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Resource management in big data initiatives: Processes and dynamic capabilities☆,☆☆

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ABSTRACT

Effective management of organizational resources in big data initiatives is of growing importance. Although academic and popular literatures contain many examples of big data initiatives, very few are repeated in the same organization. This suggests either big data delivers benefits once only per organization or senior managers are reluctant to commit resources to big data on a sustained basis. This paper makes three contributions to the Special Issue's theme of enhancing organizational resource management. One is to establish an archetype business process for big data initiatives. The second contribution directs attention to creating a dynamic capability with big data initiatives. The third identifies drawbacks of resource based theory (RBT) and it's underpinning assumptions in the context of big data. The paper discusses lessons learnt and draws out implications for practice and business research. The paper's intellectual and practical contributions are based on an in-depth case study of the European ICT Poles of Excellence (EIPE) big data initiative and evidence from the extant literature.
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1. Introduction

This paper develops an archetype business process for big data initiatives and the roles required for effective big data resource management. The literature assumes processes for big data initiatives exist and that resources are managed accordingly. This assumption appears baseless as the literature lacks coherent processes for big data initiatives within which to manage resources. This concern is compounded by vast amounts of resources businesses (public, private and third sector) put into big data. The analysis identifies limitations in resource based theory in the context of big data initiatives.

This paper has three objectives; the first objective is to set out an archetypical business process for big data initiatives. The literature has several reported examples of big data successes, see for example Davenport (2013) yet, very few examples are of repeated success by the same organization. Big data appears to be a 'one off' incident in most organizations. This paper argues that for big data to be truly strategic, senior leaders need a process they can implement to ensure benefits are delivered from investments made in organizational resources for big data. Previous scholarly studies show little or no attention is given to proposing a coherent and sustainable process for implementing big data initiatives. The tradition of developing archetypes is established in the management literature (Greenwood & Hinings, 1993). More contemporary examples include studies of buyer and supplier archetypes (Kim & Choi, 2015).

The second objective is to examine roles in big data initiatives. The concern is that lack of clarity in various roles necessary for big data initiatives hampers organizations from using resources strategically. Conventional approaches to strategy suggest mission critical roles are carried out by organizations or their close partners. This paper argues that in big data programs many roles are outside organizations and the nature of relationships are more transitory than previous partner relationships formed through alliances, joint ventures or outsourcing agreements.

The third objective is to challenge mindsets related to big data resources. The concern is big data is implemented using resource based theory (RBT) thinking about organizational resource management. The paper argues big data overturns many of RBT's assumptions

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about resources to achieve competitive advantage. Yet, scholars face difficulties overcoming vested interests in research steeped in theories found wanting by big data. Agarwal and Dhar (2014) observe that while big data is premised on open access to data so that prior knowledge can be tested and falsified (Popper, 1963), academics base their work on data that they do not release for others to challenge or confirm those findings. RBT needs questioning in the context of big data.

This paper makes three contributions to big data. First is an archetype process for big data initiatives. Second is to direct attention towards big data as dynamic capability in organizations. Third is to explore limitations of RBT when applied to big data initiatives. The paper sets out implications for practice and business research.

Big data is a global phenomenon (Brumfiel, 2011). Big data has potential to increase economic returns by gaining deeper insights from oceans of data available. Various estimates of sources and volumes of data being produced include CISCO's estimate “by 2020, the gigabyte (GB) equivalent of all movies ever made will cross the global Internet every 2 minutes” (Cisco Visual Networking Index, 2016, p.4). Amazon, Google, Facebook, Twitter and other social media as well as telecommunications companies produce massive quantities of data. Data sources include smart phone applications, the internet of things, machines, meters and sensors that ubiquitously collect data. Big data has led to the creation of new technologies, methods, data capture applications, visualization techniques, and data aggregation capabilities. Drawing on established business intelligence, data mining and analytics practices, big data methodologies spawn new generations of algorithms and renew interest in mathematics, statistics and quantitative analysis.

Much of the extant research focuses upon defining big data in terms of Vs (exactly how many is outside this paper's scope): Volume, Variety, Velocity, Validity, Veracity, Value and Visibility (Erevelles, Fukawa, & Swayne, 2016; Power, 2014). Another significant area of study is big data infrastructure, namely technologies, analytics and methods organizations use to enable big data (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). Scholars recognize big data is more than a technological issue and, to be fully effective, big data needs to become part of the fabric of organizations (Davenport, Barth, & Bean, 2012). Big data should be incorporated into strategic activities such as marketing and new product development (Xu, Frankwick, & Ramirez, 2016). Others recognize big data affects organizational culture, as decision making becomes more evidence-based (Erevelles et al., 2016; Irani, 2010). The literature assumes big data is beneficial for all organizations and this may not be the case.

An assumption underpinning big data is that data is an asset. As with other assets, data can be used to improve competitiveness, innovation and efficiencies in organizations. These arguments by proponents of big data are not new. Organizations have been collecting, storing and analyzing data contained in customer relationship management, enterprise resource planning or human resource management systems. Organizations spent millions of dollars on implementing information management and data warehousing systems to own and control data. Data samples were used to predict future patterns simply because there was insufficient computing power to analyze large volumes and varieties of data. These conventional practices are termed small data (Mayer-Schönberger & Cukier, 2013).

This paper is structured as follows: first the literature is reviewed. Then, an empirical exemplar case of the European ICT Poles of Excellence (EIPE) big data initiative is presented. Next, the empirical example and literature is discussed to develop the process for big data, examine big data and dynamic capabilities and consider RBT's shortcomings. Finally, following implications for practitioners, the paper identifies limitations and presents brief conclusions.

2. Theoretical foundations

Three theoretical frames of reference are relevant to develop thinking about big data. These are knowledge based views of organizations, resource based theory and dynamic capabilities. These three approaches are chosen because individually they offer selective insights into the phenomenon of big data; collectively, they provide a frame to examine big data processes, relationships and resources. Prior research in knowledge management suggests big data may yield deeper understanding for strategic action. One of several critical resources in big data is data itself and RBT provides the Value, Rarity, Imperfect Imitability and Non-substitutability (VRIN) framework to consider strategic resources. RBT addresses issues of resource ownership, attributes of resources and, most importantly, enables discussions about big data's contribution to strategic advantage. Dynamic capabilities refer to ways in which organizations configure and continually reconfigure processes to achieve beneficial outcomes. Many big data examples in the extant literature refer to ‘one-off’ big data deployments. Dynamic capabilities suggest ways in which organizations, that want to exploit big data, reconfigure resources to make big data initiatives repeatable and sustainable rather than isolated events.

2.1. Knowledge-based view (KBV) of organizations

Knowledge management (KM) is firmly established in scholarly literature since the 1990s. Early works focused upon the nature of knowledge (Nonaka & Takeuchi, 1995), its contextual sensitivity (Lam, 2000) and knowledge based systems (Davenport & Prusak, 1998). KM is examined from multiple perspectives: strategy (Barney, 2001), organization (Choo, 1996) and capabilities (Kogut & Zander, 1992). Contemporary researchers use KM as a theoretical foundation to study effects of external turbulence on organizational structures (Liao et al., 2011). The ability of organizations to incorporate external information into innovations has received much research attention since Cohen and Levinthal's (1990) treatise on absorptive capacity. Camisón and Forés (2010) argue absorptive capacity is measured using various proxy measures such as patents filed (Zhang, Baden-Fuller, & Mangematin, 2007), number of publications (Mangematin & Nesta, 1999) and employees' educational qualifications (Caloghirou, Kastelli, & Tsakanikas, 2004). Camison and Fores use Zahra and George's (2002) constructs of absorptive capacity to develop four dimensions of knowledge capabilities: Acquisition, Assimilation, Transformation and Application. According to Filippini, Güttel, and Nosella (2012), knowledge management initiatives are “characterized by a set of methods (formal descriptions of objectives and tasks), roles (social structures and responsibilities), resources (human resources, time, and infrastructure), and organizational routines that enable either exploratory or exploitative learning” (p.318). More recently, Donate and de Pablo (2015) studied leadership effects on organizations' abilities to explore and exploit knowledge. They draw upon leadership literature, arguing that knowledge-oriented leadership is important to KM initiatives. Many KM initiatives focus on acquiring, analyzing and exploiting customer information. The growth of internal databases to capture customer information and access to external data from web based sources provides organizations with unprecedented opportunities to develop innovative and tailored offerings to customers and other stakeholders. Yet, turning data into meaningful information is proving highly challenging to organizations. Rollins, Bellenger, and Johnston (2012) conclude organizations are muddling through with managers dealing with decisions in front of them “rather than taking a longer-term planned approach” (p.763).

2.2. Resource-based theory (RBT)

Wernerfelt (1984) argues organizations overlook the effects internal resources have on competitive advantage, in favor of industry, market and product related factors. Barney (1986b) suggests internal resources are greater determinants of strategic advantage than external factors. Dierickx and Cool (1989) recognize the importance of internal resources; they posit resources deployed to achieve competitive advantage must be developed and accumulated within organizations and

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cannot be bought or obtained from markets. They distinguish between strategic non-tradable assets, which they describe as asset stocks, and asset flows, which can be purchased externally.

Barney (1986a) identifies resources that form sources of competitive advantage. He suggests strategic resources have four attributes - Value, Rarity, Imperfect Imitability and Non-substitutability. The degree of heterogeneity of resources influences the potential for sustainable competitive advantage (Conner, 1991). The suggestion is the first two attributes of VRIN, Value and Rarity, confer competitive advantage, whereas, Inimitability and Non-substitutability, when present in conjunction with the other two, confer sustainability.

Conner (1991, p.133) stresses "entrepreneurial vision and intuition" are required to determine which resources contribute to sustainable competitive advantage. Mahoney and Pandian (1992) (citing Hofer & Schendel, 1980), suggest the following resource types (1) financial resources, (2) physical resources, (3) human resources, (4) organizational resources (quality control systems, corporate culture, relationships), (5) technological capabilities. To Hofer and Schendel's list they add a sixth category of intangible resources (e.g. reputation, brand recognition, goodwill), citing Grant (1991).

The influence of internal factors such as conflict, cognitive biases of managers and inertia, on the deployment of strategic resources is highlighted by Amit and Schoemaker (1993). When making deployment decisions, managers contend with (1) uncertainty (2) complexity and (3) intra-organizational conflict. They suggest new firms challenge their own beliefs, approach the future more imaginatively and are better able to handle complexity.

An approach to strategy development that starts with resources, rather than industry analysis, is proposed by Grant (1991), who describes capabilities as "teams of resources" (p.110), and mentions their similarity to "organizational routines" (p.122). In relating resources, capabilities and organizational routines, together with factors of coordination, configuration and renewal, the general outline of Dynamic Capabilities emerges, which is discussed next.

2.3. Dynamic capabilities

Teece, Pisano, and Shuen (1997) define dynamic capabilities "as the firm's ability to integrate, build and reconfigure internal and external competences to address rapidly changing environments" (p.516). Several organizational characteristics limit the extent to which dynamic capabilities develop. Path dependencies influence choices available to managers. Firms, at various points in their history, make "long-term, quasi-irreversible commitments to certain domains of competence" (p.515). The capacity to reconfigure and transform in order to renew competences distinguishes dynamic capabilities from capabilities per se. Effective reconfiguration and transformation requires an ability to sense relevant environmental changes, constant surveillance of markets and technologies, willingness to adopt best practices and benchmarking. The more frequently an organization reconfigures and transforms its capabilities the greater the likelihood of achieving competitive advantage.

Eisenhardt and Martin (2000) argue dynamic capabilities present different profiles in high-velocity markets. Dynamic capabilities are simple, experiential and iterative, in contrast to more stable markets, where they are complex, analytic and linear. Thus, high velocity markets are characterized by non-linear and unpredictable change. In such markets, existing knowledge is less relevant and the challenge is to create innovative, situation specific knowledge. Organizations face difficulties where leaders use existing knowledge to generalize from past experiences (Argote, 2012). Organizations experiment to learn new knowledge and to innovate quickly. Ideas that are demonstrated to be ineffectual are abandoned. There is extensive reliance on real-time information, cross-functional relationships, multiple options, and intensive communication, all organized in ways that adjust as new knowledge becomes available.

Zollo and Winter (2002, p.344) propose "dynamic capabilities emerge from the co-evolution of tacit experience accumulation processes with explicit knowledge articulation and codification activities". Development of dynamic capabilities invokes mechanisms that go beyond tacit accumulation of experience. Implicit knowledge is articulated through collective discussion, debriefing sessions and performance evaluation processes.

Dynamic capabilities exhibit features associated with effective processes (Eisenhardt & Martin, 2000). Some common dynamic capabilities include product development processes, resource allocation processes and knowledge creation processes. These processes create webs of collaborations among various internal and external relationships to generate resource combinations to meet or exceed stakeholders' expectations (Hill & Jones, 1995). Organizations combine skills, data, technologies and expertise to create revenue producing products and services or to generate greater efficiencies. Dynamic capabilities, ultimately, foster new thinking within organizations.

This paper argues big data programs need to go beyond one-off initiatives and become a dynamic capability within organizations. The paper develops an architype business process, one that is standardized and repeatable, to operationalize big data initiatives. Likewise, changes to the process need to be understood so that differences in outcomes can be explained.

3. Empirical evidence

An in-depth, analytical retrospective of a specific big data initiative – the European ICT Poles of Excellence (EIPE) – was conducted. Methodologically, examining an exemplar case is a powerful way to make sense of an emergent phenomenon (Eisenhardt, 1989). Researchers grasp 'what happened' and, more importantly, delve below the surface to understand reasons actions were taken and implications of taking those actions (Schutz, 1967). Retrospective case studies enable those closest to actions to reflect on their choices and decisions after events so that considered evaluations are made of outcomes achieved. The EIPE case was developed over twenty four meetings and workshops (one of the authors had first-hand interaction and experience from its inception to conclusion). Initial meetings were with European Commission (EC) senior managers. At these meetings strategic objectives and tasks were defined. As the big data initiative progressed further meetings were held formally every six months and more regularly informally. The EC meetings established central questions that outcomes from the big data initiative would address. The workshops included representatives from research and science communities. Workshops achieved different outcomes: some generated ideas, others sense checked analytical methods such as mathematical and statistical calculations. All meetings and workshops were recorded and minutes circulated among attendees for comment and approval. The longest workshop lasted two days and the shortest about half a day. In addition to meetings and workshops, there were discussions with data providers to purchase data. These discussions were conducted by phone or via email. The case study and findings reported here are based upon direct access to and insights from a member of the big data initiative who was integral to developing and implementing processes carried out to complete EIPE. This source ensured that case analysis is built upon EIPE's data, published reports, tacit understanding and unpublished activities of those at the heart of EIPE's big data initiative. The intention is to cover relevant aspects of EIPE rather than reporting on every aspect of the initiative.

3.1. Context and background

The big data initiative, EIPE, was a major EC study into information and communications technology (ICT) research and development areas of excellence in Europe. The Commission sought to strengthen Europe's leadership in ICT and, in particular, to build upon existing

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assets, namely, ICT industrial clusters spread across member states. The EC's strategic intention was to intensify efforts in ICT R&D and innovation to develop a greater number of world class centers of excellence by 2020 (Commission of the European Communities, 2009). The initiative was commissioned by DG CONNECT and the JRC Institute for Prospective Technological Studies and took three year to complete (2010 – 2013). They wanted to know about current and future centers of excellence for ICT innovation and to identify geographical locations of centers of excellence to direct policy decisions about future investment strategies. Although many R&D and innovation clusters exist across Europe, no analytical methods were available to distinguish between them, to understand dynamic changes that occur to clusters over time and to assess policy decisions on investments.

3.2. Stages of the initiative

EIPE began with a need; broadly, to develop insights into European locations of R&D and innovation centers of excellence to inform policy decisions. The EC held several discussions internally to hone their needs and clarify the questions to be addressed by EIPE. The questions are (De Prato & Nepelski, 2013b):

- How is ICT R&D, innovation and economic activity distributed in Europe?
- Which locations are attracting new investments in the ICT sector?
- What is the position of individual European locations in the global network of ICT activity?

The big data project team, once appointed, undertook a number of preliminary meetings to ensure they understood the EC's requirements. The team prepared detailed project plans setting out stages of work and milestones. Formal reviews every six months as well as regular team meetings ensured EIPE met its milestones. The team organized expert workshops to scrutinize and validate methodologies as well as disseminate findings during and after EIPE formally closed.

EIPE consisted of four key stages. First, to define characteristics of R&D and innovation centers of excellence, which is important because the team focused on data to be gathered. The second stage developed appropriate statistical methods to analyze vast data volumes to be gathered. This stage was essential to identify centers of excellence. The third stage overlaid big data findings onto a map of Europe to locate centers of excellence. The fourth stage used data to perform more detailed analysis to inform policy makers.

One challenge for the project team was to define R&D and innovations centers of excellence. They found definitions in the literature were associated with terms such as clusters, industrial parks or districts, innovation regions and centers of excellence. These definitions were problematic for two reasons: one, they were inherently unquantifiable and did not lend themselves to being specified in terms of data; two, internationalization and global networking were lacking in definitions. To distinguish their work, the team used the term ICT Poles of Excellence and the working definition "European ICT Poles of Excellence are geographical agglomerations of best performing Information and Communication Technologies R&D, innovation and business activities, located in the European Union, that exert a central role in global international networks" (De Prato & Nepelski, 2013b).

Drawing upon the literature and definition, EIPE developed a framework to operationalize data collection (see Fig. 1). The framework consists of three ICT activities: R&D, Innovation and Business Activity and their measurable characteristics: Agglomeration, Internationalization and Networking.

The framework identified 42 indicators as the basis of empirical measurements (see Table 1).

Eight data sources were used to gather data on these indicators. Official data required to analyze activities and characteristics of EIPE did not exist and these eight were highly reliable and recognized data providers (see Table 2). Two criteria for selecting these data sources included acceptance and use of data by business and academic communities.

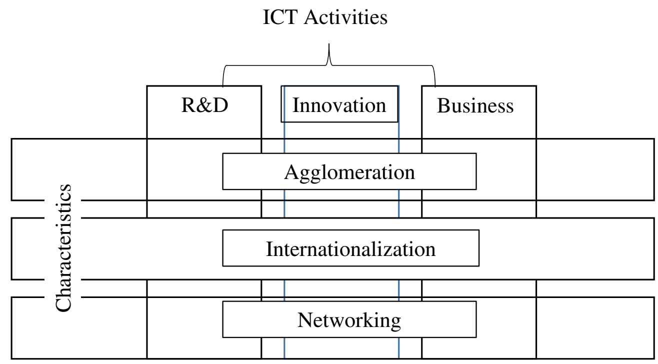

Fig. 1. The analytical framework used for the big data initiative.

Once indicators and data sources were defined, further levels of analysis were conducted for each indicator in terms of indicator measures, unit of measurement, definition of ICT dimensions, source and period of time that data was gathered. This analysis led to models and statistical methods used to examine large volumes and variety of data. The data set included, for instance, details on 120 million private companies, bibliometric data covering 11,000 journals and 40,000 inward investments to Europe from all over the world (see Table 3).

Table 1
List of indicators to measure PWCE.

Nr	Name of indicator
1	Universities ranked in the QS University Ranking
2	Academic ranking of a Computer Science faculty
3	Employer ranking of a Computer Science faculty
4	Citations ranking of a Computer Science faculty
5	R&D expenditures by ICT firms
6	FP7 funding to private organizations
7	FP7 participations
8	FP7 funding to SMEs
9	FP7 participations by SMEs
10	Location of ICT R&D centers
11	Ownership of ICT R&D centers
12	Scientific publications in Computer Science
13	Outward ICT R&D internationalization
14	Inward ICT R&D internationalization
15	Degree in ICT R&D network
16	Closeness centrality in ICT R&D network
17	Betweenness centrality in ICT R&D network
18	Eigenvector centrality in ICT R&D network
19	Investment in intangibles by ICT firms
20	Venture Capital financing to ICT firms
21	ICT patents
22	International co-inventions
23	Degree in ICT innovation network
24	Closeness centrality ICT innovation network
25	Betweenness centrality ICT innovation network
26	Eigenvector centrality ICT innovation network
27	Location of ICT Scoreboard Headquarters
28	Ownership of ICT Scoreboard affiliates
29	Location of ICT Scoreboard affiliates
30	Location of ICT firms
31	ICT employment
32	Growth in ICT employment
33	Turnover by ICT firms
34	Growth in turnover by ICT firms
35	New business investments in the ICT sector
36	Outward ICT business internationalization
37	Inward ICT business internationalization
38	In-degree in ICT business network
39	Out-degree in ICT business network
40	Closeness centrality in ICT business network
41	Betweenness centrality in ICT business network
42	Eigenvector centrality in ICT business network

Table 2
The variety of data sources used.

1.	QS World University Rankings by QS,
2.	FP7 database by EC DG Connect,
3.	Bibliometric: Web of Science by Thomson Reuters,
4.	ICT R&D centers locations: Design Activity Tool by IHS iSuppli,
5.	European Investment Monitor by Ernst & Young,
6.	Patent data: REGPAT by OECD,
7.	Company level information: ORBIS by Bureau Van Dijk,
8.	Venture Capital: Venture Source by Dow Jones

Data were drawn from a wide variety of sources; however, few of these were official EU data. Instead, data were extracted from private data sources. Data validity was achieved in two ways: firstly, using highly reliable providers and secondly, testing subsets of data for their veracity. In addition to eight primary sources, data was drawn from secondary sources such as an industrial scoreboard.

Detailed coverage of all analysis and statistical analytics carried out on data is beyond the scope of this paper and is available in technical reports (De Prato & Nepelski, 2013a). Nonetheless, for completeness an overview of significant indicators and a brief explanation of their construction is provided.

The project team set about creating indicators, where they did not exist, to measure activities and characteristics of EIPE. For example, to illustrate internationalization of innovation, patent-based indicators were used. These indicators are based on inventors residing in different regions of the world among lists of inventors on patent applications (Guellec & de la Potterie, 2001). International patent applications are defined as applications with at least two inventors residing in different countries. Hence, relationships between different locations can be described as the sum total of co-inventions developed by inventors residing in different regions from two different countries. Accordingly, the total number of patents co-invented by residents of region i in collaboration with researchers in other regions is

$$CoInn_i = \sum_{j \neq i} CoInn_{ij}.$$

Table 3
The volume of data gathered from data sources.

Name of data source	Description
Venture Capital: Venture Source by Dow Jones	This database contains information on venture capital transactions, the financed companies and the financing firms.
Regional Patent data: REGPAT by OECD	Patent data that linked to NUTS3/TLS3 regions according to the addresses of the applicants and inventors. Over 2000 regions are covered across OECD countries.
European Investment Monitor by Ernst & Young	Information on international investments in Europe by companies from all over the world. Since 1997, data is collected for all European countries and up to 2011, includes over 40,000 observations.
Company level information: ORBIS by Bureau Van Dijk	ORBIS (Bureau Van Dijk) contains comprehensive information on companies worldwide, with an emphasis on private company information. Orbis contains information on both listed and unlisted companies and has information on 120 million private companies.
ICT R&D centers locations: Design Activity Tool by IHS iSuppli	A company-level dataset including a list of R&D centers belonging to a number of high-tech companies together with their exact location and additional information on the type of R&D activity performed in these centers.
Bibliometric: Web of Science by Thomson Reuters	An online academic citation index designed for providing access to multiple databases, cross-disciplinary research, and in-depth exploration of specialized subfields within an academic or scientific discipline. It encompasses over 11,000 journals selected on the basis of impact evaluations. Coverage includes the sciences, social sciences, arts, and humanities, and across disciplines.
FP7 database by EC DG Connect	The analysis of the Framework Programme 7 programmes and participants is based on the database provided by the DG Connect in November 2011. Information on the FP7 is used and concerns only the ICT areas.
QS World University Rankings by QS	Formed in 2008, the QS World University Rankings® currently considers over 2000 and evaluates over 700 universities in the world, ranking the top 400.

3.3. Standardizing spatial units of observation

EIPE uses Nomenclature of Units for Territorial Statistics (NUTS) level 3 regional data as the unit of observation. NUTS is a European geocode standard to identify subdivisions of countries for statistical purposes. However, different data providers use different data formats when reporting names of organizations and therefore, location and geographic information, for instance, city, ZIP code, etc. were matched with its equivalent in NUTS's classification at level 3. This approach provided consistent indicators that were representative of EU member states and could be (dis)aggregated to desired levels, that is, NUTS 3 level.

3.4. Data aggregation: normalization and rescaling data

Before aggregating data, the team faced the problem that indicators are incommensurate with others and have different measurement units. For example, numbers of patent applications are expressed per capita, while share of ICT R&D centers owned by companies in a region is expressed as a percentage of total number of R&D centers owned by companies from a region.

To address this problem, indicators were made comparable by bringing them to the same measurement scale, by transforming them in pure, dimensionless numbers (Joint Research Centre-European Commission, 2008). In order to normalize EIPE data, a standardization method, namely z-scores, were used. Normalized scores were further rescaled to avoid negative scores and to assure incorporation of indicators' variability in results. This was done through the minmax rescaling procedure, whose formula is:

$$Nx_{rj} = \frac{x_{rj} - x_{j,\min}}{x_{j,\max} - x_{j,\min}} \times 100. \quad (1)$$

where Nx_{rj} is the normalized and rescaled value of indicator j in the territorial unit r, x_{rj} is the normalized raw value of indicator j in the territorial unit r, $x_{j,\min}$and $x_{j,\max}$ are the minimum and maximum values of indicator j.

3.5. Synthesising information

The selected indicators, their measurement and multiple rankings represent many of the Vs of big data: volume, variety, veracity and velocity. The sheer abundance and diversity of information made analysis at simple sight impossible. To provide comparable results for further analysis and interpretation, information contained in individual indicators was aggregated in two steps. First, the team created composite sub-indicators, for each activity: R&D, Innovation and Business. Second, a Poles of Excellence composite indicator was constructed, aggregating values of three sub-indicators in a final one.

The project team discovered a wide range of activities and participants in big data initiatives, including, clients, end users, data aggregators and visualization experts. These roles are widely dispersed with different organizations and individuals fulfilling these roles. On occasion, EIPE roles overlapped, for instance, data providers are also

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aggregators of data. Building a network of skills and capabilities was, in retrospect, an important aspect of completing EIPE.

4. Outcomes from the big data initiative

EIPE provides several results, of which two are discussed here. The analysis identifies the EU's top 34 R&D and innovation intensive regions. Of these, three regions – München Kreisfreie Stadt, Inner London East and Paris – were assessed to be first tier Poles of Excellence. Eight regions are second tier and 23 are third tier Poles of Excellence. These 34 regions are in twelve states: Germany, UK, France, Sweden, Finland, the Netherlands, Belgium, Italy, Ireland, Denmark, Austria and Spain.

Detailed analysis shows the importance of connectedness to other high performing regions. Paris, for instance, has direct connectivity to 541 separate R&D regions which is more than two thirds of regions. Taken together, the 541 regions form over 25,000 linkages which is about 90% of possible linkages. The results of connectedness of various regions are displayed in Fig. 2.

5. Lessons learned

Starting with an idea, EIPE big data initiative created a platform for answering questions relevant to policy and business decision makers and academics. A conceptual framework was created to gather competencies and methodologies and to integrate a number of tools and infrastructure. In other words, like recording a CD or writing software, development costs are high, while copying and distributing comes at a relatively lower cost.

Having gathered knowledge and accumulated necessary capabilities to operate such a platform, its maintenance creates additional value, for example, by providing nearly real-time information on R&D evolution and innovation in Europe. These insights help to understand dynamics of European ICT sectors and its position against other world regions. These kinds of insights address the original questions and suggest answers to questions not previously considered. Such information is useful to design appropriate responses in relatively short time. Thus, the platform would have enriched intelligence provided by the tool and offered a better basis for informed, evidence-based decision-making.

However, the above scenario did not materialize. Three years after formal completion of EIPE and once initial results were produced; EIPE came to its natural end. There were no further intentions or plans to maintain the platform. This decision was not related to the platform's intrinsic value. The initiative is still used by a number of organizations and individuals and has resulted in outputs that were initially not planned in the project. The authors are consulted occasionally on the initiative's methodology and results produced within the project. They receive requests for customized insights based on gathered data. Moreover, efforts to explore the application of EIPE's methodology to study of other sectors are on-going. This lack of support questions commitment

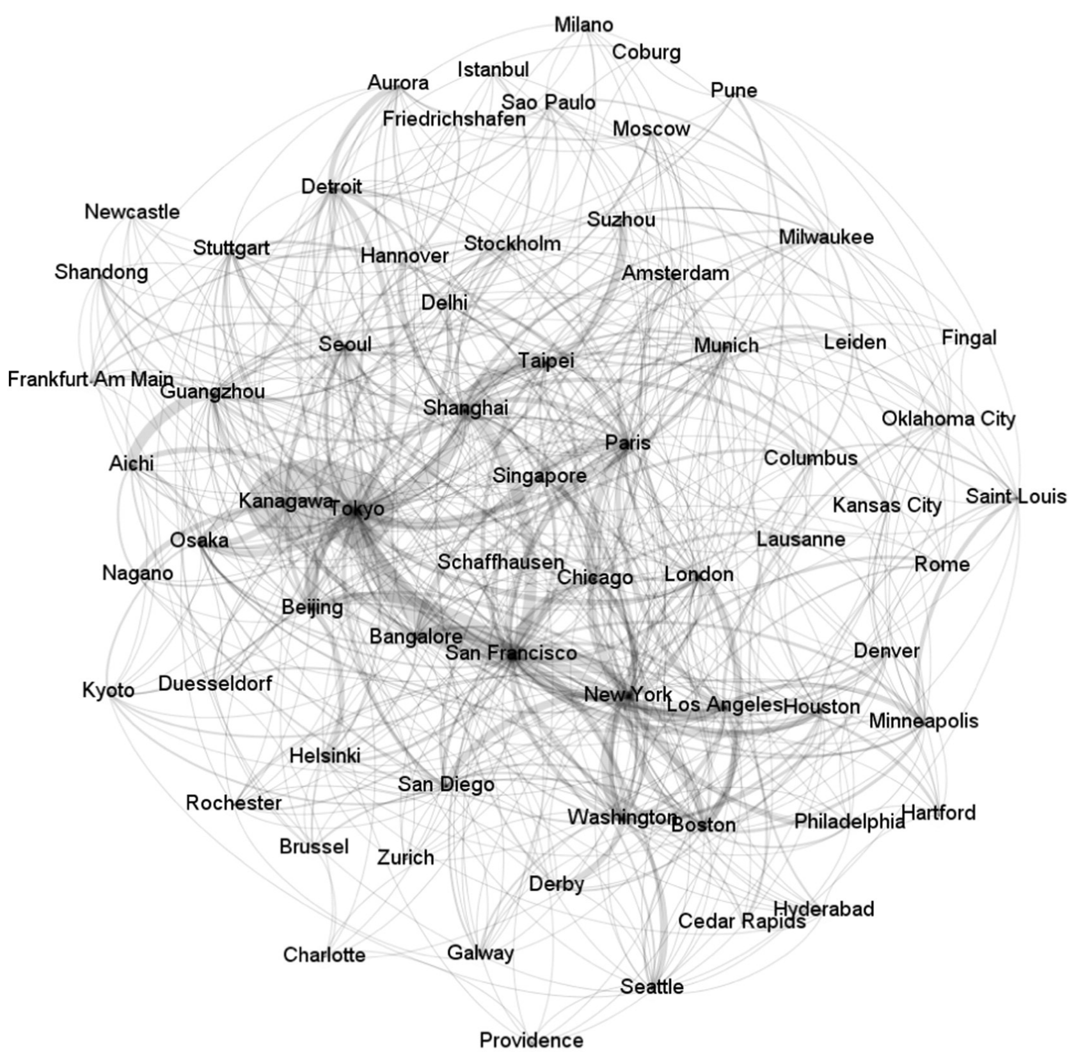

Fig. 2. Visualizing the connectedness of the Poles of Excellence regions.

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to integrate data-driven and evidence-based intelligence with organization's strategy and operations.

6. Discussion

Research shows many single instances of big data initiatives in organizations. There are few, if any, empirical examples of multiple big data initiatives in one organization. There are three possible reasons for this phenomenon. One, there is no apparent business process for big data initiatives. Two, resources required for big data initiatives are dispersed, often outside the organization's control. Three, big data relies on a range of roles brought together in a network of relationships. These relationships may be short-lived and fluid, which requires organizations to respond dynamically rather than periodically.

There are many definitions of business processes in the literature (Buchanan, 1997). For this paper, business processes are activities carried out to achieve one or more business objectives or purposes (Nelson & Winter, 2009). There does not appear to be a standardized process to manage big data initiatives. Drawing upon empirical evidence, big data process archetype is set out in Fig. 3.

The architype demarcates significant activities that organizations undertake during big data initiatives. The archetypical process appears as linear, step-by-step and axiomatic. However, in practice, implementing big data initiatives is complex and therefore activities in the process overlap, operate in parallel, are indistinct and have no clear start and stop points. Each stage requires feedback to adjust or correct prior assumptions as policy or strategic issues change. It is likely organizations iterate around activities concurrently during the implementation of big data initiatives.

Big data initiatives begin with issues business leaders consider important strategically. They, along with colleagues or big data experts, turn strategic issues into sets of questions they want answered. In the case of EIPE, the strategic aim is to increase world class European R&D centers from three to five. This aim leads to three questions, established above, big data analysis could answer.

Within each activity and at boundaries between activities, decisions taken significantly affect other activities in the process, outcomes and findings. One instance is Specify the Data activity. EIPE used eight data sources. Decisions for which eight to include and which others to reject affect datasets. Moreover, detailed choices and selections affect eventual results from big data initiatives. EIPE used QS's World Ranking of 400 universities. Arguably, another university ranking will have different institutions ranked at the top or the order of the same universities may have differed. The choice of data analytics leaves initiatives open to criticism because different methods lead to dissimilar results. Therefore, the process architype has an activity, Agree and Deploy Analytical and Statistical Methods. The inclusion or exclusion of indicators and use of measurements affects synthesis and reporting of findings. The activity Visualize the Information is an important aspect of EIPE, as shown in Fig. 2. The architype process requires senior managers to act upon results from the big data initiative, to implement plans and ensure benefits from big data are achieved. In EIPE's case, these activities are lacking. Few actions followed the report and recommendations from EIPE's big data initiative.

The EIPE case demonstrates the importance of taking systematic approaches to operationalize big data initiatives. This step includes rigorously documenting choices made and decisions taken within each activity in the process. For instance, creating records of assumptions made and rationale for selecting analytics enables those who repeat the process to understand prior decisions. Drawing on KBV of organizations, knowledge generated during big data initiatives is essential to develop longer term capabilities. This knowledge enables organizations to repeat big data initiatives and be better positioned to outsource big data activities.

Big data processes need to change due to perturbations in internal or external environments (Cepeda & Vera, 2007; Eisenhardt & Martin, 2000; Lin, Su, & Higgins, 2016). Changes to processes can be radical (in the tradition of re-engineering, cf. Hammer & Champy, 2009) or they can be improved in a systematic manner (Zollo and Winter (2002). The findings from EIPE points to routines as well as relationships changing (Wohlgemuth & Wenzel, 2016). For instance, a subsequent EU big data initiative would have different policy makers, with fresh questions that require novel analytical techniques (Pezeshkan, Fainshmidt, Nair, Frazier, & Markowski, 2016). Processes need to adapt to incorporate roles not part of earlier initiatives (Ray, Barney, & Muhanna, 2004), exemplified by interactions with data providers that work in dissimilar ways to previous providers.

Existing organizational capabilities affect big data initiatives depending upon actions that are implemented. At the end of EIPE, the EC were able to identify major R&D and innovation poles of excellence. Policy makers, EU officials, member state governments and local/regional governments may have been required to reconfigure their resources and capabilities (Teece et al., 1997). One essential requirement set out by dynamic capability scholars is for organizations to change in response to external and internal evidence. In the context of big data, these capabilities include changes to operational and tactical activities. For instance, where an organization's big data initiative suggests benefits can be gained from changes to supply chain activities, the organization would need to be reconfigure its warehouse, distribution and logistics capabilities. Big data initiatives test absorptive capacity

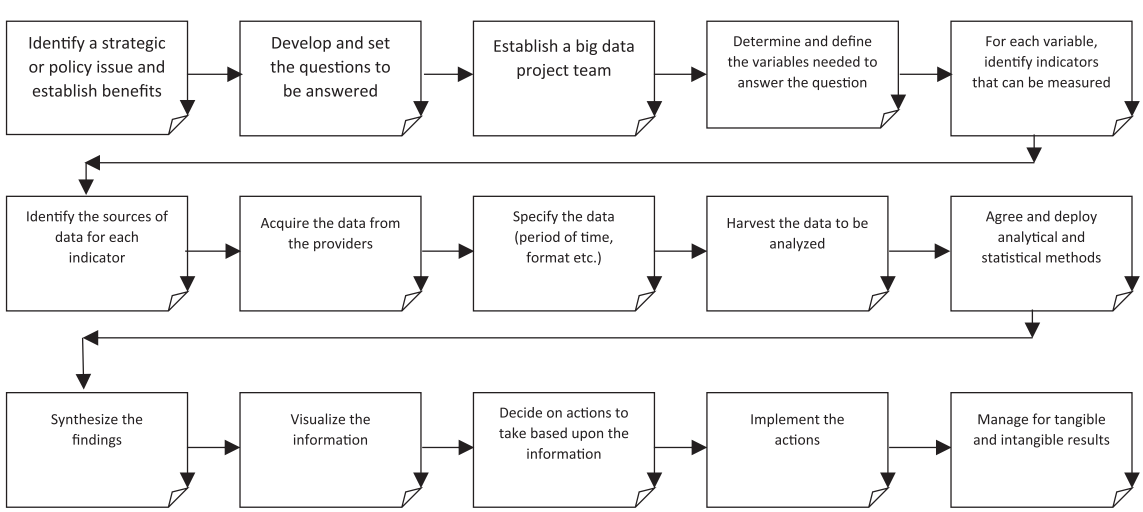

Fig. 3. An archetype big data business process.

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(Cohen & Levinthal, 1990) in terms of the ability to take action based on results from big data findings.

Resource based theory is premised on organizational resources enabling competitive advantage and performance innovations to be achieved when resources meet VRIN requirements (Barney, 1991). The theory assumes resources are owned or controlled by the organization. This theory provides a superficial explanation of big data initiatives. In RBT, resources are tangible or intangible. Tangible resources include physical capital, human capital and organizational capital which in big data contexts are exemplified by hardware, people such as data analysts and statisticians and internal organizational structures respectively. Intangible assets include knowledge, managerial skills, organizational goodwill and brand. In big data, these take the form of an organization's reputation being enhanced as a consequence a big data initiative.

The challenge to RBT is big data erodes the theory's VRIN assumptions. In big data initiatives, the core resource, data, is not rare. RBT suggests that where organizations have access to scarce resources, they use these rare resources to achieve competitive advantage. EIPE sourced data from eight providers. This data is available for anyone to access (possibly with payment) and use. Physical resources such as hardware, software, servers etc., are neither rare nor imperfectly inimitable. People with big data skills such as data scientists or individuals with highly developed mathematical, computational and statistical knowledge are harder to find. Yet, even these rare resources cannot be exploited, in RBT's sense of the word, as they can be poached by competitors. Many big data roles are carried out by actors outside the organization, which has little or no control over these resources. In EIPE, data providers, aggregators, experts and other resources important to the initiative were external, independent providers. Moreover, the EC did not own these resources. The paper posits that where any one VRIN element is not met, the extent to which big data can provide competitive advantage is limited. This argument is supported by existing studies that show some IT resources are more likely to provide competitive advantage than others. Delmonte's (2003) study of three technologies Electronic Data Interchange (EDI), Customer Relationship Management (CRM) and Knowledge Management Systems (KMS) – shows that only KMS meets all four VRIN elements. He concludes that KMS yields greater sustainable competitive advantage than EDI and CRM. In another study of RBV, Mata, Fuerst, and Barney (1995) examine four aspects of IT, namely capital requirements, proprietary technology, technical IT skills and managerial IT skills. They conclude that only managerial IT skills provide sustainable competitive advantage. In other words, not all aspects of IT meet VRIN requirements and those that fall short are less likely to provide sustainable competitive advantage.

As with all research, this paper has limitations. First, it examines one instance of big data, however, using a single exemplar case is long established in scholarly traditions. Eisenhardt (1989) distinguishes between statistical and theoretical generalizations and argues single case studies are a basis for theoretical generalization. The case is located in public policy and, arguably, RBV is better suited to business enterprises. Yet, RBV is used to study policy related factors (Morash & Lynch, 2002). Another limitation is EIPE is an EU research funded project. While there are differences between public/policy institutions and the private sector exist, contemporary literature shows drawing hard demarcation lines between the two is anachronistic – see for example, entrepreneurial universities (Raceanu, 2016) and shifts from Social Welfare State to Social Investment State (Viia et al., 2017). More research needs to be done with big data initiatives in dissimilar contexts such as private, public and third sectors.

7. Implications for practice

This research has implications for practitioners who are either planning to, or already implementing, big data initiatives. The overarching assumptions are that practitioners seek to optimize use of organizational resources dedicated to big data, achieve returns on investments made in big data initiatives and realize strategic or operational benefits from big data insights. This paper suggests that practitioners take a three phase systematic approach to big data initiatives while following processes conceptualized in Fig. 3: Phase 1 – commencement of big data initiative; Stage 2 – implementation of big data initiative; Stage 3 – benefits from big data initiative. Each stage is briefly elaborated:

7.1. Phase 1 – commencement of big data initiative

During this phase big data practitioners develop strategic or operational imperatives that the business needs to resolve or gain support to undertake speculative analysis of big data. This stage draws in people from a cross-section of the organization including, where possible, external stakeholders. The focus of these efforts is clarification of definitions, terms, outcomes and likely results. This phase sets criteria by which decisions are taken and choices made during later phases, for instance, in relation to different combinations of resources, providers and methods of visualizing results. Phase 1 is iterative, allowing discovery of potential analytical methods most appropriate to the initiative. Outcomes from this phase are clear definitions of problems or opportunities and questions to be answered from using big data. The production of a protocol to record all decisions and assumptions that underpin initiatives is critical to this phase. The big data protocol is particularly important where organizations plan to outsource their big data initiatives to third party businesses. One major reason outsourcing initiatives fail is because organizations enter into contracts with vague ideas of outcomes and actions they want from a vendor. Once big data outsourcing contracts are agreed, future changes to contractual arrangements can be expensive and could eliminate benefits gained from big data initiatives.

7.2. Phase 2 – implementation of big data initiative

At the core of this phase are decisions and choices made while conducting big data analysis. The creation of a 'trail of evidence' that sets out the rationale for choosing one set of options over another is critical during this phase. Choices made on the basis of pre-established criteria are documented as well as instances where criteria set in Phase 1 are changed. For instance, a Phase 1 criterion for selecting a data provider might be that their data exceeds a quality threshold. Where providers don't meet that criterion and therefore change, new selection criteria should be recorded to ensure future initiatives learn from decisions of earlier projects. Disputes that may arise, for instance, on choice of analytics used need to be resolved. The key outcomes of this phase are findings and insights from big data that are visually intuitive to address questions agreed in Phase 1.

7.3. Phase 3 – benefits from big data initiative

This phase may overlap or remain contiguous to previous phases. Findings are turned into plans that bring about changes to organizational resources needed to deliver results. People involved with and responsible for gaining benefits from big data are unlikely to be the same stakeholders involved in Phase 2. This phase requires management commitment to ensure change is implemented over time. Outcomes are evidenced in better economic returns, greater stakeholder satisfaction and/or greater operational efficiencies. Lessons learnt from this initiative are shared with future initiatives.

8. Future business research

The research presented here can be developed to further understanding of big data in organizational contexts. The paper open seams of research into actual processes organizations use in big data initiatives.

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Researchers gather empirical evidence from public, private and third sector organizations, nationally and internationally. Research into business aspects of big data such as decisions, processes and activities within business contexts remains largely unexplored. These empirical studies develop and refine the archetype big data process developed in this paper. Empirical evidence gathered through case study research complements much of the research into big data that scholars have published in disciplines such as computer science, technology, mathematics and statistics.

This paper shows that big data processes need to change dynamically in response to or in anticipation of external and internal influences. The study lays the groundwork for further work on dynamic capabilities and big data to map out ways in which organizations adapt and transform their capabilities based upon strategic insights they glean from big data initiatives. Researchers can examine causal relationships between findings from big data initiatives and changes required in organizations.

The extent to which big data is theoretically grounded is missing in the literature. This paper shows RBT may not be able to explain management of resources in big data initiatives. The conclusion is there is a significant amount of scope for researchers to examine big data through a variety of theoretical lenses. The aim is to encourage researchers to take this work forward, for example using institutional theory, stakeholder theory as well as other theories drawn from strategy and leadership fields.

9. Conclusions

Based on empirical data, literature and discussion three conclusions can be drawn: first, the archetype business process for big data initiatives provides a framework for effective resource management. The big data business process enables organizations to identify capabilities and roles required to ensure successful outcomes. Effective business processes overcome obstacles that prevent big data initiatives from being repeatable. Second, relationships between big data and dynamic capabilities is important because big data processes need to morph over time as organizations reconfigure or develop new capabilities to achieve results from big data insights. Therefore, big data processes cannot be allowed to ossify. Third, theoretical weaknesses of VRIN in the context of big data require further investigation to establish RBT's relevance to provide deeper insights into big data. The lasting contribution from this paper would be a greater number of big data initiatives successfully implemented, repeatedly, in the same organization.

To conclude:

1. Unless big data initiatives deliver repeated benefits in the same organization, the full potential of the big data phenomenon will be limited.
2. A reliable and sustainable big data business process is critical to initiatives being repeatable
3. Big data undermines tenets that underpin resource based theory; VRIN characteristics propounded by RBT are challenged by big data.
4. Dynamic capabilities in the field of big data are required at two levels: first, business processes and second, changes required to organizational resources to implement findings from big data analytics.

References

Agarwal, R., & Dhar, V. (2014). Editorial—Big data, data science, and analytics: The opportunity and challenge for IS research. *Information Systems Research*, *25*(3), 443–448.

Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. *Strategic Management Journal*, *14*(1), 33–46.

Argote, L. (2012). *Organizational learning: Creating, retaining and transferring knowledge.* Springer Science & Business Media.

Barney, J. B. (1986a). Organizational culture: Can it be a source of sustained competitive advantage? *Academy of Management Review*, *11*(3), 656–665.

Barney, J. B. (1986b). Strategic factor markets: Expectations, luck, and business strategy. *Management Science*, *32*(10), 1231–1241.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120.

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of Management*, *27*(6), 643–650.

Brumfiel, G. (2011). Down the petabyte highway. *Nature*, *469*(20), 282–283.

Buchananl, D. A. (1997). The limitations and opportunities of business process re-engineering in a politicized organizational climate. *Human Relations*, *50*(1), 51–72.

Caloghirou, Y., Kastelli, I., & Tsakanikas, A. (2004). Internal capabilities and external knowledge sources: Complements or substitutes for innovative performance? *Technovation*, *24*(1), 29–39.

Camisón, C., & Forés, B. (2010). Knowledge absorptive capacity: New insights for its conceptualization and measurement. *Journal of Business Research*, *63*(7), 707–715.

Cepeda, G., & Vera, D. (2007). Dynamic capabilities and operational capabilities: A knowledge management perspective. *Journal of Business Research*, *60*(5), 426–437.

Choo, C. W. (1996). The knowing organization: How organizations use information to construct meaning, create knowledge and make decisions. *International Journal of Information Management*, *16*(5), 329–340.

Cisco Visual Networking Index (2016). *The zettabyte era: Trends and analysis.* Cisco White Paper.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 128–152.

Commission of the European Communities (2009). *Strategy for ICT R&D and innovation in Europe: Raising the game (Vol. 116).* Office for Official Publications of the European Communities.

Conner, K. R. (1991). A historical comparison of resource-based theory and five schools of thought within industrial organization economics: Do we have a new theory of the firm? *Journal of Management*, *17*(1), 121–154.

Davenport, T. H. (2013). Keep up with your quants. *Harvard Business Review*, *91*(7/8).

Davenport, T. H., & Prusak, L. (1998). *Working knowledge: How organizations manage what they know.* Harvard Business Press.

Davenport, T. H., Barth, P., & Bean, R. (2012). How big data is different. *MIT Sloan Management Review*, *54*(1), 43–46.

De Prato, G., & Nepelski, D. (2013a). Identifying European ICT Poles of Excellence. *The methodology*. Seville: JRC-IPTS: JRC Scientific and Policy Reports - EUR 26264 EN.

De Prato, G., & Nepelski, D. (2013b). Defining European ICT Poles of Excellence: A literature review. *JRC technical reports – EUR 25694 EN*. Seville: Institute for Prospective and Technological Studies, Joint Research Centre.

Delmonte, A. J. (2003). Information technology and the competitive strategy of firms. *Journal of Applied Management and Entrepreneurship*, *8*(1), 115–129.

Dierickx, I., & Cool, K. (1989). Asset stock accumulation and sustainability of competitive advantage. *Management Science*, *35*(12), 1504–1511.

Donate, M. J., & de Pablo, J. D. S. (2015). The role of knowledge-oriented leadership in knowledge management practices and innovation. *Journal of Business Research*, *68*(2), 360–370.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, *14*(4), 532–550.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10 − 11), 1105–1121.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Research*, *69*(2), 897–904.

Filippini, R., Güttel, W. H., & Nosella, A. (2012). Ambidexterity and the evolution of knowledge management initiatives. *Journal of Business Research*, *65*(3), 317–324.

Grant, R. M. (1991). The resource-based theory of competitive advantage: Implications for strategy formulation. *California Management Review*, *33*(3), 114–135.

Greenwood, R., & Hinings, C. R. (1993). Understanding strategic change: The contribution of archetypes. *Academy of Management Journal*, *36*(5), 1052–1081.

Guellec, D., & de la Potterie, B. V. P. (2001). The internationalisation of technology analysed with patent data. *Research Policy*, *30*(8), 1253–1266.

Hammer, M., & Champy, J. (2009). *Reengineering the corporation: Manifesto for business revolution.* A. Zondervan.

Hill, C. W. L., & Jones, G. R. (1995). *Strategic management: An integrated approach. Vol. 3*, Boston, Mass: Houghton Mifflin Co.

Hofer, C. W., & Schendel, D. (1980). *Strategy formulation: Analytical concepts.* West Publishing.

Irani, Z. (2010). Investment evaluation within project management: An information systems perspective. *Journal of the Operational Research Society*, *61*(6), 917–928.

Joint Research Centre-European Commission (2008). *Handbook on constructing composite indicators: Methodology and user guide.* OECD publishing.

Kim, Y., & Choi, T. Y. (2015). Deep, sticky, transient, and gracious: An expanded buyer–supplier relationship typology. *Journal of Supply Chain Management*, *51*(3), 61–86.

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, *3*(3), 383–397.

Lam, A. (2000). Tacit knowledge, organizational learning and societal institutions: An integrated framework. *Organization Studies*, *21*(3), 487–513.

Liao, C., Chuang, S. H., & To, P. L (2011). How knowledge management mediates the relationship between environment and organizational structure. *Journal of Business Research*, *64*(7), 728–736.

Lin, H. F., Su, J. Q., & Higgins, A. (2016). How dynamic capabilities affect adoption of management innovations. *Journal of Business Research*, *69*(2), 862–876.

Mahoney, J. T., & Pandian, J. R. (1992). The resource-based view within the conversation of strategic management. *Strategic Management Journal*, *13*(5), 363–380.

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Mangematin, V., & Nesta, L. (1999). What kind of knowledge can a firm absorb? *International Journal of Technology Management*, *18*(3–4), 149–172.

Mata, F. J., Fuerst, W. L., & Barney, J. B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS Quarterly*, *19*(4), 487–505.

Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think.* Houghton Mifflin Harcourt.

Morash, E. A., & Lynch, D. F. (2002). Public policy and global supply chain capabilities and performance: A resource-based view. *Journal of International Marketing*, *10*(1), 25–51.

Nelson, R. R., & Winter, S. G. (2009). *An evolutionary theory of economic change.* Harvard University Press.

Nonaka, I., & Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation.* Oxford University Press.

Pezeshkan, A., Fainshmidt, S., Nair, A., Frazier, M. L., & Markowski, E. (2016). An empirical assessment of the dynamic capabilities–performance relationship. *Journal of Business Research*, *69*(8), 2950–2956.

Popper, K. R. (1963). *Conjectures and refutations. The growth of scientific knowledge. (Essays and lectures.).* London: Routledge & Kegan Paul.

Power, D. J. (2014). Using 'big data' for analytics and decision support. *Journal of Decision Systems*, *23*(2), 222–228.

Raceanu, A. R. (2016). Strategic public relations and university entrepreneurship in present European context. *Management Dynamics in the Knowledge Economy*, *4*(1), 81.

Ray, G., Barney, J. B., & Muhanna, W. A. (2004). Capabilities, business processes, and competitive advantage: Choosing the dependent variable in empirical tests of the resource-based view. *Strategic Management Journal*, *25*(1), 23–37.

Rollins, M., Bellenger, D. N., & Johnston, W. J. (2012). Customer information utilization in business-to-business markets: Muddling through process? *Journal of Business Research*, *65*(6), 758–764.

Schutz, A. (1967). *The phenomenology of the social world.* Northwestern University Press.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 509–533.

Viia, A., Toots, A., Mali, B.Č., Kerbler, B., Øverland, E. F., Terk, E., ... Sendi, R. (2017). Futures of European welfare models and policies: Seeking actual research questions, and new problem-solving arsenal for European welfare states. *European Journal of Futures Research*, *4*(1), 1–13.

Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, *165*, 234–246.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171–180.

Wohlgemuth, V., & Wenzel, M. (2016). Dynamic capabilities and routinization. *Journal of Business Research*, *69*(5), 1944–1948.

Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research*, *69*(5), 1562–1566.

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, *27*(2), 185–203.

Zhang, J., Baden-Fuller, C., & Mangematin, V. (2007). Technological knowledge base, R&D organization structure and alliance formation: Evidence from the biopharmaceutical industry. *Research Policy*, *36*(4), 515–528.

Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization Science*, *13*(3), 339–351.

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