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# Antecedents of Dynamic Capabilities and IT-dependent Initiatives in the Context of Digital Data

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## ABSTRACT

*Firms automatically and continuously capture a high amount of digital data (DD) through social media, RFID tags, smart meters, sensors, etc. However, empirical evidence on the effects of the generation of such digital data on firms remains scarce in the information systems literature. Therefore, from two complementary perspectives, i.e., dynamic capability and IT-dependent initiatives, this paper examines the antecedents of companies' ability to leverage DD, which we refer to as DD dynamic capability and DD initiatives, and investigates whether this ability directly leads to better data accessibility. We empirically test our hypotheses based on a survey from 178 firms, which include sales and IT managers, and we find that the antecedents have specific influences on both DD initiatives and DD capability, such that all the antecedents support the initiatives; however, only organizational processes strengthen DD capability. Furthermore, DD initiatives and DD capability improve the accessibility of DD. Our results show that organizational processes of sensing, coordination, integration and learning emerged as the most important sources of Dynamic Capabilities DCs - by contrast, the firm's assets and history played only a marginal, supporting role.*

**KEYWORDS:** Digital data; Dynamic capability theory; Antecedents; IT-dependent initiatives

## 1 INTRODUCTION

Much of the foundational research on technology-based initiatives - from the implementation of integrated enterprise systems, to the digital transformation of processes and products - examined their ability to sustain competitive advantages and create new competitive opportunities (Bradley et al, 2013; Chen et al, 2012; Mims, 2012; Piccoli & Ives, 2005; Sallam et al, 2013).

Today, organizations invest considerable resources in IT based/digital initiatives to search for value creation opportunities (Chen, Chiang & Storey, 2012, Braganza et al. 2017, Mola et al. 2017), drive their digital business strategies (Bharadwaj, El Sawy, Pavlou & Venkataraman, 2013) and make better informed business decisions (Eastburn & Boland, 2015; Brynjolfsson & McElheran, 2016).

All these IT-based initiatives rely on data and this data needs to be digital. Therefore, it has become more and more critical to know how data is generated and how digital data should be processed. Indeed, every day, both organizations and people generate digital data through tweets, clicks, videos and a plethora of sensors (Kietzmann & Canhoto, 2013). Furthermore, instruments and machines such as smart meters, manufacturing sensors, equipment logs and vehicle tracking systems automatically and continuously generate digital data.

The ability to generate and manage digital data creates the opportunity to reshape entire industries. In the entertainment sector, for instance, Netflix creates value in the form of personalization, through data streams. Netflix uses self-generated and external digital data, and social networks, to recommend personalized suggested titles based on a household's preferences. It gains mass visibility through real-time sensing of users and makes recommendations based on this visibility (Piccoli and Pigni 2013). Netflix's ability to collect and manage huge amounts of digital data allows the firm to design its products in a way that is not possible for the traditional movie studios. In the case of Netflix, as well as in many other cases such as Amazon, Uber, AirB&B etc. we observe that the digital nature of data constitutes a fundamental characteristic of the data itself. Digital data has unique properties that we do not find in physical infrastructures (Kallinikos, Aaltonen & Marton, 2013). It is easily shared, replicated, and combined thus presenting tremendous reuse opportunities (Lynch, 2008). At the same time, however, digital data is at risk of various forms of obsolescence (Lynch, 2008), so organizations need to leverage this data promptly.

The unique characteristics of digital data have contributed to its exponential growth (Kallinikos et al., 2013) and such growth requires new organizational approaches and specific research streams. *"Businesses appear to be on the cusp of a data-driven revolution in management. Firms capture enormous amounts of fine-grained data on social media activity, RFID tags, web browsing patterns, consumer sentiment and mobile phone usage, and the analysis of these data promises to produce insights that will revolutionize managerial decision-making"* (Tambe, 2014:1452). Such fine-grained data play an additional economic function in generating wishful content and unwitting meta-data that surround main content (Kallinikos et al., 2013; Orlikowski, 2015).

Given this rapidly changing environment, we expect organizations to increasingly develop IT-dependent and digital data (DD) initiatives so as to manage digital data as key features of successful businesses. But these initiatives are not enough in themselves. Organizations also need to develop their capacity (1) to sense and shape opportunities and threats, (2) to seize opportunities and (3) to maintain competitiveness through enhancing, combining, protecting and, when necessary, reconfiguring the firm's intangible and tangible assets (Teece, 2007) related to the generation and use of DD. In other words, organizations need to develop Digital Data Dynamic Capabilities to generate and sustain their competitive advantage, or simply to survive.

To better understand these new challenges we also argue that is central to understand what firms need, in terms of antecedents, if they are to develop such capabilities successfully (Brynjolfsson & McElheran, 2016). Therefore, we examine DD initiatives, DD capabilities, and their antecedents in terms of organizational processes, firm history and firm assets (Teece et al. 1997, Piccoli and Watson 2005), as well as their immediate outcome in terms of DD accessibility.

Despite the relevance of the topic, we lack a theoretical perspective regarding whether this new competitive scenario characterized by the ubiquity of DD, requires new IT-dependent initiatives and Dynamic Capabilities (DC); we also have little knowledge as to which antecedents might make these capabilities more effective and these initiatives more widespread.

Among the different concepts developed to date, the notion of Dynamic Capabilities promises

to be particularly meaningful in turbulent environments where changes are both complex and unpredictable (Mithas, Ramasubbu, & Sambamurthy, 2011; Pavlou & El Sawy, 2006; Rai, Patnayakuni, & Seth, 2006; Wunnavu & Ellis, 2009; Zollo & Winter, 2002).

However, the Dynamic Capabilities research construct remains a debated subject that is at times, unclear; the difficulty in addressing its origins and antecedents over time has contributed to this confusion. The paucity of research that directly addresses this question is testament to the difficulties of studying research on the emergence of dynamic capabilities. If dynamic capabilities really affect organizational competitive advantage, the explanation of their sources would give organizations tools for improving their chances of building and sustaining competitive advantage. In other words, research in this area is badly needed.

We test our model with data gathered from a survey of 178 Western European firms. In sum, to bridge an extant research gap, we address the following research questions: *To what extent do organizational processes, firm history and firm assets affect the development of DD initiatives and DD capability? To what extent do the development of DD initiatives and DD capability affect DD accessibility?*

Our study revealed the organizational processes of sensing, coordination, integration and learning emerged as the most important sources of DCs - by contrast, the firm's assets and history played only a marginal, supporting role.

In the next section, we present theories related to IT-dependent initiatives and DC and their antecedents before defining DD initiatives and DD capability as our central foci. We then apply our theoretical framework to define variables and hypotheses. After that we present our methodology and summarize the results. Finally, we discuss our contributions.

## **2 THEORY**

### **2.1 Dynamic Capability Theory**

Our research has its roots in DC theory (Augier & Teece, 2009; Peteraf, Di Stefano & Verona, 2013; Teece, Pisano & Shuen, 1997), which in turn is grounded in the resource-based view of firms (Barney, 1991). Dynamic capabilities are described as an organization's ability to create new products and processes and respond to changing market circumstances (Teece & Pisano, 1994).. They imply routinized activities directed to the development and adaptation of operating routines. DC theory addresses the role of (1) experience accumulation, (2) knowledge articulation, and (3) knowledge codification processes in the evolution of dynamic, as well as operational, routines (Zollo and Winter 2002).

So far, dynamic capabilities theory has been adapted to evaluate the implications of the efficient use and competitive advantage of specific firm resources, such as entrepreneurship (Rumelt, 1987), culture (Barney, 1986) and organizational routines (Winter & Nelson, 1982). Understanding the effects of IT resources and capabilities on firm performance remains a central issue in the management literature (Benitez-Amado & Walczuch, 2012; Galy & Saucedo, 2014; Melville, Kraemer & Gurbaxani, 2004; Wang, Hu & Hu, 2013). In particular, this perspective highlights the importance of a firm's internal resources, defined as the "assets and capabilities that are available and useful in detecting and responding to market opportunities or threats" (Wade & Hulland, 2004), to evaluate its competitive advantage (Eisenhardt & Martin, 2000; Wernerfelt, 1984).

In fast-paced environments, organizations must constantly adapt to or create market changes. That is, they must develop DC, defined as "the ability to sense and then seize new opportunities, and to reconfigure and protect knowledge assets, competencies, and complementary assets with the aim of achieving a sustained competitive advantage" (Augier & Teece, 2009:412). This adaptability can improve customer value (Sambamurthy, Bharadwaj & Grover, 2003), and it is particularly advantageous in fast-paced technological environments (Banker, Bardhan, Chang & Lin, 2006; Bhatt, Emdad, Roberts & Grover, 2010; Teece et al., 1997). For example, pervasive computing, sensor networking, real-time data streaming and the Internet represent trends with clear potential to create new competitive opportunities (Bradley, Barbier & Handler, 2013; Chen et al., 2012; Jabr et al., 2012; Piccoli & Ives, 2005; Sallam, et al., 2013). Therefore, in high-velocity markets, DC specifically refer to "the firm's ability ... to address rapidly changing environments" (Teece et al., 1997:516), often with simple rules or processes (Peteraf et al., 2013). For example, Apple possesses strong DC related

to its rules and processes for sensing; these have enabled the company to recognize the weaknesses of existing MP3 players, mobile telephones, and laptops and then to overcome these weaknesses by creating the iPod, iPhone, and iPad, respectively (Tece, 2011).

## **2.2 Digital Data Dynamic Capabilities DD DC**

In our study, we define Digital Data Dynamic Capabilities – DD DC - as the *ability to seize new opportunities in digital data through a fourfold organizational process that involves:*

- 1) “Choosing IT” (CIT) to generate and capture data unobtrusively in digital form;
- 2) “Integrating IT” (IIT) into the appropriate business processes;
- 3) “Managing digital data” (MDD) produced; and
- 4) “Reconfiguring” (REC) business processes, competencies or assets based on internal and external conditions.

We theorize digital data capabilities as dynamic capabilities for two complementary reasons. First, Digital Data Dynamic Capabilities - DD DC - involve the ability to deploy new configurations of operational processes, assets or competencies relative to the competition. Second, DD DC involve dynamically reconfiguring and protecting existing combinations of assets and competencies to adapt to changing environmental conditions (Pavlou & El Sawy, 2006). These reconfigured and protected assets include IT and DD. The degree to which an ineffective organizational process related to DD can be reconfigured into a more promising process that matches its environment and that is better, faster and less expensive than competitors’ processes determines the capability’s dynamic quality (Eisenhardt & Martin, 2000).

## **2.3 Digital Data Initiatives**

We decline the construct of IT-dependent initiatives (Piccoli & Ives, 2005) to Digital Data (DD) initiatives. As far as an IT-dependent initiative is an identifiable move by an organization that relies on at least one IT artifact, a DD initiative is *an identifiable move by an organization that relies on at least one IT artifact that can generate digital data.*

A simple example of DD initiative might be a waiter entering food orders directly into a hand-held electronic device at the table. Similarly, a DD initiative needs to be set to allow customers issue their own orders through a touchscreen, such as an iPad available at their tables. In contrast, there is no DD initiative if a waiter writes down an order in a paper notebook. Other examples of DD initiatives include the possibility to search online through Siri or Google or the automatic (e.g., RFID-enabled) toll-collection booth to enter a highway. IT artifacts are building blocks for any DD initiative (e.g., a hand-held device for a waiter, iPhone for Siri, an RFID transponder for a tollbooth). Moreover, DD initiatives can be strategic, whether they have been designed to lead to sustained improvement in an organization’s competitive position or not (Piccoli & Ives, 2005).

The DD initiative of equipping the waiters of a restaurant with electronic devices may not be strategic, as such an initiative could easily and successfully be replicated by competitors. In contrast, the DD initiative associated with Apple’s iPod was strategic in that attempted replications were not successful. DD initiatives and DD capabilities imply different perspectives and relations to competitive advantage. The difference, in terms of creating a competitive advantage for an organization, is related not to the DD initiative (e.g., the development of an MP3 player and related software) but to the organizational capabilities to exploit the potential benefits of DD and this highlights the importance of analyzing DD initiatives and DD capabilities in parallel. Furthermore, a DD initiative by itself cannot determine whether an organization can deploy new configurations of operational competences (i.e., initiative success in the short run) or whether it has the ability to reconfigure existing DD processes (i.e., initiative value in the long run). Rather, DD initiatives are preliminary moves for creating DD capability, again strengthening the reason for studying both DD initiatives and DD capabilities simultaneously. Indeed we propose two models, which we test in parallel.

## **2.4 Antecedents of Dynamic Capabilities and IT-dependent Initiatives**

While several studies have investigated dynamic capabilities and their effects on competitive advantage (Montealegre, 2002; Pavlou & El Sawy, 2006; Tanriverdi, 2005; Teece et al., 1997; Zahra et al., 2006; Zollo & Winter, 2002), much less attention has been paid to their sources. We propose an integrative research model of the sources of dynamic capabilities, choosing to build it on the DD DC because of its significance in fast-paced contemporary IT environments and we build our understanding of those sources on those identified by Teece et al. (1997).

The concepts of DC (Teece et al., 1997) and IT-dependent initiatives (Piccoli & Ives, 2005) have spurred research on their antecedents, which we have categorized into three main groups:

- *Organizational processes*, including sensing, coordination, integration, and learning.
- *Firm assets*, which define a firm's strategic position.
- *Firm history*, which accounts for the path-dependent nature of a firm

Together, these three theoretical sources can yield a competitive advantage based on the performance of organizational processes, exploitation of the firm's assets and being grounded in its history (Montealegre, 2002).

### *2.4.1 Organizational processes*

Organizational processes, in terms of sensing, learning, coordinating and integrating, can constitute the antecedents of DC (Kale & Singh, 2007; Kogut & Zander, 1996; Maritan, 2007; Pavlou & El Sawy, 2006; Ravishankar & Pan, 2012; Schreyögg & Kliesch-Eberl, 2007; Teece, 2007; Zahra, Sapienza & Davidsson, 2006). In terms of IT-dependent initiatives, the literature mainly identifies learning processes (Piccoli & Ives, 2005; Karhade et al., 2009; Duhan, 2007) and to a lesser extent sensing, integration and coordination processes as antecedents (Braunscheidel & Suresh, 2009; Karhade et al., 2009).

Sensing implies understanding the environment and the capacity to identify market needs and opportunities (Teece, 2017). Companies that want to exploit DD need to sense the environment to gather market intelligence on market needs, competitor moves and new technologies (Nan & Tanriverdi, 2017). In this way, managers can identify new opportunities to be exploited through DD.

Learning involves developing new thinking and generating new knowledge to enhance existing resources. Once a market opportunity has been identified, a decision must be made to revise existing operational capabilities (Teece, 2007). Companies that want to take advantage of market opportunities in a changing environment must engage in learning to find new solutions, create new knowledge and reconfigure existing capabilities and initiatives. Accordingly, companies that want to develop DD initiatives and capabilities must acquire new knowledge and skills related to using DD (Brynjolfsson & McElheran, 2016).

Coordinating refers to allocating and mobilizing resources, assigning tasks, and synchronizing firm activities. Coordinating is related to a firm's ability to assign resources to tasks (Helfat & Peteraf, 2003), including appointing the right person to the right task (Henderson, 1994). Therefore, when firms develop their DD capability and DD initiatives, they also need to think in terms of coordinating related tasks and activities so as to exploit DD successfully.

Finally, integrating entails developing new patterns of interaction to respond to environmental changes or market evolutions and implementing the resulting operational competency configurations. Developing DD capability and DD initiatives requires a collective logic and shared interaction patterns in order to exploit related opportunities (Pavlou & El Sawy, 2006).

Because sensing, learning, coordinating and integrating facilitate DD initiatives and DD capability, organizations with effective organizational processes should have engaged more extensively in DD initiatives and they should therefore have higher DD capability. Thus, we propose the following hypotheses:

H1a: The effectiveness of sensing, learning, coordinating and integrating processes has a positive impact on engaging in DD initiatives.

H1b: The effectiveness of sensing, learning, coordinating and integrating processes has a positive impact on the effectiveness of DD capability.

### 2.4.2 Firm assets

Different assets, including technological, financial, reputation, structural, institutional, or market structure resources, can contribute to developing novel DC (Teece, 2017; Teece, 2007; Teece et al., 1997) and IT-dependent initiatives (Piccoli & Ives, 2005). We specifically predict that IT assets are significant antecedents of DD capability and DD initiatives (Brynjolfsson & McElheran, 2016). As IT assets co-specialize with other complementary assets, they eventually become amalgamated into IT platforms, rendering the creation, management, reproduction, trading, or imitation of these IT assets by competitors more difficult (Teece, 2007; Teece, 2011; Gandomi & Haider, 2015).

Two types of assets are prominent in the IT category: infrastructure and information repositories (Piccoli & Ives, 2005). The former refers to “the base foundation of the IT portfolio, shared through the firm in the form of reliable services,” (Piccoli & Ives, 2005:753) such that it provides the functionalities on which business applications and services can be built. The latter are “collection(s) of logically related data, organized in a structured form, that [are] accessible and usable for decision-making purposes” (Piccoli & Ives, 2005:755). Both IT infrastructure and information repositories are subject to asset stock accumulation dynamics (Dierickx & Cool, 1989). That is, when a new piece of IT or information becomes part of an organization’s IT asset stock, it widens the preexisting stock, some of which may be leveraged to create option value. The greater the width of the existing stock, the higher the possibility of disposing of a portion that can be effectively leveraged. Thus, wide IT asset and long standing information repositories should facilitate the technical and informational requirements of DD initiatives, for example an IT infrastructure that can generate data in digital form and information repositories that provide insights about the most important value creation opportunities, basing on historical data trends (Gandomi & Haider, 2015). This accumulated IT asset stock constitutes a possible antecedent of a DD initiative. Wide IT asset stock may also offer services, functionalities and data to support IT choices, generate DD and manage new data sets. Accordingly, wide IT asset stock is likely to be an antecedent of a DD capability, and we propose the following hypotheses:

H2a: The width of IT assets has a positive impact on engagement in DD initiatives.

H2b: The width of IT assets has a positive impact on the effectiveness of a DD capability.

### 2.4.3 Firm history

A firm’s history helps to explain its existing position and current endowments in technology, intellectual property, complementary assets, customer bases and external relationships with suppliers and competitors (Teece, 2017; Teece, 2007; Teece et al., 1997). It also influences the firm’s future opportunities and frames its path dependencies, available strategic alternatives, and possible returns (Chen et al., 2008). The persistence of DC over time makes these factors particularly relevant in explaining organizational path dependencies. New initiatives may slightly depend on a firm’s existing initiatives; however, new initiatives and DC largely depend on existing capabilities, as learning tends to be local and related to existing processes (Teece et al., 1997; Zahra et al., 2006). The antecedents of DD capability and DD initiatives should therefore be closely related to historical DC. As IT artifacts represent the building blocks for any DD, we predict that a firm’s historical IT dynamic capability (IT DC) is the most influential DC for DD capability and DD initiatives. Thus, historical IT DC increases the ability of IT personnel to recognize the potential for generating and capturing DD. Historically good relationships between IT personnel and line management should also help to integrate such IT into appropriate business processes. In contrast, the historical lack of an IT DC will delay DD initiatives and render ineffectual the process of choosing and integrating IT and managing DD. Accordingly, we propose the following hypotheses:

H3a: The effectiveness of historical IT DC has a positive impact on engagement in DD initiatives.

H3b: The effectiveness of historical IT DC has a positive impact on the effectiveness of DD capability.

#### 2.4.4 Accessibility of DD

We also empirically consider direct DD outcome. An organization with DD capability or a DD initiative does not automatically achieve a sustained competitive advantage because of the influences exerted by various mediating and moderating variables. Instead, DD enable the informational representation of real objects, facts and events without significant delays (i.e., in real time). Their digital format also increases their accessibility, or the extent to which a user perceives that any given source is available for use and accessibility is a primary determinant of whether people use a given source (Zimmer, Henry & Butler, 2007). In our study context, the direct outcome of DD capability and DD initiatives is accessible DD, which can be exploited for various purposes such as information processing, sophisticated analytics, decision making and monitoring. In this sense, DD accessibility parallels information accessibility (i.e., the perceived extent to which any given source is available for use); thus, it is likely to drive information source choices. This DD accessibility contrast with long lasting information repositories, which even if they store precious pieces of information, the information could not be easily and promptly accessible (Zimmer et al., 2007).

Accessibility of DD is particularly important when firms operate in rapidly changing environments. As well as dynamic capabilities are precious sources of competitive advantage in turbulent markets, in the similar environments, promptly accessible digital data could make the difference between a timely and appropriate decision making and an outpaced and misplaced one (Ren et al., 2017). Hence, accessible digital data is a key feature of successful businesses, nonetheless not sufficient by it-self to grant it. Therefore, we propose the following hypotheses:

H4a: The engagement in DD initiatives has a positive impact on the accessibility of DD.

H4b: The effectiveness of a DD capability has a positive impact on the accessibility of DD.

For model parsimony, we measure accessibility as a sole outcome variable, although clearly DD could also affect other outcome variables, such as information quality. Figure 1 depicts our proposed hypotheses. Model A refers to the “a” hypotheses, and Model B describes the “b” hypotheses.

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Insert Figure 1 about here  
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### 3 MATERIAL AND METHODS

The study method follows four main steps to prepare the main survey: a pilot study, an expert panel, an empirical case study, and a q-sorting procedure.

First, we conducted a pilot study to operationalize the “choosing IT” dimension of DD capability. We included the four indicators available from the prior literature, specifically concerning the choosing IT concept (Williams, 2003). We pilot tested these four indicators because they had not previously been empirically tested. In line with the original definition of the concept (Williams, 2003), choosing IT measures the firms’ ability to select IT to unobtrusively collect valuable DD. We recruited, via a professional intermediary specialized in IT surveys, 35 managers working in small, medium and large United States enterprises in different industries to participate in the study. To reduce common method bias, the four focal indicators appeared within a wider set of 26 questions around IT investments and business characteristics. The responses indicated that the scale was reliable with all four items, (Cronbach’s alpha = .837). For parsimony, we reduced it to three items, deleting the least performing item. For all of the other constructs, we used validated scales (see Table 1 and Appendix A).

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Insert table 1 about here  
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Second, we consulted an expert panel to adapt the chosen scales to our research context and to assess their content validity. The expert panel included seven Sales managers and two IT managers who proposed and validated the adaptations of the items in each construct. Moreover, during the interviews with this expert panel, we extensively discussed what we meant by the term “DD”, “enterprise” and “efficacy”. The experts appeared to be more comfortable addressing DD concepts by using terminology such as “digital data generation”; thus, in the final item wording, we refer to DD as “digital data generation”. At the end, we included the explicit definitions of three keywords (enterprise, efficacy and digital data generation) in the introduction to the questionnaire to make them homogeneous for all the survey’s participants.

Third, an author of this study supervised a Doctorate in Business Administration student in his development of an empirical case study on the same research topic (Prescott, 2014). The understanding and knowledge learned from this supervision was incorporated into this study to improve the scales.

Fourth, we used Q-sorting method to re-assess and to refine the content validity. Participants were asked to class item statements in one single category, representing the construct. The Q-sorting required four rounds of refinement and a total of 119 respondents to reach a threshold of at least 50% attributions for each item to the correct construct. The respondents for this Q-sorting task were mainly employees of different organizations, between 20 and 40 years of age, equally distributed between men and women. Overall, our measurement scales passed through a long, complex adaptation process that featured a pilot test, an expert panel, a case study and a Q-sorting procedure. For some of the variables, this process prompted multiple adaptations, such that the final scales differ from the original ones. In addition, the process highlighted the importance of reducing the length of the survey instrument as much as possible by limiting the number of items for each construct.

Concerning the main survey, we identified that the best level to measure DC was that of organizational-process (Li, van Heck & Vervest, 2009). We thus surveyed sales managers involved in the investment decisions of their business units, as given their strong focus on customer relations, sales managers tend to be relatively advanced in terms of DD practices, (Piccoli & Watson, 2008).

We used a convenience sample of Western Europe companies. Nonetheless, we searched for sample heterogeneity to facilitate the generalization of results. Indeed, we gathered our sample by exploiting the professional contacts directly accessible by the authors of this study or indirectly accessible via the authors’ affiliations: a French business school (220 contacted organizations), an Italian engineering school (402 contacted organizations) and an Italian multi-disciplinary university (370 contacted organizations). Our complete sample pool thus included 942 organizations, which we contacted by telephone or e-mail to request participation. Most of the data collection occurred over the telephone or during face-to-face interviews, although several of the respondents chose to answer autonomously by accessing an online questionnaire.

We also surveyed IT managers from the same organizations by using a subset of the questions mainly related to IT in order to reduce common method bias. In the survey, we asked all respondents whether their organization engaged in DD initiatives by using a dummy yes/no question. If the organization engaged in DD initiatives, we asked the informants to provide examples so that we could check the reliability of their answers. The provided examples did not reveal substantial differences in terms of DD initiatives among companies, compared to the affiliation of the author who provided the company contact. We used ANOVA analyses to check whether there were statistically significant differences between the subsamples and we found that no differences in terms of size, revenues and year of foundation.

In as much as the measure of the DD capability construct is grounded on items measuring the effectiveness of the organizational processes required to implement a DD initiative, if respondents did not have at least one DD initiative in their enterprise, they would not be able answer the related questions. Hence, to avoid spurious data, the DD capability construct was measured only for firms that engaged in DD initiatives.

For the hypotheses tests, all the other variables were measured independently of the existence of DD initiatives. The data collected from the main survey were analyzed to address our research questions. We employed principal component analysis, Cronbach’s alpha, collinearity analysis, multiple discriminant analysis, exact logistic regression (elrm), independent sample t-tests, and partial least squares (PLS) structural equation modeling.

Firstly, we assessed the validity, reliability, and collinearity of the measurement model. The principal component analysis, including the square root of the average variance extracted (AVE) for each variable and the correlations (Varimax Rotation with Kaiser Normalization) between the constructs, were employed to provide support of discriminant validity. Reliability was measured by Cronbach's alpha values. The collinearity analysis was based on observations of the correlation matrix, the tolerance value computations and the variance inflation factors.

Secondly, we tested our hypotheses. To test the set of "a" hypotheses, we noted the dichotomous DD initiative construct at the center of the model. Box's M test assessed the similarity of the dispersion matrices of the antecedents between organizations with and those without DD initiatives. For the hypotheses regarding the antecedents of DD initiatives, we relied on multiple discriminant analyses, applied with the simultaneous estimation method, in SPSS, for larger samples and exact logistic regression in the *elrm* package of the R-project statistical software, for smaller samples (UCLA Statistical Consulting Group, 2012). With these two approaches, we observed the distribution of antecedent variables across organizations with and without DD initiatives, as measured by the DD initiative dichotomous variable. Regarding the hypotheses related to DD accessibility, we used independent sample t-tests in SPSS to observe the distribution of the outcome variable across organizations with and without DD initiatives, once again leveraging the DD initiative dichotomous variable.

The set of "b" hypotheses related to the antecedents and outcome for DD capability were tested with PLS in SmartPLS, which is "the most accepted variance-based structural equation modelling technique because it can accommodate models that combine formative and reflective constructs" (Gruber, Heinemann, Brettel & Hungeling, 2010:1342), but not dichotomous variables, as our DD initiative measure. PLS can accommodate reflective construct models, such that we could use the PLS path modeling technique with reflective indicators in SmartPLS to assess data validity and reliability (Ringle, Sven & Alexander, 2005). In addition, PLS is particularly useful for testing models that involve DC (Wilden, Gudergan, Nielsen & Lings, 2013), especially in their early development stages (Fornell & Bookstein, 1982) as is the case for our model. Finally, PLS is appropriate for small sample sizes (Fornell & Bookstein, 1982) as it provides higher statistical power than other statistical alternatives.

We also evaluated the model overall by calculating the goodness-of-fit (GoF) score (Tenenhaus, Vinzi, Chatelin & Lauro, 2005; Wetzels, Odekerken-Schröder & Van Oppen, 2009), a global fit measure for PLS path modeling that is bounded between 0 and 1.

## **4 RESULTS**

### **4.1 Demographics**

We collected 202 questionnaires from the different organizations (overall response rate = 21%); however, we discarded 24 questionnaires that were missing more than 10% of the data. A French business school (220 contacted organizations), an Italian engineering school (402 contacted organizations) and an Italian multi-disciplinary university (370 contacted organizations). In the final set of questionnaires, 94 of the questionnaires were answered by both sales and IT managers, and 84 were answered only by Sales managers. Among the responding organizations, 115 were engaged in DD initiatives. We did not discriminate among the firms by size or age, because the IT-dependent initiative and DC concepts are applicable even for very small, entrepreneurial initiatives (Boccardelli & Magnusson, 2006; Gibcus & Stam, 2012). The sales manager respondents were mainly sales department managers (29%), senior sales managers (12%), mid-level sales managers (12%), or business unit managers responsible for sales (14%). The IT manager respondents were mainly CIOs (28%), senior IT managers (10%), mid-level IT managers (18%), or junior IT managers (24%). The sample thus represented a broad range of industries and organizational sizes (see Table 2). No statistically significant relationship in DD initiatives or DD capability had previously been identified for these firms. We also used ANOVA analyses to check whether there were statistically significant differences between the three subsamples of companies from the three contact sources and we found no differences in terms of size, revenues and year of foundation.

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#### **4.2 Evaluation of the Measurement Model**

We assessed the validity, reliability, and collinearity of the measurement model. According to a principal component analysis, all the items shared more variance with their respective constructs than with any other construct in the model, thus supporting discriminant validity (see Tables 3 and 4). The square root of the average variance extracted (AVE) for each variable and the correlations between the constructs also indicated sufficient discriminant validity, because the square roots of the AVE were greater than the latent variable correlations with any other variable (see Tables 5 and 6).

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Insert table 3 about here  
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Notes: The correlations of the indicators with their respective constructs are highlighted (Varimax Rotation with Kaiser Normalization). Threshold = eigenvalue of 1.

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Insert table 4 about here  
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Insert table 6 about here  
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Reliability, measured by Cronbach's alpha values, was also satisfactory (Tables 7 and 8). The collinearity analysis, based on observations of the correlation matrix, tolerance value computations and variance inflation factors (which ranged from 1.5 to 2.8 and averaged 2.2), indicated no risk of multicollinearity.

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Insert table 7 about here  
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Insert table 8 about here  
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#### **4.3 Model A: Antecedents on DD Initiatives**

Box's M test assesses the similarity of the dispersion matrices of the antecedents; it was not significant (0.58) for the data for sales managers. Therefore, the dispersion matrices did not differ between organizations with and without DD initiatives. The discriminant analysis, which was applied with a simultaneous estimation method, was significant at 0.006, and the Wilks' Lambda equaled 0.93, with a chi-square value of 12.33 and an eigenvalue of 0.08. The canonical correlation coefficient was equal to 0.27; that is, approximately 8% of the variance in the dependent variable (presence or

absence of DD initiatives) could be accounted for by the discriminant analysis model. All three antecedents had significant ( $\leq 0.05$ ) differences in their group means (see Table 9), and the loadings were above the 0.4 threshold for identifying substantive discriminating variables. On average, organizations with DD initiatives showed significantly higher mean scores for the antecedents (Table 9).

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Insert table 9 about here  
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A discriminant analysis was not possible for data collected from IT managers, as the responses from 94 of the organizations indicated that only 20 did not engage in DD initiatives. Thus, the set was too small for a discriminant analysis (Hair, 2006). Instead, we applied elrm in the R-project software to approximate an exact logistic regression, as is suitable for small samples (UCLA Statistical Consulting Group, 2012). The statistical results showed that organizations with DD initiatives exhibited significantly higher historical IT DC on average (0.05 level and 22%) than organizations without DD initiatives (Fink & Neumann, 2007). This result corroborates the results of the discriminant analysis on the sales manager data, as firms with DD initiatives showed significantly higher mean scores on the antecedents.

#### **4.4 Model A: DD Initiatives on DD Accessibility**

The independent sample t-test (adjusted for differences in variance) was significant and revealed differences in DD accessibility for organizations that undertook DD initiatives versus those that did not. Organizations with DD initiatives scored higher ( $M = 5.7$ ,  $SD = 1.3$ ) than organizations without DD initiatives ( $M = 4.9$ ,  $SD = 1.7$ ), and the t-test values were equal to 3.3 ( $p$ -value = 0.001). In support of H4a, DD initiatives demonstrated positive effects on DD accessibility.

#### **4.5 Model B: From Antecedents to DD Accessibility via DD Capability**

The statistical validity of Model B was evaluated with SmartPLS to measure the impact of the antecedents on DD capability and the impact of DD capability on DD accessibility. The SmartPLS analysis highlighted that all the outer loadings were significant at the 0.05 level and that the cross-validated redundancy and communality ratios remained high and positive. The coefficients of determination (R-square values) for the four endogenous variables (0.20–0.50) also indicated the satisfactory explanatory power of our model. The results in Table 10 show significant relationships of the organizational processes of sensing, learning, integrating, and coordinating with DD capability as well as of DD capability with DD accessibility.

We also evaluated the model overall by calculating the goodness-of-fit (GoF) score (Tenenhaus, Vinzi, Chatelin & Lauro, 2005), a global fit measure for PLS path modeling that is bounded between 0 and 1. The GoF score for Model B was 0.581. The GoF cut-off value for a model with medium effect sizes should be 0.25 (Wetzels, Odekerken-Schröder & Van Oppen, 2009). Because our models easily exceeded this recommendation, we establish that our models fit well. In turn, we find that organizational processes have positive, direct effects on DD capability and that stronger DD capability leads to greater DD accessibility. Figure 2 presents the tested model.

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Insert Figure 2 about here  
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Insert table 10 about here  
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## 5. DISCUSSION

We have aimed to contribute to the emerging literature regarding the antecedents of IT capabilities and IT-dependent initiatives, by developing a model that integrates organizational processes, firm history, and firm assets as antecedents of the emerging DC and IT-dependent initiatives that we refer to as DD capability and DD initiatives. We found no systematic differences related to the presence of DD initiatives according to size or industry. This empirical evidence confirms our research design and our a priori decision not to identify any particular organization size or industry in which DD initiatives should spread more readily. In contrast, DD initiatives are more widespread in settings that are marked by high levels of the three examined antecedents. In practical terms, DD initiatives are more widespread when organizational personnel engage in more effective processes for sensing, learning, integrating, and coordinating, as well as when the organization has a well-accumulated IT asset stock and a historically consolidated IT capability. Inasmuch as a DD initiative is an IT-dependent initiative, our results align with previous research (Piccoli & Ives, 2005). Additionally, our results extend previous research on organizational processes. That is, we enrich existing theory that highlights the positive influences of the organizational processes of sensing, integrating and coordinating beyond learning. Our methodology also allows us to predict that the results for H1a, H2a, and H3a are likely generalize to any IT-dependent initiative. For these initiatives, it is critical to take into account the organizational processes of learning, coordinating, integrating, and sensing, rather than simply for IT assets and historical IT capabilities, to ensure their success.

Our model also confirms the existence of a DD capability that involves the reconfiguring of existing combinations of resources and deploying new configurations of operational competences (Pavlou & El Sawy, 2006). That is, a DD capability empowers an organization to continuously innovate its own processes. Our tests enabled us to specify that the organizational processes of learning, sensing, integrating, and coordinating affect DD initiatives and DD capability, whereas the other antecedents (firm history and firm assets) only affect DD initiatives but not DD capability. The crucial role of organizational processes is well established (Montealegre, 2002; Tanriverdi, 2005; Zahra et al., 2006), whereas the lack of effect of a firm's assets and history on DD capability has not previously been demonstrated empirically.

Our extended contribution arises from the combined results of multiple discriminant analyses, structural equation modeling and data that were gathered from organizations with and without DD initiatives and with different levels of DD capability. Through this triangulation, we discovered that organizations seem to require a certain level of IT assets and historical IT capability to launch DD initiatives. Our measures show around half point of statistical difference on the three antecedents between firms with and without DD initiatives. The companies with DD initiatives place them over the 5 out of 7 point scale measuring antecedents' levels. It means that firms should have high enough values for their organizational processes, their IT assets stocks and their historical IT capabilities to successfully launch DD initiatives. Firms with low values on the three antecedents tend to not have DD initiatives. The discriminating threshold between low and high value is in our sample around 5 out of 7 point scale. However, beyond this threshold, further IT asset accumulation and historical IT capability development will not improve firm DD capability (i.e., H1b confirmed; H2b and H3b not confirmed). Additional increases in IT asset stocks and historical IT capabilities do not generate additional effectiveness in the DD DC. Only the additional improvements to organizational processes of sensing, learning, integrating and coordinating continue to bring benefits to DD DC whatever their respective values.

This threshold effect is unlikely to be specific to DD capability; rather, it should also apply to other IT-dependent DC. For example, the ubiquity of sophisticated IT assets makes them widely accessible (Bhatt et al., 2010) such that they no longer constitute a source of capability differentiation but simply represent determinants of whether a firm will launch an IT-dependent initiative. Accordingly, IT assets would not be a significant source of IT DC, as an IT-dependent initiative can be undertaken solely through investment in IT assets.

Our finding that only organizational processes affect DD capability seems to confirm that firm history and firm assets are relevant only when an organization must invest in technology dependent initiatives that support the production of data that are natively digital. Conversely, when we analyze DD capability, assets and history seem irrelevant, and only organizational processes make a

difference. This result reinforces the dynamism of DD capability.

Finally, regarding outcome, DD initiatives make DD more accessible. The DD that result from DD initiatives are more available for use than DD that are gathered through digitization. Moreover, DD capability improves the accessibility of DD for an organization's personnel, where stronger DD capability implies greater DD accessibility (H4b). In turn, inasmuch as accessibility is the dimension most relevant for IS users (Zimmer et al., 2007), we contribute to IS theory by strengthening the manner in which a characteristic of data, namely, being digital, is a potential independent variable that influences accessibility.

Our findings also offer important managerial implications. First, organizations that aim to improve their data accessibility or ground their competitive advantage in accessible data, should look to DD initiatives and DC as key levers for developing or maintaining their IT-dependent competitive advantage. Second, to launch DD initiatives and develop related DD DC, firms should invest in the organizational processes of learning, sensing, coordinating, and integrating. Investments in IT assets or support to historical IT capabilities are required but only up to a certain threshold. Beyond this threshold, organizations should no longer invest in IT assets and sustain historical IT capability.

## 6 CONCLUSION

To help explain variations in competitive advantages through IT-dependent initiatives and IT capabilities, we highlight the role of three types of antecedents: organizational processes, firm assets and firm history. We test our predictions in the context of DD initiatives and DD capability. All three antecedents support DD initiatives. We also specify the strongly positive role played by the organizational processes of sensing, integrating and coordinating, as well as learning, for engagement in DD initiatives. Moreover, only the organizational processes of learning, sensing, coordinating, and integrating strengthen DD capability, whereas we find thresholds for the effects of IT assets and historical IT capability, beyond which these antecedents do not improve DC. Finally, we reveal that DD initiatives and DD capability improve the accessibility of DD, which represents the first and main outcome of DD capability and DD initiatives. Consequently, we suggest that the digital characteristic of data offers a theoretically promising independent variable with a strong potential influence on accessibility. Further research could be directed toward the deepening of the links between the two parallel models presented in this study and eventually integrating them. The data we collected and the theory we mobilized restrained us from testing a single integrative model combining DD initiatives and DD DC. Similarly, the different organizational processes could be measured more extensively and be split in the model to refine the understanding of their impact on the DD initiatives and DD DC. Finally, we identified a sort of threshold in IT asset stocks and historical IT capabilities, discriminating between companies with and without DD initiative. Beyond this threshold, the IT asset stocks and the historical IT capabilities emerge to not influence the effectiveness of the DD DC. This threshold required further investigation to check for its stability and its generalizability.

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