15	3.91	0.82
	medium	74	3.66	0.79	*Financials*	22	3.76	0.71
	large	196	3.92	0.79	*Health care*	22	3.86	0.84
					Industrials	76	4.00	0.66
					Technology	69	3.69	0.91
					Telecommunications	28	4.04	0.72
Dataset	*small*	17	3.64	1.27	*Consumer service*	15	3.80	0.74
	medium	76	3.57	0.82	*Financials*	22	3.65	0.85
	large	196	3.86	0.77	*Health care*	22	3.95	0.64
					Industrials	73	3.99	0.71
					Technology	73	3.58	0.87
					Telecommunications	28	3.96	0.64
Toolset	*small*	18	3.72	1.12	*Consumer service*	15	4.00	0.67
	medium	76	3.65	0.82	*Financials*	21	3.90	0.77
	large	194	4.01	0.73	*Health care*	21	3.84	0.89
					Industrials	76	4.01	0.69
					Technology	72	3.76	0.85
					Telecommunications	28	4.06	0.65
Readiness	*small*	17	3.75	1.12	*Consumer service*	15	3.99	0.63
	medium	72	3.71	0.67	*Financials*	21	3.87	0.61
	large	185	4.02	0.62	*Health care*	21	3.94	0.75
					Industrials	70	4.07	0.55
					Technology	67	3.78	0.78
					Telecommunications	27	4.07	0.55

[1] We thank an anonymous reviewer for suggesting this analysis

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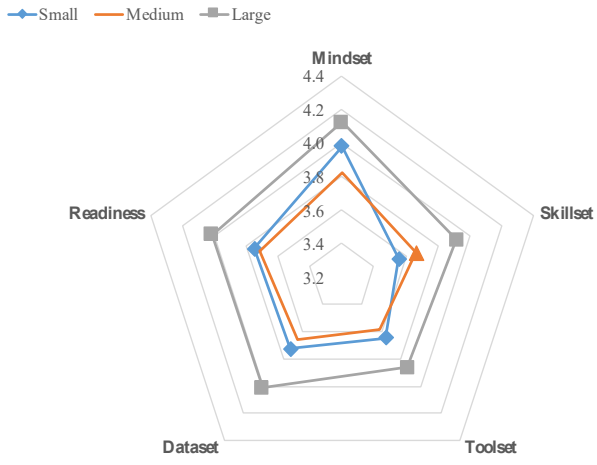
Table 8 The DDS Readiness and its components



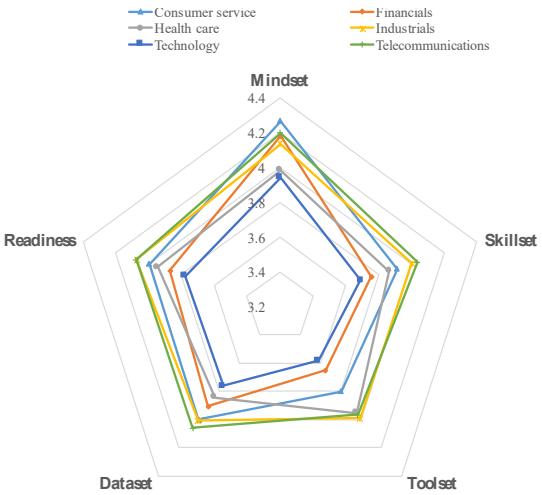


Figure 1a DDS readiness index by size **Figure 1b DDS readiness index by industry**

The analysis clearly showed a significant difference in DDS readiness and components scores among firms of different sizes. Large firms (>500 employees) presented a greater readiness along all the four dimensions compared to small (10-50) and medium (51-500) ones (Figure 1a). Interestingly, small firms appear to be relatively more culturally ready to appreciate the opportunity of DDSs and manifest a greater interest in pursuing these initiatives. However, managers in both small and medium firms perceive a lack of preparedness on DDS readiness structural components compared to larger firms. This perception of a lesser structural preparedness of SMEs reflect the traditional resource scarcity of SMEs and the overall limited IT infrastructure (Street, Gallupe, & Baker, 2015).

In terms of industry (Figure 1b), technology firms appear to be the most cautious in both structural and psychological components. Probably, because of the greater awareness of these managers of the technological challenges related to DDSs value extraction. Indeed, as respondents are IS managers and executives, the perceived lack of readiness concerning the toolset and skillset, points toward an effective lack of IT resources and skills for pursuing DDS initiatives, eventually hindering their deployment.

Firms in the telecommunication and industrial sectors exhibit an overall higher DDS readiness. This finding is not surprising as these firms have traditionally managed real-time DDS for their operations, and while confident in their structural dimensions, they present a marginally lower preparedness in terms of mindset.

7 Discussion

The literature only recently begun the systematic study of digital data streams as a new opportunity for value creation (Piccoli et al., 2016). While the interest in DDS is increasing, further research is still needed to better understand how firms may extract value from them. With this study, we advance the DDS readiness index as a measure of organizational readiness to exploit real-time digital data. We built the index based on previous literature on organizational readiness and change management, and leveraged, other than ours, the experience of experts of the domain either from academia and the industry. The basic assumption of our work is that a firm's ability to leverage DDSs is based on the interplay of four organizational dimensions: mindset, skillset, toolset and dataset. We contribute to the

measurement of DDS readiness by designing and validating a multiple-item scale. We then show how the index can capture both structural and psychological traits of organizational readiness.

This contribution is of interest as organizations rely increasingly on data to determine and meet customers' needs. The increasing data availability and lower data latency influence a firm's ability to create value, enabling the introduction of new products, services, or processes. The emergence of DDSs is creating strategic opportunities for existing firms and enabling new ones to push current boundaries, in some cases redefining entire industries (e.g., Uber, Airbnb). The catalyst for this seismic change is the massive generation of real-time DDSs that organizations can leverage. In this scenario, the DDS readiness index is a multiple-item scale that, by integrating the structural and the psychological views, provides a reliable measure of a firm's readiness to exploit DDS opportunities. This measure, coupled with a precise definition of DDS, is an important preliminary step for developing of a cumulative research tradition. Specifically, the DDS readiness index represents an original contribution to the literature. This index and its four dimensions will be useful in advancing IS and managerial research, enabling consistent measurement across studies. In the IS literature, it represents a current and validated operationalization of the suggested integrative view on organizational readiness, and in this sense, it contributes to this particular stream of research.

7.1 Theoretical and practical implications of DDS readiness

The DDS readiness index represents an original contributor for the IS literature. Table 9 summarizes the key themes we believe IS researchers may be interested in investigating using the DDS readiness index. We grouped them in four areas: value creation, organizational change, operational goals, and business and IS alignment.

Value creation refers to the study of the DDS opportunity concerning how value can be created and which factors may facilitate, or hinder it. With the readiness index, we already set the foot for future research looking into how mindset, skillset, dataset and toolset may influence initiatives performance, or, in other words, in understanding how effective are organizations in leveraging DDS for value creation. While in this study we did not explore this dimension, we believe that the new value creation opportunities afforded to firms by DDSs, and how DDS initiatives contribute to the creation of competitive advantage (Pigni et al., 2016) are promising research themes.

The real-time nature of DDS allows organizations to sense and react faster to market events, opening the field of new strategies leveraging low latency opportunities impacting decision making, product launches, supply chains and network orchestration (Bharadwaj et al., 2013). Studying how DDS readiness may impacts these outcomes, could shed light on how organizations should prepare for this change. DDS are set to impact organizations both strategically, providing new value opportunities, and operationally, impacting current business practices (e.g., Herterich et al., 2016). This transformation will require firms to develop new capabilities and skills demanding greater collaborations among different organizational unit, actualizing the debate on business and IT alignment (Luftman, Lyytinen, & Zvi, 2017).

Future research could focus on studying DDS implications at company level because it is the next frontier for innovation, competition, and productivity.

Research area	Research questions related to the DDSs
Value creation	- How effective are organizations in leveraging DDS for value creation? - Are DDDs initiatives contributing to firm performance and competitive advantage?
Organizational change	- Are organizations ready for exploiting DDS? - Do organizations structure workflows and incentives in ways that optimize the use of DDS to make better decisions and take more informed actions?

	- How effective are organizations in deriving insights from DDS? - How psychological and structural aspects of DDS readiness intertwine?
Operational goals	- How effective are DDSs in accelerating new product launches? - How effective are DDSs in speeding up learning for improving operational decision-making? - How effectively do DDSs optimize the management of internal processes such as energy consumption and production levels? - How effectively are DDSs exploited for cost-reduction opportunities? - How effectively are DDSs exploited for time-reduction opportunities?
Management and IS alignment	- Are managers ready to exploit the opportunities offered by DDSs? - Are managers ready to understand the value of DDSs? - Are managers ready to change the culture of the companies in order to exploit the potentials of DDSs?

Table 9 Key themes of DDS readiness

The DDS readiness index is a useful instrument for understanding whether organizations are ready to exploit DDSs. The DDS readiness index can potentially be applied in all organizations enabling benchmarking practices at firm and industry level.
At organizational level, the DDS readiness index can guide managerial decisions in preparing for the organizational changes related to the exploitation of DDSs. In particular, it could be used as a diagnostic tool for the identification of the organization areas requiring corrective actions. Moreover, the DDS readiness index suggests that managers should properly consider the complementary resources needed for DDSs exploitation. The availability of the appropriate IT tools to integrate and process DDSs in current workflows is clearly not sufficient. Firms must evaluate the quality of both internal and external DDSs and develop the necessary mindset, skillset, toolset and dataset to envision and pursue new DDS-enabled competitive strategies. Therefore, the DDS readiness index is both a framework and a diagnostic tool for strategizing on DDSs. Firms can use this instrument for benchmarking themselves against other firms in the same or in other industries, or against companies of the same size or presenting similar structural features.

8 Conclusions and limitations

Organizations are investing considerable resources in strategic initiatives based on the "new oil" of digital data. We focused our attention on Digital Data Streams (DDS). Drawing on the organizational readiness concept, we develop the DDS readiness index as a measure of organizational readiness to exploit real-time digital data. We conceptualize, define, operationalize and validate the index by grounding its development in the integration of the structural and the psychological views of organizational readiness and identify four dimensions: mindset, skillset, dataset and toolset as the elements of the DDS readiness index.
We included these factors because of their relevance for the context and for their aptitude at including the two faces of organizational readiness. Although we took particular care in developing a generalizable measure, we focused on organizational specific factors. Further research may consider to extend the actual measure integrating exogenous and performance factors (e.g., business readiness, firm performance).
In the assessment of the different constructs, we formulated the items asking respondents to reference to the organization (e.g., "We use..", "We have..") focusing their attention on the collective perception of readiness, at the organizational level. However, the methodology we used to form the panel prevented the implication of multiple respondents from the same organization, relying on the perception of single managers. In the future, data could be collected involving multiple managers and executives from the same organization to obtain a more accurate assessment of DDS readiness.
Despite its limitations, we believe that the results of our study will assist researcher in extending the current understanding of DDS initiatives in organizations. While the readiness index is a

first step in advancing an integrated view on readiness, further research may fruitfully look into how mindset, skillset, dataset and toolset determine initiatives performance, how firms should organize change for maximizing DDSs potential for value creation. More practically, the DDS readiness index may be used as a diagnostic and benchmarking tool, effectively enabling organizations to measure their progress toward being able to extract value from pervasive DDS.

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