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**The Roles of the Antecedents in the emergence of a Dynamic Capability: the case of Born Digital Data capability**

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**ABSTRACT**

Explaining variations in competitive advantage across organizations remains a persistent question for strategic management and organizations scholars. We empirically contribute to this explanation through an understanding of the different influences of the antecedents of dynamic capabilities (DCs), organizational processes, firm history, and firm assets, in the case of Born Digital Data (BDD) Capability. We define a BDD as the real-time inception in digital form of an informational representation of an entity state or event. BDD is an emerging phenomenon on which IT-dependent initiatives and DC can create new competitive opportunities. We contribute to the literature on DC antecedents in high-velocity markets by evaluating DC antecedents' influence on DC in IT-dependent initiatives in the case of BDD. Finally, we highlight the influence of BDD initiatives and BDD Capability on its output in terms of digital data accessibility. Our results show the different influences of the antecedents. The organizational processes of sensing, integrating, and coordinating the firm's history with its assets support BDD initiatives. The organizational processes of learning, sensing, coordinating, and integrating strengthen the BDD capability. Finally, BDD initiatives and BDD capability improve the accessibility of digital data.

**Keywords**

Born Digital Data, Dynamic Capability Theory, Antecedents, IT-dependent initiatives

## **The Roles of the Antecedents in the emergence of a Dynamic Capability: the case of Born Digital Data capability**

### **INTRODUCTION**

Much of the foundational research on technology-based initiatives has examined their ability to sustain competitive advantage and create new competitive opportunities (Bradley et al., 2013; Chen et al., 2012; Mims, 2012; Piccoli and Ives, 2005; Sallam et al., 2013). Recent research has focused attention on particular Information Technology (IT) artefacts, underlining the relevance of data-related problems for business activities. “Business intelligence and analytics (BI&A) has emerged as an important area of study for both practitioners and researchers, reflecting the magnitude and impact of data-related problems to be solved in contemporary business organizations” (Chen et al., 2012, p. 1165). This quotation introduces an emerging phenomenon that, until now, has received little attention from a theoretical point of view. How are these data born and how should they be born?

The phenomena involving the real-time inception of an informational representation of an event or state of an entity in digital form are spreading. Events, experiences, and actions are increasingly born digital (Piccoli and Watson, 2008). Data, simply seen as informational representations, are increasingly collected directly in electronic and digital forms and shared in electronic and digital formats. Here, we specifically employ the term of “Born Digital Data” (BDD) to refer to informational representations that are directly born, at their inception, via digital technologies. We propose that the digital nature of data, or more precisely, the fact that data originates in a digital form constitutes a fundamental characteristic of the data itself. This requires different organizational thinking and specific research streams.

We attribute importance to this new phenomenon because we are surrounded by BDD. This is the result of the diffusion of enterprise information technologies, such as customer relationship management applications and enterprise resource planning suites and much more. When firms use radio frequency identification (RFID) technology to track items along the supply chain, they produce BDD; and when customers “click” on a website, digital data are born. Piccoli & Watson (2008) explain how Caesars-Harrah’s Entertainment (the largest casino company in the United States) uses its well-known Total Rewards loyalty points program to collect extensive data about its customers’ gambling behaviour by providing customers with cards that link names to transactions, and allows Caesars-Harrah’s to monitor behaviour over time. Armed with this infrastructure for collecting customer data, Caesars-Harrah’s can extract value from data, and tailor the gaming experience to each customer. This diffusion of BDD goes beyond the company's physical boundaries through portable IT devices, such as smart phones and tablets (Kietzmann et al., 2013). These devices are the results of technology-based initiatives that were introduced to generate digital data right from the start.

As these examples show BDD phenomena are different from mere digitalisation, i.e., the process of converting analogue data into digital form (McQuail, 2010). Does this fact make any difference? Does it matter if data has been digital since its creation? Given the rise of this phenomenon, we expect the development of IT capability to handle BDD should represent nowadays a key ingredient for a successful business.

The notion of IT capability refers to the deployment of IT-based resources in combination with, and leveraging the value of, other resources and capabilities (Bharadwaj, 2000). These recent developments offer companies the opportunity to make prompt and accurate decisions based on readily available digital data (McAfee and Brynjolfsson, 2012; Piccoli and Watson, 2008).

Despite the relevance of the topic, what is missing from a theoretical point of view is research on whether this new competitive scenario, characterized by the ubiquitous presence of data, needs to develop new capabilities and what are their antecedents that make these capabilities effective.

In this article, we aim to define the different roles played by the antecedents of DC (Teece et al., 1997; Teece, 2007) both in BDD initiatives and in BDD Capability. IT-dependent initiatives and their related DCs do not automatically imply the achievement of a sustained competitive advantage because mediating and moderating variables can intervene (Helfat & Winter, 2011; Mithas et al., 2011). Thus, it may be interesting to study IT-dependent initiatives and IT-related DC without including competitive advantage as the focal dependent variable. Such research is both challenging and necessary. Accordingly, we evaluate the influence of DC antecedents on IT-related DC, and we assess the same antecedents' influence on the IT-dependent initiative that underlies the IT-related DC. Finally, we determine the influence of the IT-dependent initiative and the IT-related DC on the ultimate DC output. That is, we aim to contribute to the emerging literature related to the antecedents of DCs by developing a model that integrates organizational processes, firm history, and firm assets as antecedents of an emerging DC, which we have named BDD Capability. Therefore, this study represents an attempt to bridge the above-mentioned research gap by addressing the following research question: To what extent do the antecedents of the dynamic capabilities impact on the development of the BDD initiatives and BDD capability and BDD output?

To examine our research questions, we tested eight hypotheses by combining data gathered from a survey of 178 Western European firms, successfully replicated two years later for a subset of 76 firms.

In the following section, we will present the theory related to DCs and their antecedents before defining BDD as the focal IT-related trend we are testing. We then apply our theoretical framework regarding DC antecedents to the BDD case and thereby specify our variables and hypotheses, as well as BDD-related DC output. After

we present our research methodology, we summarize and our results in detail. Finally, we conclude with a discussion of our study contributions.

## **THEORY AND HYPOTHESES**

### **Dynamic Capability theory**

Our research has its roots in dynamic capability (DC) theory (Teece et al., 1997; Augier and Teece, 2009; Peteraf et al., 2013) which is grounded in the resource-based view of the firm (Barney, 1991). Dynamic capability theory has been used in several fields to evaluate the efficient use and competitive advantage implications of specific firm resources such as entrepreneurship (Rumelt, 1987), culture (Barney, 1986), and organizational routines (Winter and Nelson, 1982). In the IS literature the resource-based view has been used to theoretically ground studies on firm-level competitive advantage and its sustainability (Nevo and Wade, 2010; Wade and Hulland, 2004). Understanding the effects of IT resources and capabilities on firm performance remains a central issue in the IS and management literature, e.g. (Melville et al., 2004; Benitez-Amado and Walczuch, 2012; Wang et al., 2013; Galy and Saucedo, 2014).

This perspective highlights the importance of the firm's internal resources for the evaluation of its competitive advantage (Eisenhardt and Martin, 2000; Wernerfelt, 1984). Resources are the "assets and capabilities that are available and useful in detecting and responding to market opportunities or threats" (Wade and Hulland, 2004). In today's fast-paced environment, organizations must constantly adapt to or create market changes; they must develop dynamic capabilities. A Dynamic Capability is "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 and Teece, 2009). This adaptability has been identified as improved customer value (Sambamurthy et al., 2003) and is particularly advantageous in fast-paced technological environments (Banker et al., 2006).

Dynamic Capability theory offers meaningful insights into high-velocity markets, including those that are technology based (Teece et al., 1997), particularly when IT can sustain competitive advantages (Bhatt & Grover, 2005). For example, pervasive computing, sensor networking, real-time data streaming, and the Internet represent trends with the clear potential to create new competitive opportunities (Bradley et al., 2013; Chen et al., 2012; Mims, 2012; Piccoli & Ives, 2005; Sallam et al., 2013).

In high-velocity markets, dynamic capabilities refer to "the firm's ability ... to address rapidly changing environments" (Teece et al., 1997: 515), often with simple rules or processes (Peteraf et al., 2013). For example, Apple possesses strong DCs related to its rules and processes for sensing, which enables it to

recognize the weaknesses of existing MP3 players, mobile telephones, and laptops; it overcame these weaknesses by creating the iPod, iPhone, and iPad (Teece, 2011).

### **Born Digital Data as Dynamic Capability**

In our study, we define BDD capability as the ability to seize new opportunities in born digital data by a four-fold organizational process that consists of: 1) “Choosing IT” (CIT) to generate and capture data unobtrusively in born digital form; 2) “Integrating IT” (IIT) in the appropriate business processes; 3) “Managing born digital data” (MDD) that is so produced; and 4) “Reconfiguring” (REC) business processes, competences or assets based on internal and external conditions. BDD capability has been empirically explored and supported by a preliminary case study (Prescott, 2014).

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

### **Born Digital Data Initiatives**

We extend the construct of technology-based initiatives to the construct of BDD initiatives. We define BDD initiatives as all technological implementations with at least one IT artefact as able to generate natively digital data. A simple example of BDD initiative might be a waiter entering food orders directly into a handheld electronic device at the table. Similarly, BDD phenomenon occurs if customers issue their own orders through a touchscreen such as an iPad that is available at their tables. In contrast, no BDD initiative exist if a waiter writes down an order and then transfers it to an electronic order system. In this case, the data existed in another form before becoming digital. Whether the order moves through a handheld device or an electronic order system at the cash register, digital data acquisition has taken place; here, timeliness is crucial to distinguish BDD phenomenon from other phenomena that also produce digital data.

Other examples of BDD phenomena include searching online through Siri or Google or entering a highway through an automatic (e.g., RFID-enabled) toll-collection booth. Electronic devices represent the building

blocks of any BDD initiative (e.g., handheld device for the waiter, iPhone for Siri, and RFID transponder for the tollbooth), which provide the necessary concurrency between the digitization process and real-life events.

A BDD initiative is an identifiable move by an organization (that relies on BDD) that has been designed to lead to a sustained improvement in the organization's competitive position. Thus, BDD initiatives constitute a form of IT-dependent initiatives (Piccoli & Ives, 2005). For example, for customers, entering orders or information into an electronic device is an example of the BDD phenomenon; for the launching organization, a BDD initiative might equip employees with electronic devices and training, and then collecting relevant data. This simple presentation suggests that such an initiative is not strategic in the sense that it can be easily and successfully replicated by competitors. In contrast, the BDD initiative of Apple's iPod is strategic because attempted replications have not been successful. What makes the difference in creating a competitive advantage for an organization is not the BDD initiative itself (such as the development of an MP3 player and related software) but the organizational capabilities to exploit the potential benefits of BDD.

Alone, a BDD initiative does not imply that an organization can deploy new configurations of operational competences (i.e., initiative success in the short run), nor does it include the ability to reconfigure existing BDD processes (i.e., initiative value in the long run). Rather, BDD initiatives are preliminary moves for creating BDD Capability. There are several examples of BDD Capability, such as those in Harrah's Corporation. For several years, Harrah's has systematically and repeatedly integrated unobtrusive new IT (e.g., computerized slot machines and radio frequency identification [RFID] chips) to gather valuable digital data about customers' behaviors. It then exploits these new data to improve its customer profiles and better reward its most valuable customers.

### **Antecedents of the Dynamic Capabilities**

Substantial progress has resulted from the concept of DC (Teece et al., 1997), which has spurred definitional debates (Peteraf et al., 2013) and disagreements about its antecedents (Blome et al., 2013). Antecedents can be classified into three groups (Teece, 2007; Teece et al., 1997):

- Organizational processes, including sensing, coordination, integration, and learning;
- Firm assets, which define its strategic position;
- Firm history, which accounts for the path-dependent nature of its dynamic capabilities.

Together, these antecedents tend to improve the establishment and performance of organizational rules and processes in support of DCs. For example, a new product development (NPD) DC might rely on an antecedent

of IT-leveraging competences (Pavlou & Sawy, 2006), such that the NPD work unit's ability to use IT functionalities effectively improves its IT-related rules and processes for developing new products. However, instead of NPD, our research model applies existing literature (Bhatt & Grover, 2005; Kim et al., 2011; Montealegre, 2002; Pavlou & Sawy, 2006; Tanriverdi, 2005; Zahra et al., 2006; Zollo & Winter, 2002) to the framework of Teece's (2007; Teece et al., 1997) three-fold classification of antecedents, to an emergent kind of IT-dependent initiatives, the BDD initiatives, and to an IT-related DC, the BDD Capability.

### **Organizational processes of sensing, learning, coordinating, and integrating**

Organizational processes can constitute antecedents of a DC (Kale & Singh, 2007; Kogut & Zander, 1996; Maritan, 2007; Pavlou & Sawy, 2006; Schreyögg & Kliesch-Eberl, 2007; Teece, 2007; Zahra et al., 2006). Sensing relates to understanding the environment and identifying market needs and opportunities. Learning involves developing new thinking and generating new knowledge to enhance existing resources. Coordinating pertains to allocating and mobilizing resources, assigning tasks, and synchronizing firm activities. Finally, integrating entails developing new patterns of interaction to face environmental changes or market evolutions, then implementing the resulting operational competency configurations. Sensing, learning, coordinating, and integrating facilitate BDD initiatives and enhance BDD capabilities. Organizations with effective organizational processes should be better able to initiate BDD and implement processes to ensure reliable IT choices and digital data management. Therefore, we propose the following hypotheses:

H1a: Organizations that engage in BDD possess are more effective at sensing, learning, coordinating, and integrating processes.

H1b: For the organizations engaged in BDD, effective sensing, learning, coordinating and integrating processes strengthen BDD Capability

### **Firm assets**

Different assets—technological, complementary, financial, reputation, structural, institutional, or market structure—can contribute to the development of novel DCs (Teece, 2007; Teece et al., 1997). We theorize that IT assets are significant antecedents for BDD because its DC is grounded in the processes of selecting IT and managing digital data. As IT assets co-specialize with complementary assets, they are eventually amalgamated into IT platforms, which make their creation, management, reproduction, trading, and imitation by others more difficult (Teece, 2007, 2011).

Two types of assets are prominent in the IT category: IT infrastructure and information repositories (Piccoli & Ives, 2005). The former is “the base foundation of the IT portfolio, shared through the firm in the form of reliable services”, such that it provides the functionalities upon which business applications and services can be built, whereas 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 (Ingemar & Cool, 1989). When a new piece of IT or information becomes part of an organization’s IT asset stock, it extends the pre-existing stock, some of which might be leveraged to create option value. The greater the extension of the existing stock, the higher the possibility of disposing of the portion that can be effectively leveraged. Thus, extended IT asset stock should facilitate the technical and informational requirements of BDD initiatives such as an IT infrastructure that can generate data in digital form at its inception and information repositories that can store and retrieve these data. This accumulated IT asset stock would constitute an antecedent of a BDD initiative.

Meanwhile, the same extended IT asset stock could offer services, functionalities, and data to support choices about IT, generate digital data at their inception, and manage new data sets. Accordingly, accumulated IT asset stock is a likely antecedent of a BDD Capability, and we hypothesize the following:

H2a: Organizations that engage in BDD have more extended IT assets.

H2b: For organizations engaged in BDD, IT assets strengthen BDD Capability.

### **Firm history**

A firm’s history helps explain its existing position and current endowments in technology, intellectual property, complementary assets, customer base, and external relations with suppliers and competitors (Teece, 2007; Teece et al., 1997). History also influences the firm’s future opportunities and frames the path dependencies of the organization, the strategic alternatives available to it, and possible returns. New initiatives depend on the existing firm’s initiatives, and new dynamic capabilities depend on its existing capabilities, which might constrain newer options because learning tends to be local and related to existing processes (Teece et al., 1997; Zahra et al., 2006). That is, the antecedents of BDD Capability are closely related to historical DCs. Given that electronic devices represent the building blocks of any BDD, we hypothesize that historical IT DC is the most influential DC for BDD.

We define an IT DC as a multidimensional, enterprise-wide ability to leverage IT (Bharadwaj et al., 1999). This historical DC increases the ability of IT personnel to recognize the potential that emerging or enabling IT can generate and capture digital data. Good relationships between IT personnel and line management can help integrate such IT into appropriate business processes. In contrast, the lack of an IT DC would delay BDD initiatives and make the process of choosing IT and managing digital data ineffective. Accordingly, we hypothesize that:

H3a: Organizations that engage in BDD already had a more effective IT DC.

H3b: For the organizations engaged in BDD, an effective historical IT DC strengthens BDD Capability.

### **Output of BDD Capability**

We also empirically consider direct DC outputs. The performance of an organization with a BDD Capability does not automatically enjoy a sustained competitive advantage because of the potential influences of mediating and moderating variables. Instead, BDD enables informational representations of real objects, facts, and events without any significant delays (i.e., in real time). The digital format of these representations increases their accessibility. In general, accessibility is the extent to which an individual perceives that any particular source is available for use. Accessibility has been shown to be the primary factor in the determination of source use (Zimmer et al., 2007). In our particular context, the direct output of BDD is accessible digital data, which can be exploited for various purposes such as information processing, sophisticated analytics, decision making, and monitoring.

Given that digital data accessibility is a parallel form of information accessibility (defined by the perceived extent to which any particular source is available for use), it likely drives information source choices (Zimmer et al., 2007). Therefore, we hypothesize the following:

H4a: Organizations that engage in BDD have more accessible digital data.

H4b: For the organizations engaged in BDD, effective BDD Capability makes digital data more accessible.

For the sake of parsimony of the model, accessibility is the only output variable measured, even though we acknowledge that BDD could impact other less important output variables, such as information quality.

Figure 1 presents the synthesis of our hypotheses. Model A will describe the Hxa hypotheses, while Model B describes the Hxb hypotheses. We test these separately, as the ‘A’ set of hypotheses constitutes associations (simple lines) while the ‘B’ set constitutes causation hypotheses (arrows).

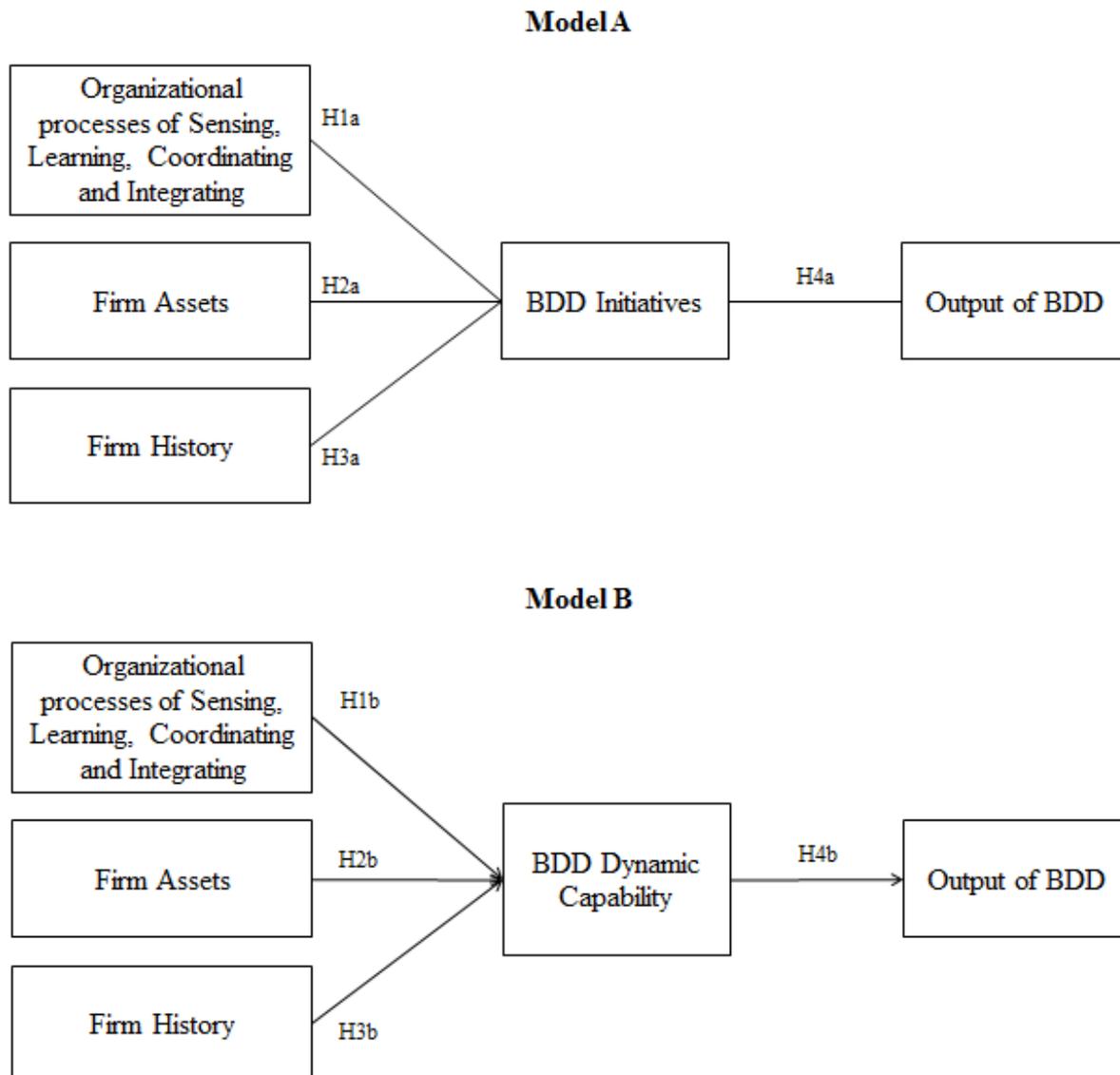


FIGURE 1: THE PROPOSED MODEL

## RESEARCH DESIGN AND METHODOLOGY

The best level for measuring DCs is the organizational-process level (Li et al., 2009). We surveyed sales managers because sales departments tend to be particularly advanced in BDD practices, particularly through their focus on customer relations (Piccoli & Watson, 2008).

Similarly, we surveyed IT managers from the same organizations to reduce common method bias. We asked a subset of questions that mostly pertained to IT.

First of all, we asked everyone if their organization had launched BDD initiatives through a dummy yes or no question. If the organization had launched BDD initiatives, we directed the informant to provide examples to double check the reliability of their answers. By this method, the BDD capability construct was only measured for organizations that had launched BDD initiatives. To test our hypotheses, all other variables were measured independently from the existence of BDD initiatives. We operationalized the model's constructs using existing measurement scales that had been previously tested, with the exception of the 'Choosing IT' dimension of BDD capability. This construct was needed to measure the firm's ability to select IT to unobtrusively collect valuable digital data. To develop this construct, we conducted a pilot study, beginning with four indicators available from prior literature (Williams, 2003) that had never been tested empirically. We recruited 35 managers from small, medium, and large enterprises in different industries from the United States to participate. The four focal indicators were inserted within a set of 26 questions to reduce common method bias. The responses indicated that the scale was reliable (Cronbach's  $\alpha = 0.837$ ); for parsimony, we reduced it to three items. For all other constructs, we used the validated scales (see Table 1 and Appendix A).

*Table 1. Study Measures*

| Construct                | Dimension                  | Adapted measurement scale                                  | Original source                                |
|--------------------------|----------------------------|--|--|
| BDD Cap output           | Digital data accessibility | Information accessibility                                  | Zimmer et al. (2007)                           |
| BDD Cap                  | Choosing IT                | Choosing   | Williams (2003)                                |
|                          | Integrating IT             | IT Business process integration                            | Bharadwaj et al. (1999)                        |
|                          | Reconfiguring              | Reconfigurability  | Pavlou & Sawy (2006)                           |
|                          | Managing digital data      | Information management                                     | Marchand et al. (2002)                         |
| Firm history             | Historical IT DC           | IT personnel capability                                    | Fink & Neumann (2007)                          |
| Firm assets              | IT infrastructure          | IT infrastructure capability                               | Fink & Neumann (2007)                          |
|                          | Information repository     | Union of knowledge document repository and data repository | Freeze & Kulkarni (2005)                       |
| Organizational processes | Sensing                    | Market orientation   | Kohli & Jaworski (1990); Pavlou & Sawy (2006)  |
|                          | Learning                   | Absorptive capacity  | Cohen & Levinthal (1990); Pavlou & Sawy (2006) |
|                          | Coordinating               | Coordination capability                                    | Malone & Crowston (1994); Pavlou & Sawy (2006) |
|                          | Integrating                | Collective mind  | Pavlou & Sawy (2006); Weick & Roberts (1993)   |

Before the main data collection, we consulted an expert panel and used Q-sorting methods to adapt the chosen scales to our research context, as well as to assess their content validity. The expert panel included seven sales managers and two IT managers who proposed and validated adaptations of the items in each construct. The Q-sorting involved four rounds of refinement before we reached, for each item, a threshold of 50% of attributions to the correct construct (see Appendix A). One hundred and nineteen respondents (mainly employees of different organizations between 20 and 40 years of age and equally distributed between men and women) participated in the Q-sorting procedure. As a complement, BDD capability has been empirically explored and supported by a preliminary case study (Prescott, 2014).

Our measurement scales passed through a long and complex adaptation process including: expert panel, Q-sorting, and case study. On the one hand, for some variables this process brought in many adaptations explaining the extent to which our final scales differ from the original scales. On the other hand, this process highlights the importance of reducing the length of the survey instrument and hence, for the sake of parsimony, of reducing the number of items for each construct as far as possible.

To address our research questions, we employed multiple discriminant analysis, exact logistic regression (elrm), independent sample t-tests, and partial least squares (PLS) structural equation modelling. To test the A hypotheses, our choice was consistent with the dichotomous BDD initiative construct at the center of our A model. The presence of dichotomous variables excluded many statistical tests such as structural equation modelling. Moreover, we did not advance any clear direction of causality because it is equally possible that having BDD initiatives leads to better antecedents and outputs, or conversely, having better antecedents and output could be what leads them to create BDD initiatives. To empirically test the causality, the A hypotheses linking antecedents to the BDD initiative are tested also on longitudinal data. For the A hypotheses that pertained to the antecedents of

BDD initiatives, we relied on multiple discriminant analysis in SPSS and the exact logistic regression (elrm) in the elrm package of the R-project statistical software. These two approaches involved observing the distribution of the antecedent variables across organizations with and without BDD initiatives, as measured with by a dichotomous variable. To test the A hypotheses related to the output of BDD initiatives, we used independent sample t-tests in SPSS, such that we observed the distribution of the output variable across organizations with and without BDD initiatives. To test the B hypotheses related to the antecedents and output of BDD Capability, we chose PLS in SmartPLS as “the most accepted variance-based structural equation modelling technique because it can accommodate models that combine formative and reflective constructs” (Gruber et al., 2010: 1342). PLS is able to accommodate reflective construct models giving us the possibility to use the PLS path modelling technique with reflective indicators in Smart-PLS to assess the validity and reliability of the data (Ringle et al., 2005). Additionally PLS seems particularly useful in testing models involving dynamic capabilities (Wilden et al., 2013), particularly for a model in the early stage of development (Fornell and Bookstein, 1982), as it is our model. Finally, PLS appears more appropriate when having access only to small sample sizes (Fornell and Bookstein, 1982), showing higher statistical power than other statistical alternatives. To empirically test the causality, the B hypotheses linking antecedents to the dynamic capability are tested also on longitudinal data.

## **RESULTS**

### **Demographics**

We turned to three sources to reach a sufficient number of organizations and their sales managers. First, we surveyed 220 sales and IT manager contacts that a French business school maintained in its customer-relationship management application, most of whom worked in the Rhône-Alpes French region—the same region as the headquarters of the

French business school. Second, 402 organizations from the Piedmont region of Italy, which had previously participated in a survey run by an Italian engineering school in the same region, provided data. Third, we gathered a selection of 370 organizations from Veneto, another Italian region, which represented the various corporate trade-union members of the region, to ensure diversity in organizational sectors and sizes. Such heterogeneity in the sample also facilitated the generalization of the results.

Thus, our complete sample pool included 942 organizations, which we contacted by telephone or e-mail to request participation. The data collection occurred most often over the telephone or through face-to-face interviews, although several respondents chose to answer autonomously by accessing an online questionnaire.

We collected 202 questionnaires from different organizations (the overall response rate was 21%) but discarded 24 questionnaires because they were missing more than 10% of data. Out of the final set of questionnaires, 94 questionnaires were answered by the sales and the IT managers, while 84 questionnaires were answered only by the sales managers. Of the responding organizations, 115 were engaged in BDD initiatives. 76 organizations, out of our final set, were successfully surveyed 2 years later on a subset of questions. We did not discriminate the firms by their size or their age, as dynamic capability concept has been proven useful even for very small entrepreneurial initiatives at their very beginning (Gibcus and Stam, 2012; Boccardelli and Magnusson, 2006). Out of these 76 organizations, 40 organizations had BDD initiatives, while the remaining 36 did not have any BDD initiative.

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 represented

a broad range of industries and a wide variety of organizational sizes (see Table 2). No statistically significant relationship with BDD had previously been identified for these firms.

*Table 2. Industry and Size Distribution of the Sample*

| <b>Industries</b>   | <b>Total</b>  | <b>With BDD</b> | <b>Without BDD</b> |
|---|---------------|-----------------|--------------------|
| Communications, electric, gas, sanitary services, public administration, and other services | 15.4%         | 8.0%            | 7.4%               |
| Construction  | 3.7%          | 3.2%            | 0.5%               |
| Wholesale and retail trade  | 17.0%         | 10.1%           | 6.9%               |
| Finance and insurance   | 3.7%          | 3.2%            | 0.5%               |
| Real estate   | 0.5%          | 0.5%            | 0.0%               |
| Agriculture, food and beverage  | 3.7%          | 1.6%            | 2.1%               |
| Manufacturing and mining  | 36.2%         | 23.4%           | 12.8%              |
| B2B services  | 18.6%         | 10.6%           | 8.0%               |
| Transportation  | 1.1%          | 0.0%            | 1.1%               |
| <b>Total</b>  | <b>100.0%</b> | <b>60.6%</b>    | <b>39.4%</b>       |
| <b>Number of employees</b>  |               |                 |                    |
| 1   | 2.6%          | 1.0%            | 1.6%               |
| 2 to 9  | 11.5%         | 6.8%            | 4.7%               |
| 10 to 49  | 34.0%         | 20.4%           | 13.6%              |
| 50 to 199   | 27.2%         | 15.7%           | 11.5%              |
| 200 to 499  | 8.9%          | 5.2%            | 3.7%               |
| 500 to 1999   | 8.4%          | 5.8%            | 2.6%               |
| 2000 and more   | 7.3%          | 5.2%            | 2.1%               |
| <b>Total</b>  | <b>100.0%</b> | <b>60.2%</b>    | <b>39.8%</b>       |

### **Evaluation of the measurement model**

We conducted an assessment of the validity, reliability, and collinearity of the measurement model. According to a principal component analysis, all items shared more variance with their respective constructs than with any other construct in the model, which supports discriminant validity (see Table 3 and Table 4).

Table 3. Principal Component Analysis of Data from Sales Managers

| Code | Construct      | Item | C            | A            | B            | D            | E            |
|------|----------------|------|--------------|--------------|--------------|--------------|--------------|
| A    | BDD Cap        | 1    | 0.283        | <b>0.766</b> | 0.391        | 0.608        | 0.476        |
| A    | BDD Cap        | 2    | 0.392        | <b>0.771</b> | 0.409        | 0.546        | 0.556        |
| A    | BDD Cap        | 3    | 0.425        | <b>0.847</b> | 0.251        | 0.645        | 0.444        |
| A    | BDD Cap        | 4    | 0.456        | <b>0.846</b> | 0.349        | 0.588        | 0.499        |
| A    | BDD Cap        | 5    | 0.357        | <b>0.853</b> | 0.241        | 0.513        | 0.552        |
| A    | BDD Cap        | 6    | 0.397        | <b>0.731</b> | 0.240        | 0.532        | 0.437        |
| A    | BDD Cap        | 7    | 0.218        | <b>0.614</b> | 0.083        | 0.255        | 0.318        |
| A    | BDD Cap        | 8    | 0.426        | <b>0.813</b> | 0.216        | 0.509        | 0.344        |
| A    | BDD Cap        | 9    | 0.456        | <b>0.793</b> | 0.265        | 0.560        | 0.324        |
| B    | Firm assets    | 1    | 0.468        | 0.276        | <b>0.762</b> | 0.427        | 0.429        |
| B    | Firm assets    | 2    | 0.457        | 0.306        | <b>0.793</b> | 0.490        | 0.436        |
| B    | Firm assets    | 3    | 0.430        | 0.313        | <b>0.897</b> | 0.493        | 0.429        |
| B    | Firm assets    | 4    | 0.410        | 0.271        | <b>0.890</b> | 0.420        | 0.409        |
| B    | Firm assets    | 5    | 0.390        | 0.317        | <b>0.802</b> | 0.474        | 0.346        |
| C    | Firm history   | 1    | <b>0.928</b> | 0.472        | 0.464        | 0.596        | 0.523        |
| C    | Firm history   | 2    | <b>0.909</b> | 0.423        | 0.492        | 0.580        | 0.619        |
| D    | Org pro        | 1    | 0.499        | 0.556        | 0.346        | <b>0.773</b> | 0.526        |
| D    | Org pro        | 2    | 0.499        | 0.485        | 0.448        | <b>0.799</b> | 0.377        |
| D    | Org pro        | 3    | 0.519        | 0.656        | 0.451        | <b>0.815</b> | 0.565        |
| D    | Org pro        | 4    | 0.503        | 0.535        | 0.534        | <b>0.893</b> | 0.449        |
| D    | Org pro        | 5    | 0.382        | 0.399        | 0.404        | <b>0.696</b> | 0.336        |
| D    | Org pro        | 6    | 0.412        | 0.478        | 0.438        | <b>0.735</b> | 0.494        |
| D    | Org pro        | 7    | 0.611        | 0.615        | 0.512        | <b>0.839</b> | 0.603        |
| D    | Org pro        | 8    | 0.497        | 0.698        | 0.336        | <b>0.804</b> | 0.479        |
| D    | Org pro        | 9    | 0.515        | 0.584        | 0.433        | <b>0.857</b> | 0.548        |
| D    | Org pro        | 10   | 0.509        | 0.408        | 0.446        | <b>0.716</b> | 0.497        |
| D    | Org pro        | 11   | 0.565        | 0.539        | 0.486        | <b>0.817</b> | 0.488        |
| D    | Org pro        | 12   | 0.576        | 0.462        | 0.541        | <b>0.765</b> | 0.488        |
| E    | BDD Cap output | 1    | 0.615        | 0.538        | 0.436        | 0.603        | <b>0.911</b> |
| E    | BDD Cap output | 2    | 0.492        | 0.482        | 0.453        | 0.506        | <b>0.887</b> |

Notes: The correlations of the indicators with their respective construct are highlighted. Threshold = eigenvalue of 1.

Table 4. Principal Component Analysis of Data from IT Managers

| Code | Construct    | Item | A    | B    |
|------|--------------|------|------|------|
| A    | BDD Cap      | 1    | 0.85 | 0.29 |
| A    | BDD Cap      | 2    | 0.76 | 0.38 |
| A    | BDD Cap      | 3    | 0.85 | 0.29 |
| A    | BDD Cap      | 4    | 0.73 | 0.44 |
| A    | BDD Cap      | 5    | 0.8  | 0.4  |
| C    | Firm history | 6    | 0.32 | 0.9  |
| C    | Firm history | 7    | 0.41 | 0.86 |

Notes: The correlations of the indicators with their respective construct are highlighted (Varimax Rotation with Kaiser Normalization). Threshold = eigenvalue of 1.

The square root of the average variance extracted (AVE) for each variable and the correlations between the constructs provided a test of discriminant validity on the construct level. We found sufficient discriminant validity—the square roots of the AVE were higher than the latent variable correlations with any other variable (see Table 5 and Table 6).

*Table 5. Construct Level Correlation and Discriminant Validity of Data from Sales**Managers*

|                | First history | BDD Cap | Firm assets | Org pro | BDD Cap output |
|----------------|---------------|---------|-------------|---------|----------------|
| First history  | 0.918         |         |             |         |                |
| BDD Cap        | 0.488         | 0.785   |             |         |                |
| Firm assets    | 0.519         | 0.359   | 0.831       |         |                |
| Org pro        | 0.640         | 0.688   | 0.558       | 0.794   |                |
| BDD Cap output | 0.619         | 0.569   | 0.493       | 0.619   | 0.899          |

Notes: The square roots of the AVE are on the diagonal, and correlations are on the off-diagonal.

*Table 6. Construct Level Correlation and Discriminant Validity of Data from IT Managers*

|              | BDD Cap | Firm history |
|--------------|---------|--------------|
| BDD Cap      | 0.77    |              |
| Firm history | 0.73    | 0.91         |

Notes: The square roots of the AVE are on the diagonal, and correlations are on the off-diagonal.

Reliability, as measured by Cronbach's alpha values, was satisfactory (see Table 7 and Table 8). The collinearity analysis, based on observation of the correlation matrix together with the tolerance value computations and the variance inflation factors (which ranged between 1.5 and 2.8 and averaged 2.2), indicated no risk of multicollinearity.

*Table 7. Construct Reliability of Data from Sales Managers*

| Construct      | $\alpha$ |
|----------------|----------|
| BDD Cap        | 0.92     |
| Firm assets    | 0.887    |
| Firm history   | 0.81     |
| Org pro        | 0.95     |
| BDD Cap output | 0.76     |

*Table 8. Construct Reliability of Data from IT Managers*

| Construct    | Cronbach's Alpha |
|--------------|------------------|
| BDD Cap      | 0.92             |
| Firm history | 0.91             |

**Antecedents of BDD initiatives**

The Box's M test, which assesses the similarity of the dispersion matrices of the antecedents, was not significant (0.58) for the data from the sales managers. Therefore, the dispersion

matrices did not differ between organizations with and without BDD initiatives. The discriminant analysis, applied with a simultaneous estimation method, was significant at 0.006, and the Wilks' Lambda was equal to 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 BDD initiatives) could be accounted for by the discriminant analysis model. All three antecedents had significant ( $\leq 0.05$ ) differences in group means (see Table 9), and the loadings were above the 0.4 threshold for identifying substantive discriminating variables. On average, organizations with BDD initiatives showed significantly higher mean scores for the antecedents (Table 9).

We did not advance any clear direction of causality, because we hypothesize that it is equally possible that having BDD initiatives leads to better antecedents and outputs, or conversely, having better antecedents and output could be what leads them to create BDD initiatives. We empirically test this lack of causality for the A hypotheses linking antecedents to the BDD initiative, leveraging our longitudinal data on our 76 organizations who were successfully surveyed two years later. The Box's M test, which assesses the similarity of the dispersion matrices of the antecedents, was not significant (0.52) for the data from the sales managers, but the discriminant analysis was not significant. Thus, causality is not found the results indicate support for H1a, H2a, and H3a.

*Table 9. Multiple Discriminant Analysis.*

| Independent variables   | Significance level | Group means and Standard deviation |                         |             | Wilks' Lambda | Hypothesis |
|---|--------------------|------------------------------------|-------------------------|-------------|---------------|------------|
|   |                    | With BDD initiatives               | Without BDD initiatives | Full sample |               |            |
| Org pro   | *                  | 5.22                               | 4.84                    | 5.08        | 0.97          | H1a        |
| Firm assets   | **                 | 5.83                               | 5.15                    | 5.58        | 0.96          | H2a        |
| Firm history  | ***                | 5.27                               | 4.68                    | 5.05        | 0.93          | H3a        |
| Overall Wilks' Lambda = 0.93**  |                    |                                    |                         |             |               |            |
| Canonical correlation = 0.27  |                    |                                    |                         |             |               |            |
| ***Significant at 0.001. ** Significant at 0.01. * Significant at 0.05. |                    |                                    |                         |             |               |            |

Discriminant analysis was not possible for the data collected from IT managers because out

of responses that represented 94 organizations, only 20 did not engage in BDD initiatives. Thus, the set was too small for discriminant analysis (Hair et al., 2006). Instead, we applied the exact logistic regression (elrm) in R-project to approximate an exact logistic regression, which is suitable for small samples (UCLA Statistical Consulting Group, 2012). The statistical results showed that the firm history of organizations with BDD initiatives was significantly higher on average (at the 0.05 level and 22%) than the firm history of organizations without BDD initiatives in terms of the historical IT DC of IT personnel (Fink & Neumann, 2007). This output strengthens the results of the discriminant analysis, confirming that organizations with BDD initiatives showed significantly higher mean scores for the antecedents.

### **BDD initiatives on output**

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

Overall, these results confirm that organizations that engage in BDD achieve more effective sensing, learning, coordinating, and integrating processes. They also gather more extended IT assets, had already possessed greater effectiveness in IT DCs, and had more accessible digital data.

### **Antecedents of BDD Capability on output**

The statistical validity of our conclusions about the antecedents of BDD Capability and its output is strong. SmartPLS highlighted that all the outer loadings were significant at the 0.05 level, and the cross-validated redundancy and communality ratios remained high and

positive. The coefficient of determination R-square values for the four endogenous variables (0.20–0.50) also indicated the satisfactory explanatory power of our model.

Overall, the results in Table 7 indicate significant relationships between (1) the organizational processes of sensing, learning, integrating, and coordinating and BDD Capability, and (2) BDD Capability and its output for digital data accessibility. The causal relationship between the organizational processes of sensing, learning, integrating, and coordinating and BDD Capability is confirmed significant (at 0.05) over a two-year lapse time, with a path coefficient equal to 0.48. On the other hand, the other two antecedents, Firm history and Firm assets repeat their statistically insignificant relationships with BDD Capability, giving a R-Square for this longitudinal test equals to 0.16.

We evaluated our model overall by calculating the Goodness of Fit (GoF) score, as suggested by Tenenhaus et al. (2005), as a global fit measure for PLS path modelling, bounded between 0 and 1. The GoF score for model B was 0.581. The GoF score slightly reduced to 0.35 for the longitudinal test of the model B. According to Wetzels et al. (2009), the GoF cut-off value for a model with medium effect sizes should be 0.25; our models exceeded this recommendation easily, which indicates that our models fit well. *Table 7. PLS Structural Model Estimation.*

| Hypothesis | Independent construct |   | Dependent dimension | Beta Path coefficient | t-value | Significance p-value | R-Square |
|------------|-----------------------|---|---------------------|-----------------------|---------|----------------------|----------|
| H1b        | Org pro               | → | BDD DC              | 0.66                  | 6.328   |                      |          |
| H2b        | Firm assets           | → | BDD DC              | -0.06                 | 0.784   | Not sig              |          |
| H3b        | Firm history          | → | BDD DC              | 0.10                  | 0.991   | Not sig              |          |
| H4b        | BDD DC                | → | BDD DC output       | 0.57                  | 7.399   | ***                  | 0.48     |
|            | BDD DC output         |   |                     |                       |         |                      | 0.32     |

\*\*\* Significant at 0.001. This demonstrates that organizational processes have positive, direct effects on BDD Capability and that stronger BDD Capability lead to greater digital data accessibility.

Figure 2 shows the tested model. The rectangles and their connectors in Model A refer to the multiple discriminant analysis test, and the ellipses and the red connectors in Model A refer to the independent sample t-tests. The rectangles and their connectors in Model B refer to the partial least squares (PLS) structural equation modelling.

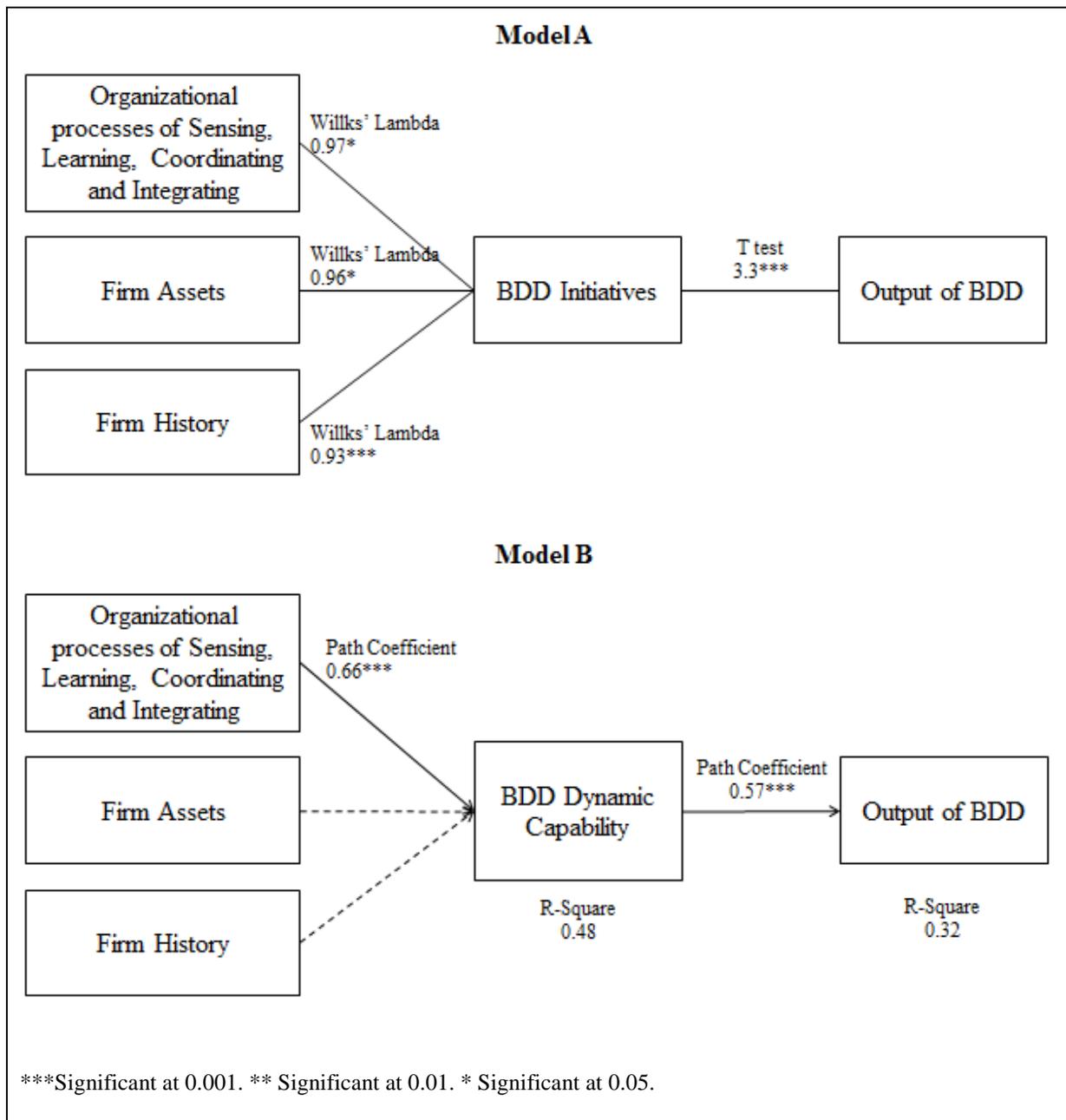


FIGURE 2: THE TESTED MODEL

## DISCUSSION

We aimed to contribute to emerging literature related to the antecedents of DCs by developing a model that integrates organizational processes, firm history, and firm assets as antecedents of an emerging DC we call BDD Capability. Given that we found no systematic differences related to the presence of BDD initiatives according to size or industry, the empirical evidence confirmed our research design. *A priori*, we did not identify any particular organization size or industry in which BDD initiatives spread more readily. In contrast, BDD initiatives were more diffuse where the three antecedents from Teece et al.'s (1997) model were higher. In practical terms, BDD initiatives diffuse more when the 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. When a BDD initiative is an IT-dependent initiative, our results align with (but also extend) previous research (Piccoli & Ives, 2005); that is, we enrich existing theory that highlights the positive influences of organizational processes of sensing, integrating, and coordinating beyond learning. Our methodology also allows us to predict that the results pertaining to H1a, H2a, and H3a likely generalize to any IT-dependent initiatives. For such initiatives, it is critical to account for the organizational processes of learning, coordinating, integrating, and sensing, not simply of IT assets and IT capabilities, to ensure their success.

Our model also confirms the existence of a BDD Capability that entails reconfiguring existing combinations of resources for BDD Capability and deploying new configurations of operational competences (Pavlou & Sawy, 2006). That is, BDD Capability empowers an organization to continuously innovate its own processes. Given that we tested the existence of this BDD Capability empirically, we can specify that the organizational processes of learning, sensing, integrating, and coordinating affect BDD initiatives and their DCs,

whereas the other antecedents (firm history and firm assets) affect only BDD initiatives. 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 BDD Capability has not previously been empirically demonstrated. Our extended contribution results from the combined results of our multiple discriminant analyses, structural equation modelling, and data gathered from organizations with and without BDD initiatives or different levels of BDD Capability. Through this triangulation, we discovered that organizations need a certain level of IT assets and historical IT capability to launch BDD initiatives. However, after certain thresholds, further IT asset accumulation and IT capability development do not improve BDD Capability (H1b confirmed; H2b and H3b not confirmed). We posit that this threshold effect is not specific to a BDD Capability only; rather, it is seemingly valid for other IT-dependent DCs. For example, the ubiquity of sophisticated IT assets makes them widely accessible (Bhatt & Grover, 2005), such that they no longer offer a source of capability differentiation but simply a determinant of whether the firm launches an IT-dependent initiative. Accordingly, IT assets would not be a significant source of IT-dependent DC, but the IT-dependent initiative can be undertaken only through investments in IT assets.

The fact that only organizational processes affect BDD Capability seem to confirm that firm history and firm assets are considered relevant when the organization has to invest in technology that allows for the production of data that is natively digital. Conversely, when we analyze BDD as a capability, assets and history seem to be irrelevant and only organizational processes make a difference, which reinforces the dynamism of BDD Capability.

Finally, with regard to outputs, BDD initiatives make digital data more accessible. The digital data that result from BDD initiatives are therefore more available for use than digital

data gathered through digitization. Moreover, BDD Capability improves the accessibility of these digital data to the organization's personnel: a stronger BDD Capability implies greater digital data accessibility (H4b). In turn, accessibility is the dimension most relevant for information system users (Zimmer et al., 2007). Thus, we contribute to information systems theory by highlighting the characteristic of data of being digital as a possible independent variable with a strong influence on accessibility.

Our findings also offer important managerial implications. First, organizations wanting to improve their data accessibility or ground their competitive advantage in accessible data should look to BDD (initiatives and DC) as a key lever for developing or maintaining their IT-dependent competitive advantage. Second, to launch BDD initiatives and develop a related DC, firms should invest in their organizational processes of learning, sensing, coordinating, and integrating. Investments in IT assets and IT capabilities are required, but only to a certain threshold. Past this threshold, organizations should no longer invest in IT assets and IT capability.

## **CONCLUSION**

To help explain variations in competitive advantages across business organizations, we highlight the role of three kinds of DC antecedents: organizational processes, the firm assets, and firm history. We have tested our predictions in the context of BDD, an emerging phenomenon that can stimulate new IT-dependent initiatives and DCs. All three antecedents support BDD initiatives. We also specify the strongly positive role played by the organizational processes of sensing, integrating, and coordinating, in addition to learning. Moreover, only the organizational processes of learning, sensing, coordinating, and integrating strengthen BDD Capability, but we find thresholds for the effects of IT assets and IT capability, beyond which these antecedents do not improve DCs.

Finally, we have revealed that BDD initiatives and DCs improve the accessibility of digital data, which represent the first and main output of BDD initiatives and capability. Consequently, we suggest that BDD offers a theoretically promising independent variable with a strong potential influence on accessibility.

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**Appendix A: Questionnaire**

To collect consistent data from different respondents, we request that you answer the following questions, keeping in mind that:

- With the term ‘enterprise,’ we refer to the smallest organizational unit you work in, that is, an autonomous business unit in its investment decisions;
- With the term ‘digital data generation,’ we refer to the production or capture of data in digital form, from its inception. Example: the use of a personal digital assistant (PDA) by a waiter in a restaurant to collect orders from the customers to deliver to the kitchen is digital data generation, as opposed to the use of a note pad and a pen by the waiter to collect orders and take them to the kitchen, which is not digital data generation;
- With the term ‘effective,’ we mean ‘producing the desired effect.’

Please rate your level of agreement with the following items, on a seven-point scale ranging from one to seven, where one refers to 'not at all' and seven to 'yes, to a very large extent.'

|                          |   |   | Sales Managers   | IT Managers   |
|--------------------------|---|---|--|---|
| BDD Cap                  | Choosing IT (Williams, 2003)                  | 1 | Our sales personnel have effective methods for the choices of digital data generation.                                 | Our IT personnel effectively select Digital Data Generation Technology  |
|                          |   | 2 | The choices of digital data generation make their case for our sales process.  | Our IT personnel appropriately chose Digital Data Generation Technology                                       |
|                          | Integrating IT (Bharadwaj et al., 1999)       | 1 | The integration of digital data into the enterprise processes makes our sales personnel more effective.                | Digital Data Generation Technology is seamlessly integrated into our Sales processes                          |
|                          |   | 2 | Digital data generation is successfully integrated into our sales processes.   | Our IT personnel successfully integrate Digital Data Generation Technology into our Sales processes           |
|                          | Managing digital data (Marchand et al., 2002) | 1 | Our sales personnel effectively handle the digital data that they obtain.  |   |
|                          |   | 2 | Our sales personnel effectively process the data that they obtain in digital form.                                     |   |
|                          |   | 3 | Our sales personnel have effective methods for managing the digital data that they obtain.                             |   |
|                          | Reconfiguring (Pavlou & Sawy, 2006)           | 1 | When our digital data generation must evolve, our sales personnel successfully steer its evolution.                    | When our Digital Data Generation Technology must evolve, our IT personnel successfully steer its evolution    |
|                          |   | 2 | When our digital data generation must evolve, our sales personnel effectively lead its reorganization.                 | When our Digital Data Generation Technology must evolve, our IT personnel effectively lead its implementation |
| Organizational processes | Sensing (Pavlou & Sawy, 2006)                 | 1 | Our sales personnel effectively look for new business opportunities.   |   |
|                          |   | 2 | Our sales personnel effectively observe customers' preferences.  |   |
|                          |   | 3 | Our sales personnel effectively gather feedback from our partners.   |   |
|                          | Learning (Pavlou & Sawy, 2006)                | 1 | Our sales personnel effectively put into practice recently acquired knowledge.   |   |
|                          |   | 2 | Our sales personnel are effective in applying new knowledge.   |   |
|                          |   | 3 | Our sales personnel effectively employ new knowledge about our customers.  |   |
|                          | Coordinating (Pavlou & Sawy, 2006)            | 1 | Our sales personnel effectively coordinate their different work activities.  |   |
|                          |   | 2 | Our sales personnel set up a well-coordinated team.  |   |
|                          |   | 3 | Each member of the sales department effectively coordinates with the rest of the sales department.                     |   |
|                          | Integrating (Pavlou & Sawy, 2006)             | 1 | Each member of the sales department effectively integrates his or her job with others towards a collective result.     |   |
|                          |   | 2 | Each member of the sales personnel promptly contributes in the collective solution of the sales department's problems. |   |
| Firm history             | IT capability (Fink & Neumann, 2007)          | 1 | In the recent past, our IT personnel have proven effective in developing IT applications.                              | In the recent past, our IT personnel have proven effective in carrying IT projects                            |
|                          |   | 2 | In the recent past, our IT personnel have proven effective in exploiting IT.   | In the recent past, our IT personnel have proven effective in leveraging IT                                   |
| Firm assets              | IT infrastructure (Fink & Neumann, 2007)      | 1 | The range of our communication technologies (e.g., websites, call centres, telephony) has widened over time.           |   |
|                          |   | 2 | The range of our information technologies (e.g., applications, software, servers) has widened over time.               |   |

|                |  |   |  |  |
|----------------|--|---|--|--|
|                |  | 3 | The range of our network technologies (e.g., broadband, intranet, extranet) has widened over time. |  |
|                | Information repository (Freeze & Kulkarni, 2005) | 1 | Our information repositories span over a long period of time.                                      |  |
|                |  | 2 | Our information repositories cover a long history of events.                                       |  |
|                |  | 3 | Our information repositories have been long standing.  |  |
| BDD Cap Output | Digital data accessibility (Zimmer et al., 2007) | 1 | Our digital data are rapidly available to our sales personnel.                                     |  |
|                |  | 2 | Our digital data are easily obtainable for our sales personnel.                                    |  |

**Appendix B: A list of abbreviations used in the paper**

|      |  |
|------|--|
| AVE  | average variance extracted                           |
| B2B  | business to business                                 |
| BI&A | business intelligence and analytics                  |
| DC   | dynamic capability BDD          digital data genesis |
| IT   | information technology                               |
| NPD  | new product development                              |
| PDA  | personal digital assistant                           |
| PLS  | partial least squares                                |
| RFID | radio frequency identification                       |
| SPSS | IBM software used for the analysis                   |