Has the development of the Digital Data Genesis dynamic capability effect on data quality and data accessibility?

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Abstract. In the big data era, huge amount of data are created in digital forms. Due to the frequent technological changes and developments that are happening in this era, organisations need to constantly match with market changes. Therefore they need to develop dynamic capabilities based on digital data, in order to reach valuable outputs. Specifically, this study examines whether the development of the Digital Data Genesis dynamic capability in firms leads to valuable outputs: data quality and data accessibility. We empirically test our model using a questionnaire-based survey answered by 125 sales managers. Results suggest that firms able to develop dynamic capabilities based on digital data obtain higher outputs in terms of data quality and accessibility. Managerial implications of our results are finally offered.

Keywords. Digital Data Genesis; dynamic capabilities; data quality; data accessibility.

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1. Introduction

In the big data era, huge amount of data are created in digital forms every day [1]. Managers have the opportunity to measure, and hence know, radically more about their businesses, their customers’ tastes, and needs, by analyzing digital data. Explaining whether and how leveraging on the capability of exploiting digital data can be a way for firms to achieve success and higher outputs is becoming an evergreen issue in management and Information Systems fields.

Previous studies have conceptualized various types of capabilities, categorizing them in generic, organizational, ordinary, dynamic, heterogeneous, and homogeneous [2]. However, in the big data era, since market changes occur very quickly, focusing on the development of dynamic capabilities at firm level, based on the exploitation of digital data, is becoming even more important [3]. Therefore, in this article, we seek to contribute to the emerging literature on Information Technology (IT) dynamic capabilities investigating their linkage with possible outputs, as data quality [4] and data accessibility [5]. In so doing, we innovate in the choice of the dynamic capability object of our study: Digital Data Genesis (DDG). We define DDG as the coming into being of digital data. Specifically, DDG represents the naissance of digital data: it is a phenomenon (an observable fact or event) that involves the direct generation of new data in digital form, and takes place when information representative of a physical action, event or condition is created digitally concurrently with the event taking place. DDG thus enables real time digital representations of objects and events - so that these objects and events can exist as symbolic representations that can interact and be manipulated in the information space. For example, when a waiter takes an order using a palm device, an informational representation of the customer wishes is created in real-time in digital form.

Thus, since dynamic capabilities allow organizations to reconfigure organizational capabilities in response to changes in the business environment, and since data is a precursor to many organizational processes, we decided to study DDG dynamic capability and their output at firm level.

2. Theoretical background and hypotheses development

In the bog data era, more than before, organisations need to constantly match market changes by developing dynamic capabilities, defined as “the firm’s processes that use resources - specifically the processes to integrate, reconfigure, gain and release resources - to match and even create market change” [6]. Thus, dynamic capabilities have the potential to create, to evolve and to recombine internal existing resources to allow the firm to adapt continuously to changes [7]. This adaptability has been argued as offering improved customer value [8], and is especially required in fast-paced technological environments [9].

We define DDG dynamic capability as the four-fold organizational process of: 1) “choosing IT” in order to unobtrusively generate and capture data in digital form; 2) “integrating IT” in the existing processes; 3) “managing digital data” so produced; and 4) “reconfiguring IT” in the appropriate business processes. The technology embedded in a DDG initiative may be emerging IT - a new technology not yet commercially viable (e.g., retinal implants for blind people) - or may be an enabling IT: an established technology used by a firm in an innovative application (e.g., RFID in gaming chips to track table play in a gambling context).

We theorize DDG as a dynamic capability for two complementary reasons. First, it consists of deploying "new configurations of operational competencies relative to the competition" [10] - in other words, a firm with a DDG dynamic capability can identify opportunities for digital data generation and for recombining internal existing resources and data to adapt to changing environmental conditions, through the collection and production of new digital data. Second, the DDG dynamic capability includes the dynamic reconfiguring of the existing combinations of resources for digital data generation [10]. The degree to which an ineffective DDG process can be reconfigured into a more promising one that matches its environment, better, faster, and cheaper than the competition determines the capability's dynamic quality [6]. Therefore, the higher its degree of reconfigurability, the more dynamic the DDG dynamic capability is. Examples of DDG dynamic capabilities exist, such as the Harrah Corporation. For several years, Harrah has systematically and repeatedly integrated new IT (such as computerized slot machines or RFID chips) to gain - unobtrusively, and always in new ways - valuable digital data on customers' behavior at the Harrah's casinos and has exploited these new data to improve its customers' profiles and to better reward customers.

Furthermore, DDG dynamic capability may aim at outputting accessible, accurate, complete and current digital data. The use in, for example, analytical processes of the gained digital data will depend on their accessibility, accuracy, completeness and currency ([11], [12], [13]). Specifically, information accessibility is the extent to which an individual perceives that any particular source is available for use [13]. Information accessibility is the most important driver for information source selection for use, with people consistently choosing and using lower-quality sources that are more accessible over higher-quality sources that are less accessible ([11], [12], [13]).

Since DDG enables informational representations of real objects, facts, and events without any significant delays (i.e., in real time), the digital format of these representations may increase their accessibility, which means that the direct output of DDG can be accessible digital data, which can be exploited for various purposes such as information processing [14], sophisticated analytics [15] and 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 [16].

Also information quality is important because when sources are equally accessible, individuals will consistently choose and use sources that are perceived of higher quality ([16], [12]). Information Accuracy, Completeness and Currency are dimensions of the quality of the information retrieved from an information system ([18], [4]). Accuracy refers to the degree to which information correct, unambiguous, meaningful, believable, and consistent. Completeness is about the degree to which all possible states relevant to the user population are represented in the

stored information. While currency concerns the degree to which information is up-to-date and precisely reflecting the current state of the world that it represents.
Harrah's corporation appreciates the quality and accessibility of the collected data on customers at the slot machines. Basing on the accessibility, accuracy, completeness and currency of the accumulated transactional data from past guests, Harrah's can quickly estimate the customer's future value within minutes of the player joining the program. This enables the casino to start treating the customer according to his or her future value rather than having to wait for observed play before starting to provide rewards [19].
Based on these considerations, the hypotheses we propose are following listed:
H1: The development of high DDG dynamic capability will positively influence the data accessibility.
H2: The development of high DDG dynamic capability will positively influence the data quality.

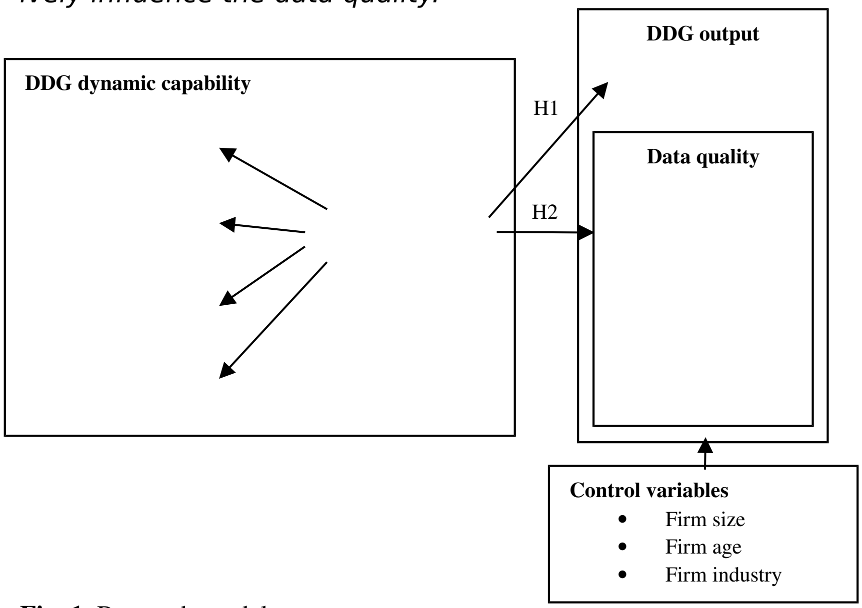

Fig. 1. Research model

3. Methodology

3.1 Data collection

To test our hypotheses, we conducted a questionnaire-based survey between 2012 and 2013 that was delivered to firms located in Western Europe.

Because dynamic capabilities are best measured at the organisational-process level [20], we surveyed sales managers. We made this choice because sales departments tend to be advanced with respect to the DDG phenomenon relative to other firm departments because of their focus on customer relations, in particular [19]. In addition, we operationalised the model constructs using existing measurement scales that had previously been tested, with the exception of the Choosing IT dimension of DDG dynamic capability. This construct measured firms' ability to select IT to unobtrusively collect valuable digital data. We conducted a pilot study, beginning with four indicators from the prior literature [21] that had not been previously tested empirically. We recruited 35 managers from small, medium, and large enterprises in different industries in the US. Our 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.

Before the main data collection, we consulted an expert panel and used Q-sorting methods both to adapt the chosen scales to our research context and to assess the scales' content validity. The expert panel included seven sales managers who proposed and validated adaptations of the items with respect to each construct. The Q-sorting involved four rounds of refinement before we reached a threshold of 50 per cent of attributions to the correct construct for each item. One hundred and nineteen respondents (primarily employees of different organisations between 20 and 40 years of age, equally distributed between men and women) participated in the Q-sorting procedure.

We consulted three sources to ensure heterogeneity in the sample, thus facilitating the generalisation of our results. First, we surveyed 220 sales managers using contacts from customer-relations management applications maintained by a French business school. Most of those sales managers worked in the Rhône-Alpes region in which the business school is headquartered. Second, we listed 402 organisations from the Piedmont region of Italy that previously had participated in an Italian engineering school's survey in that same region. Third, we gathered a selection of 370 organisations from Italy's Veneto region, which represented various corporate trade-union members in that region and ensured diversity of organisational sectors and sizes. Our complete sample pool thus included 942 organisations; we contacted these organisations by telephone or e-mail to request their participation. Data were primarily collected over the telephone or through face-to-face interviews, although a few respondents chose to answer autonomously by accessing an online questionnaire. In this latter case, three weeks after the initial mailing, we sent a reminder postcard to sales managers asking them to complete the survey if they had not previously done so. We also said that we would provide the results of the study to those who completed the questionnaire. 125 questionnaires from different organisations (an overall response rate equal to 21%) were analysed. Such a high response rate is uncommon in survey research [22].

3.2 Measurement

All the research variables that constitute the DDG dynamic capability were measured using multi-item Likert scales from 1 (not at all) to 7 (to a large extent) based on prior empirical research (Table 1) with the exception of the “Choosing IT” construct, which we empirically tested directly through our pilot study.
“Integrating IT” adapts the ability to integrate IT solutions into business processes [23]. “Managing digital data” adapts the information-management dimension of the information capability measurement scale [24] to measure the ability to manage digital data. “Reconfiguring” adapts the reconfigurability measurement scale [25] to estimate the potential to reconfigure DDG dynamic capability. The final construct, DDG dynamic capability, was measured as a second-order construct based on the four components of DDG dynamic capability, each of which was compounded as the mean of the related items.
Looking at the outputs, data quality was measured through three variables: data accuracy, data completeness, and data currency [4]. Instead, data accessibility was based on the measure proposed by Zimmer et al., 2007 [13].

Table 1 Survey items for testing the model

Construct	Item	Survey questions	Source
Choosing IT (CIT)	CIT1	Our sales personnel have effective methods for DDG choices	[21]
	CIT2	DDG choices make their case for our sales process	[21]
Integrating IT (IIT)	IIT1	The integration of digital data into the enterprise processes makes our sales personnel more effective	[23]
	IIT2	DDG is successfully integrated into our sales processes	[23]
Managing digital data (MDD)	MDD1	Our sales personnel effectively handle the digital data that they obtain	[24]
	MDD2	Our sales personnel effectively process the data obtained in digital form	[24]
	MDD3	Our sales personnel have effective methods for managing the digital data that they obtain	[24]
Reconfiguring (REC)	REC1	When our DDG must evolve, our sales personnel successfully steer its evolution	[25]
	REC2	When our DDG must evolve, our sales personnel effectively lead its reorganisation	[25]
Data Accuracy (AC)	AC1*	Our digital data are incorrect	[4]
	AC2	Our digital data contain very few errors	[4]
	AC2	Our digital data are accurate	[4]
Data Completeness (CO)	CO1*	Our digital data are incomplete	[4]
	CO2	Our digital data are comprehensive	[4]
	CO3	Our digital data cover all our data needs	[4]
Data Currency (CU)	CU1	Our digital data are recent	[4]
	CU2	Our digital data are up-to-date	[4]
	CU3*	Our digital data are obsolete	[4]
Data Accessibility (AE)	AE1	Our digital data are rapidly available to our Sales personnel	[13]
	AE2	Our digital data are easily obtainable for our Sales personnel	[13]

* The variable was reversed while computing the final factor

We introduced also control variables in the models: firm size (number of employees), firm age (number of years since each company was founded), and firm industry (four dummies for the four industries following list: traditional manufacturing, high-tech manufacturing, material services, and information services).

3.3 Data analysis

We employed SmartPLS and SPSS software for our data analysis. We choose PLS in SmartPLS as "the most accepted variance-based structural equation modelling technique because it can accommodate models that combine formative and reflective constructs" [26]: p. 1342). The PLS path modelling technique with reflective indicators in Smart-PLS was used to assess the validity and reliability of the data [27] complemented with SPSS calculations. This approach was better equipped to handle formative measures ([28]; [29]). Modelling moderating relationships in PLS required adding moderating variables as direct relationships to outcome variables and then calculating interaction variables based on the predictor variables.

4. Results and Analysis

4.1 Respondent characteristics

As can be observed by Table 2, the sample of our study was balanced.

Table 2 Respondent characteristics

Characteristics		Frequency	Percentage
Industry type	Traditional manufacturing	41	32.8%
	High-tech manufacturing	24	19.2%
	Material service	32	25.6%
	Information service	28	22.4%
Number of employees	1	2	1.6%
	2 to 9	12	9.6%
	10 to 49	42	33.6%
	50 to 199	36	28.8%
	200 to 499	10	8.0%
	500 to 1999	13	10.4%
	2000 and more	10	8.0%
Firm age	1-10 years	21	16.8%
	11-20 years	43	34.4%
	21-30 years	27	21.6%
	31-40 years	18	14.4%
	41+ years	16	12.8%
Country	France	60	60.0%
	Italy	40	40.0%
Respondent	Sales department director	36	29.0%
	Senior sales managers	15	12.0%
	Mid-level sales managers	15	12.0%
	Business unit managers responsible for sales	18	14.0%
	Others sales employees	41	33.0%

Specifically, the companies surveyed cover four industry groups [27] and were almost homogeneously distributed. The majority of the surveyed companies are between 11 and 20 years of age, with the oldest at 77 years old[1]. In terms of the countries in which firms operate, the sample is balanced. Finally, the sales-manager respondents are primarily sales-department directors.

4.2 Tests for validity and reliability of the measures .3 provides information about the psychometric properties of variables used in this study.

Table 3 Psychometric table of measurements

Construct	Item	Loading	CR	AVE	CA
Digital Data Genesis dynamic capability (DDG DC)			0.936	0.786	0.909
	CIT	0.869			
	IIT	0.843			
	MDD	0.948			
	RIT	0.883			
Choosing IT (CIT)			0.908	0.832	0.779
	CIT1	0.914			
	CIT2	0.910			
Integrating IT (IIT)			0.827	0.706	0.728
	IIT1	0.879			
	IIT2	0.799			
Managing digital data (MDD)			0.942	0.843	0.879
	MDD1	0.937			
	MDD2	0.917			
	MDD3	0.900			
Reconfiguring IT (REC)			0.946	0.898	0.871
	REC1	0.945			
	REC2	0.950			
Data accuracy (AC)			0.824	0.615	0.604
	AC1	0.605			
	AC2	0.835			
	AC2	0.885			
Data completeness (CO)			0.838	0.635	0.689
	CO1	0.669			
	CO2	0.855			
	CO3	0.853			
Data currency (CU)			0.837	0.633	0.636
	CU1	0.836			
	CU2	0.822			
	CU3	0.724			
Data accessibility (AE)			0.905	0.827	0.747
	AE1	0.906			
	AE2	0.913			

Note: CR = Composite reliability; CA = Cronbach's alpha; AVE = Average variance extracted

In a confirmatory factor analysis, the loadings of the measures on their respective constructs ranged from 0.605 to 0.948. We checked the recommended levels for reliability (measured by composite reliability and Cronbach's alpha) and average variance extracted (AVE). Nunnally (1978) [31] suggests a value of 0.70 as a benchmark for modest composite reliability. Churchill (1979) [32] suggests that a

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Cronbach's alpha value of 0.6 is acceptable. Bagozzi and Yi (1988) [33] suggest that AVE must be higher than 0.50.

In this study, factor loadings, composite reliability and AVE values were generated as a part of the SmartPLS output. Using SPPS18, the Cronbach's alpha scores were computed. The composite reliability (CR) of all constructs range from 0.824 to 0.946, Cronbach's alphas ranged from 0.604 to 0.909, and AVE ranged from 0.615 to 0.898, all acceptable results because they are of higher values than the acceptable thresholds. These results demonstrate convergent validity in the measurement model.

The square root of average variance extracted for each construct was compared with the correlations between it and other constructs [34]. Each construct shared greater variance with its own measurement items than with constructs having different measurement items. Therefore, discriminant validity was also supported.

4.3 Tests of the research model

The results of the structural model assessment in SmartPLS are presented in Table 4. Our results supported Hypothesis 1: the development of Digital Data Genesis dynamic capability has a significant positive effect on data accessibility (β=0.385, t=4.654, p-value<0.001). Further, results support Hypothesis 2: the development of Digital Data Genesis dynamic capability has a significant positive effect on data quality. Path coefficients of data accuracy, data completeness and data currency are all positive and significant. Specifically, the path coefficients are respectively equal to 0.355, 0.269, and 0.366, and all of them are significant with a p-value less than 0.001

Table 4 SmartPLS results

Independent variable	Dependent variable	Path Coefficient	t-value	Significance	Hypothesis	R-Square
DDG DC	Data accessibility	0.385	4.654	***	H1	18.10%
DDG DC	Data accuracy	0.355	3.297	***	H2	12.80%
DDG DC	Data completeness	0.269	2.431	**	H2	17.20%
DDG DC	Data currency	0.366	3.958	***	H2	14.80%

Note: *** denotes p-value < 0.001; ** p < 0.01; * p < 0.05.

5. Discussions

The study results highlight that the theorization of DDG dynamic capability, as a four-fold organizational process, is supported by the empirical data analysis. More importantly, DDG dynamic capability aims at outputting accessible, accurate, complete and current digital data. The data analysis confirms that DDG dynamic capability releases information resources of higher quality and of higher accessibility. Hence, this better output could be levered to match or create market changes,

as expected by dynamic capabilities [6]. Thus, DDG dynamic capability could potentially create, as follow-up, significant data output.
DDG dynamic capability makes the information more accessible, hence easily available for use. As far as, information accessibility is the most important driver for information source selection for use, the quality of the digital data coming out from the DDG are at stake. Otherwise low quality but easily accessible digital data would make the worst combination ([10], [12], [13]). Notwithstanding, DDG dynamic capability increases also the accuracy, the completeness and the currency of the digital data. Hence, in synthesis DDG dynamic capability delivers higher quality data.
These results have important managerial implications. Companies could successfully exploit their DDG dynamic capability to develop data-based strategic initiatives, comforted by their high data quality and data accessibility. Indeed, managers of firms should become more aware about the potentiality that the usage of digital data can have on the activities that they conduct and should invest more in the capability of using digital data since it increases data accessibility and quality.

6. Conclusions

The Information Systems literature provided less empirical studies that investigated the relationship between the development of dynamic capabilities based on digital data, and their output in the big data era. By analysing a sample of 125 companies, we find that DDG capability is associated with several outputs as data quality and data accessibility.
Specifically, DDG capabilities make digital data more accessible and of higher quality to the organisation's personnel. Specifically, the development of a DDG dynamic capability enable companies to dispose of more accurate data, as fewer errors, of more complete data, since data become more comprehensive and not inconsistent, more current, since thanks to the continuous ability of generate digital data they are recent, up-to-data and not obsolete. They are also more accessible, since digital data are promptly and easily available to sales personnel. In this way, companies have updated data about their customers and can take advantage from timely and qualified information about their customers.

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