Case research on the European ICT Poles of Excellence (EIPE) big data programme and the results of that research form the basis of the study's intellectual and practical contributions.

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Abstract:
It is becoming more crucial for organisations to efficiently manage their resources while pursuing considerable data efforts. There are numerous enormous data efforts in academic and popular literature, but relatively few are replicated within the same company. Therefore, the advantages of big data are one-time only per business, or top-level executives are hesitant to invest in big data. This study adds three new insights to the Special Issue's discussion on better managing organisational resources. The first is to create a standard operating procedure for big data projects. The second advancement emphasises using big data projects to build a dynamic capability. Third, problems with resource-based theory (RBT) and its underlying assumptions are highlighted about extensive data. Both practical and theoretical implications for future business studies are drawn from the paper's discussion of lessons learned. Evidence from the existing literature and an in-depth case analysis of the European ICT Poles of Excellence (EIPE) extensive data programme provides the basis for the intellectual and practical contributions of the research.

1. Introduction:

This article defines a standard business procedure for big data projects and the functions necessary for efficient management of large data resources. The literature takes as given the existence of mechanisms for big data projects and the proper management of allocated resources. Since there are no well-defined procedures for managing large data project resources in the existing literature, this claim seems to be without foundation. The fact that so many organisations invest so much money in big data further adds to these security concerns, which exist throughout the public, corporate, and non-profit sectors. The investigation highlights the shortcomings of resource-based theories in the setting of big data projects.

There are three goals for this article, the first of which is to outline a typical business process for big data efforts. There are a number of instances of big data triumphs described in the literature, however relatively few of them involve the same business experiencing success many times. The advent of big data looks to be a one-time occurrence for most businesses. This article claims that in order for big data to be genuinely strategic, top-level executives need a method for making sure their company reaps benefits from their investments in big data infrastructure. Little has been done in the way of academic research to provide a logical and long-lasting method for enacting big data efforts. Management literature has a long history of using archetype development. Studies of archetypical customers and vendors are more recent instances.

The importance of big data projects is the focus of our second aim. The worry is that firms can't use their resources strategically due to a lack of clarity in the numerous roles essential for big data efforts.

Traditional strategic thinking holds that organisations and their closest allies should be responsible for carrying out mission-critical functions. This study claims that traditional partner connections, such as those created via alliances, joint ventures, or outsourcing agreements, are more stable than the nature of partnerships in big data initiatives, where various roles are played by external companies.

Lastly, we want to change how people think about the value of big data. Big data implementations that are grounded on resource-based theory (RBT) assumptions about how to best manage an organization's assets raise certain red flags. According to the paper's findings, RBT's assumptions regarding the efficacy of various resource allocations for gaining a competitive edge are undermined by the advent of big data. Researchers, however, have a hard time putting aside their attachment to outdated beliefs that big data has shown to be wrong. noting that academics base their work on data that they do not provide for others to contest or corroborate those conclusions, but big data is predicated on free access to data to test and falsify existing knowledge. In the age of big data, RBT must be questioned.

There are three new insights on big data presented in this research. As a first step, we provide an archetype method for large data projects. The second is to highlight big data as an adaptable organisational capacity. Our third objective is to investigate the caveats of using RBT for large data projects. Business research and practical applications are discussed in the study.

2. Methodology:

The European ICT Poles of Excellence (EIPE) programme had a comprehensive, analytical retrospective completed on it. To better understand a novel phenomenon, it might be helpful to look at an illustrative case study. Researchers not only comprehend 'what occurred,' but also the underlying motivations for and consequences of the participants' behaviour. Case studies that look backwards allow individuals closest to the action to reflect on their judgements and actions after the fact, allowing for more objective assessments of results to be made. Over the course of twenty-four meetings and workshops, the EIPE case was built (one of the writers participated in all of these stages). The first round of meetings included high-ranking officials from the European Commission (EC). Strategic goals and actions were decided upon at these conferences. Every six months, official meetings were conducted to discuss the big data programme, and more frequent, ad hoc meetings were held as needed. Central questions to be answered by the big data project were developed during EC sessions. Workshop participants included researchers and scientists. In some workshops, participants developed new ideas, while in others, they tested analytical tools including mathematics and statistical computations. Minutes of all meetings and workshops were sent to participants for review and approval. The two-day workshop was the longest and the half-day programme was the shortest. Conferences and seminars were held, and conversations were held with data sources. These talks were held through phone or electronic mail.

Access to, and information from, a member of the big data project who was integral to planning and executing activities carried out to complete EIPE formed the basis for the case study and conclusions described here. Case analyses were based on the data, public reports, tacit knowledge, and unpublished actions of people essential to EIPE's big data project, thanks to this reliable source. The goal is to report on the most important components of EIPE, rather than covering every facet of the programme.

The European Commission's Big Data Initiative, or EIPE, was a comprehensive look at leading research and development in ICT throughout the continent. The Commission's goal was to further establish Europe as a global leader in information and communication technology by capitalising on the region's strengths, particularly its many ICT industrial clusters. The European Commission's long-term goal has always been to boost the number of top-tier research and development (R&D) facilities in the field of information and communication technology (ICT) by the year 2020. It took three years (from 2010 to 2013) for DG CONNECT and the JRC Institute for Prospective Technological Studies to accomplish the initiative. They sought information on existing and potential hubs of ICT innovation in order to better inform policy choices about where to allocate resources in the future. Despite the prevalence of research and development (R&D) and innovation clusters across Europe, there has been a lack of analytical tools with which to differentiate between them, comprehend the dynamic shifts that occur within clusters over time, and evaluate the effectiveness of policy decisions regarding investment.

The initial impetus behind EIPE was a desire to better inform policy choices with more accurate information on the locations of key research and development (R&D) and innovation hubs throughout Europe. Within the EC, several conversations were undertaken to sharpen the organization's requirements and make clear the questions to be answered by EIPE. The issues we're interested in answering are as follows:

- How are research and development (R&D), innovation (I), and economic activity (EA) in ICT
- Where are companies most likely to invest in the information and communication technology industry?
- Where do different European countries stand in terms of the worldwide web of ICT production and consumption?

Once in place, the big data project team had a series of preparatory meetings to ensure they were on the same page as the EC. The group built comprehensive blueprints outlining the project's phases, tasks, and milestones. EIPE was successful because of the formal evaluations performed at regular intervals (every six months) and the consistent team meetings held throughout the year. Throughout and after EIPE's official end, the team held expert seminars to review and evaluate methodology and disseminate results.

There were four major phases of EIPE. Since the team's primary focus was on the information that needed to be obtained, they began by defining the characteristics of leading research and development (R&D) and innovation facilities. The second phase included the creation of suitable statistical tools for analysing the massive amounts of data that will eventually be gathered. The ability to identify potential hubs of excellence relied heavily on this step. The final step included superimposing the results of the big data analysis onto a map of Europe to identify outstanding institutions. In the last phase, analysts dug deeper into the data to provide policymakers with actionable insights.

The project team had some difficulty defining research and development and innovation hubs. Clusters, industrial parks/districts, innovation areas, and centres of excellence were all phrases they came across while searching for definitions in the literature. These definitions were problematic for two reasons: first, they lacked definitions for internationalisation and global networking; and second, they were fundamentally unquantifiable and did not lend themselves to being stated in terms of data.

According to the team's 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 inter-national networks," the term "ICT Poles of Excellence" was coined to describe these hubs of innovation and excellence.

EIPE created a framework to operationalize data gathering based on existing research and their own characterization of the problem (see Fig. 1). The framework is comprised of three distinct ICT pursuits—research and development (R&D), innovation (I), and commercial activity (CA), as well as three observable features of each.

For this approach, we were able to zero down on 42 indicators that would serve as the foundation for empirical evaluations (see Table 1). On this analysis, we collected information for these indicators from eight distinct data sets. These eight were very credible and renowned data providers, but the official data needed to examine EIPE's actions and characteristics was not available (see Table 2). The acceptability and usage of data by the commercial and academic groups were two factors used to identify these sources.

After settling on a set of indicators and data sources, we dove further into each metric to determine its measurements, units of measurement, the dimensions of ICT by which they were defined, its data source, and the time frame for which it was collected. As a result of this study, new models and statistical techniques for analysing big datasets of varying types were developed. Details on 120 million private enterprises, bibliometric information for 11,000 publications, and 40,000 in- ward investments into Europe from throughout the globe were all included in the dataset (see Table 3).

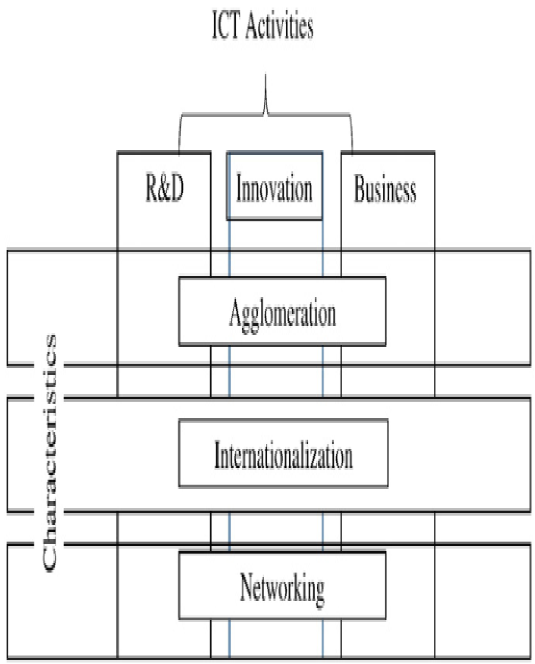

Fig. 1. The analytical framework used for the big data initiative.

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

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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.

The smallest observable unit for EIPE is at the regional level, using data from the Nomenclature of Units for Territorial Statistics (NUTS). For statistical reasons, European nations may be broken down into regions using the NUTS geocode system. Location and geo- spatial information, such as city, ZIP code, etc., were matched with its counterpart in NUTS's categorization at level 3, as reported by various data suppliers whose data formats vary. This method yielded stable indicators that were both representative of all EU member states and amenable to (dis)aggregation at any level, including the NUTS 3 level.

The team ran into trouble since the indications aren't comparable to one another and use different measuring units, so they couldn't combine them. The proportion of all R&D centres held by firms in an area that focus on information and communication technologies, for instance, is stated as a percentage of the total number of R&D centres owned by companies in the region.

Indicators were normalised so they could be compared to one another; this was accomplished by making them all fit into the same measuring scale by having them converted into pure, dimensionless numbers. Standardization techniques, namely z-scores, were used to achieve this normalisation of EIPE data. To prevent negative scores and ensure that the variability of the indicators was included into the findings, the normalised scores were rescaled further. The minmax rescaling method (whose formula is) was used for this.

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

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.

Many of the "Vs" of big data (volume, variety, veracity, and velocity) are reflected in the indicators chosen, their measurements, and the many rankings created from them. Because of the enormous volume and variety of data, a superficial study was just not feasible. The data included in the different indicators was aggregated in two stages to provide consistent findings for further investigation and interpretation. At first, the group developed R&D, innovation, and business composite sub-indicators. Second, we built a composite indicator called Poles of Excellence by combining the results of three individual indicators.

Clients, end users, data aggregators, and visualisation specialists were just few of the many roles the project team identified in big data endeavours. A vast variety of groups and people perform these functions. The EIPE responsibilities sometimes merged into one another, such as when data suppliers also acted as data aggregators. In hindsight, one of the most useful results of finishing EIPE was expanding one's personal and professional network of talents and abilities.

The EIPE yields several outcomes, two of which are mentioned here. The study ranks the top 34 R&D and innovation-heavy areas in the European Union. These were evaluated, and it was determined that the areas of Munich's Kreisfreie Stadt, Inner London East, and Paris were all first-tier Poles of Excellence. There are eight "Poles of Excellence" at the second-tier, and twenty-three at the third-level. There are a total of 34 areas represented here, spread over 12 different countries: Germany, the United Kingdom, France, Sweden, Finland, the Netherlands, Belgium, Italy, Ireland, Denmark, Austria, and Spain.

Connectivity to other high-performing areas is shown via in-depth investigation. As an example, Paris has direct connections to 541 R&D areas, or more than two-thirds of all regions. Together, these 541 areas make up more than 25,000 connections, or around 90% of all conceivable ones.

The EIPE big data effort began as a concept, and has now grown into a forum for addressing topics of interest to policymakers, industry leaders, and academics. To centralise skills and procedures while coordinating various pieces of hardware, software, and networking, a conceptual framework was developed. In other words, creating anything new has significant upfront costs, such as when making a CD or developing software, but the expenses associated with making copies and marketing them are cheaper. Having learned and developed the skills required to run such a platform, continuing to keep it up and running adds value, for instance by giving near real-time data on the development and innovation of R&D in Europe. These findings are useful for assessing the state of the European ICT industry and comparing it to those of other areas across the globe.

These kind of realisations provide answers to the initial inquiries and point the way to other lines of inquiry that can be pursued. This kind of data is helpful for quickly formulating effective countermeasures. By doing so, the platform would have improved the tool's intelligence and created a stronger foundation for well-considered, data-driven choices.

The aforementioned event, however, did not occur. It was only logical for EIPE to stop three years after it had officially concluded and early findings had been provided. Keeping the site online was never a goal, and there were no future plans to do so. In other words, the choice had nothing to do with the platform's inherent worth. Many groups and people are still making use of the effort, and it has led to outcomes that weren't anticipated at the outset. On occasion, the writers are asked for advice on the project's technique and output. Data scientists often are asked to provide individualised analysis for clients. Additionally, work is being done to determine whether or not EIPE's technique may be used to examine other industries. The dedication is under doubt due to the absence of backing.

3. Discussion:

Big data efforts have been undertaken by many different organisations, as has been discovered via research. Multiple big data efforts inside a single company are an extreme rarity. This occurrence might have three different causes. One, big data projects don't seem to follow any established business procedures. Two, the necessary big data resources are widely spread and often outside the control of the company. Third, the big data ecosystem is dependent on several interconnected functions. Companies need to react quickly rather than regularly to these relationships since they may not last long and might change drastically. Multiple definitions of business processes may be found in the academic literature. This article defines business processes as the actions taken by an organisation to fulfil its goals and objectives. Management of large data projects does not seem to follow an uniform procedure.

The archetype defines the main steps that businesses follow while implementing big data projects. The prototypical procedure seems to be sequential, logical, and axiomatic. However, in reality, the complexity of executing big data projects means that activities in the process often overlap, run in parallel, are unclear, and lack definite beginnings and endings. Because of the dynamic nature of policy and strategic challenges, it is essential to get input at each level to modify and refine previous hypotheses. While implementing big data efforts, it is expected that firms may iterate on many operations simultaneously.

Problems that top executives believe are strategically important are the starting point for many big data efforts. Strategic challenges are transformed into sets of questions they want addressed by working with colleagues or specialists in big data. The long-term goal of the EIPE is to double the number of top-notch R&D facilities in Europe from three to five. Based on this goal, three questions have been identified that may be resolved using big data analysis.

It's important to remember that the choices you make inside each action and at the borders between activities have far-reaching effects on the other activities, the results, and the findings. Such an instance is the Specify the Data activity. Eight different data sources were utilised by EIPE. Datasets are impacted by the decisions made over which eight to include and which others to exclude. Moreover, the ultimate outcomes of big data projects are affected by the decisions and filters that are applied to the data. The QS World University Ranking was utilised by EIPE. It might be argued that a different ranking of universities would place other institutions higher or rearrange the same universities in a different order. Initiatives may be criticised based on the data analytics used, since various approaches provide varying outcomes.

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As a result, there is an Agree and Deploy Analytical and Statistical Methods activity in the process archetype. Synthesis and reporting of results are influenced by the indicators and metrics used and their inclusion or removal.

As can be seen in Fig. 2, the EIPE action Visualize the Information plays a vital role in the process. The archetype process necessitates that top-level executives take use of the information provided by the big data project, put plans into motion, and make certain that the program's promised advantages are realised. Not enough of these kind of things are happening at EIPE. Though the EIPE big data effort produced a report and suggestions, few were implemented.

The EIPE example highlights the need for methodical approaches to the implementation of big data projects. In this phase, you will be responsible for meticulously recording all of the decisions and options that were considered during the whole of the process. If you want others who repeat your steps to understand your logic and your assumptions, you should document both. Knowledge gained through big data projects, which may be gleaned from KBV of enterprises, is crucial for the development of longer term skills. With this information in hand, businesses may launch similar big data projects in the future and are in a stronger position to outsource big data tasks.

The success of big data efforts is contingent on the organization's current skill set. When EIPE was over, the EC had pinpointed many key centres for R&D and new product development. It's possible that policymakers, EU officials, government officials from member states, and local/regional government authorities all have to reorganise their capacities and resources. Scholars of "dynamic capabilities" stress the need of organisations adapting to new information from both inside and beyond. Alterations to operational and tactical procedures are one example of the possibilities made possible by big data.

For instance, if a company's big data endeavour indicates that it might profit from adjusting its supply chain operations, that company will need to reorganise its storage facilities, distribution networks, and transportation hubs. The ability to absorb and act upon the findings of big data projects is being put to the test.

According to resource-based theory, organisations may gain a performance edge and implement novel approaches to problem solving if their resources are up to par with what is known as the "VRIN" standard.

The notion is based on the premise that all necessary resources are already held or under the control of the organisation. Big data initiatives are only partially explained by this notion. To be a resource in RBT is to have either a physical or immaterial value. Hardware, personnel (such data analysts and statisticians), and established procedures are all examples of tangible resources applicable to big data projects. Knowledge, management ability, organisational goodwill, and a recognisable brand are all examples of intangible assets. These may be seen in the form of a company's improved standing in the market after implementing a big data strategy.

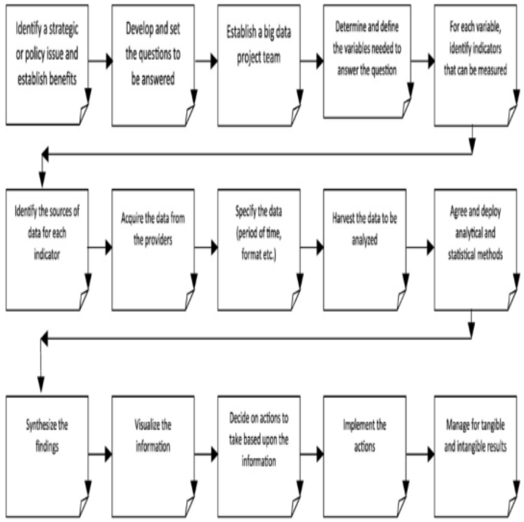

Figure 2: big data business process

4. Implementation on practical contributions.

Practitioners who are thinking about or actively implementing big data efforts might benefit from this study. Practitioners, it is assumed, want to maximise the value of the time and money their organisations spend on big data, get a return on the money they invest in big data projects, and utilise the insights they gain to improve their operations strategically or operationally. This article proposes that practitioners follow the steps depicted in Fig. 2 when they undertake big data initiatives in three distinct phases: Step one is launching the big data programme; step two is carrying it out; and step three is reaping the rewards of big data. It describes each step in short detail:

4.1. Phase 1 – commencement of big data initiative:

At this stage, big data professionals formulate strategic or operational imperatives that the company must address or get buy-in for before proceeding with big data speculative analysis. Participants from all around the company, and even outsiders if necessary, are invited to this phase of the process. The goals of these initiatives centre on elucidating key concepts and providing more insight into potential next steps and outcomes. During this stage, criteria are established that will be used to guide decision making and option selection in subsequent stages; for example, with respect to various resource, provider, and visualisation options. With Phase 1's iterative design, we may learn which kind of analyses would be most suited to the project. The outcomes of this stage are the challenges, opportunities, and questions that can be solved by using big data. It is crucial at this stage to create a protocol to document the fundamental choices and assumptions behind initiatives. When companies seek to hire other companies to handle their big data tasks, the big data protocol becomes very crucial. Organizations often fail in their outsourcing efforts because they enter into contracts with just a general concept of what they need and want from their vendors. Once agreed upon, revisions to big data outsourcing contracts may be costly and may nullify the advantages of big data projects.

4.2. Phase 2 – implementation of big data initiative:

The selections and options you make when analysing large amounts of data are essential at this stage. During this stage, it is crucial to establish a "trail of evidence" to back up your decision to choose one path over another. Decisions made using specified criteria, as well as instances when criteria established in Phase 1 were modified, are recorded. One consideration for choosing a data source in Phase 1 may be that their data meets or exceeds a certain quality bar.

If a supplier doesn't match the requirements and is subsequently replaced, the reasoning used to make that choice should be documented so that subsequent projects may benefit from the lessons learned from the original effort. It's important to settle any disagreements that come up, including who gets to decide which metrics to employ. Findings and insights from big data that are visually understandable and answer questions agreed upon in Phase 1 are the main products of this stage.

4.3. Phase 3 – benefits from big data initiative:

There may be some overlap with the preceding phase, or it may continue in continuous fashion.

The findings are then used to shape strategies that reallocate company assets to better achieve the desired outcomes. The stakeholders in Phase 2 are not likely to be the same people who were active in Phase 1, even if they are the ones ultimately responsible for reaping the advantages of big data. At this stage, leadership buy-in is essential to ensure the change is sustained. Greater economic returns, stakeholder satisfaction, and/or operational efficiency are all possible indicators of success. In this way, the lessons learned from this project may be used to similar projects in the future.

5. Conclusions:

There are three inferences that can be made from the available empirical data, research, and debate. Firstly, the prototypical business process for big data initiatives offers a framework for efficient resource management. In order to guarantee positive results, businesses may use the big data business process to pinpoint the skills and responsibilities needed for a winning strategy. The difficulties that stop big data efforts from being repeated may be overcame with the help of efficient business procedures. A second reason why connections between big data and dynamic capabilities are crucial is because big data processes evolve when businesses reorganise or create new ways of working to take advantage of the insights provided by big data. As a result, we can't let our big data procedures become rigid. Third, further research is needed to show RBT's relevance to give deeper insights into massive data and address the theoretical shortcomings of VRIN in this context. Having more big data projects done effectively, over and over again, in the same company would be the most significant contribution of this study.

To sum up: 1. The full potential of the big data phenomenon will be constrained until big data efforts generate recurrent advantages in the same firm.

Second, initiatives can only be repeated if they are based on a trustworthy and long-lasting big data business process.

Third, resource-based theory is challenged by big data, namely the VRIN features espoused by RBT.

Fourth, Big data requires dynamic skills on two fronts: first, in terms of business processes; second, in terms of the adjustments to organisational resources that must be made in order to put into action the results of big data analytics.

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