Unveiling the Roots of Big Data Project Failure: a Critical Analysis of the Distinguishing Features and Uncertainties in Evaluating Big Data Potential Value

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Abstract

The potential value intrinsic in Big Data represents an opportunity for companies and organisations, which invest their resources in search of a return on investment capable of guaranteeing efficiency in production and procurement processes, cost reduction and support to decision-making processes through targeted strategies. However, the implementation of Big Data-driven strategies often does not generate the expected value, recording a failure rate of over 80 per cent. Such percentages lead to think of a systemic error, probably inherent in the management models used. For these reasons, we analysed the major Big Data frameworks discussed in the literature and their respective characteristics, specialising them into three classes. By comparing these frameworks with those used in software engineering and IT projects, on which they are based, it was possible to understand the differences between the two generations of models and identify the critical aspects in Big Data initiatives. So, the analysis led to the definition of a first model for the implementation and management of Big Data driven strategies, highlighting what requirements a modelling framework should necessarily have to support companies and organisations in the transformation of the **Big Data Potential Value** in **Big Data Business Value**.

Keywords

Big Data, Value Framework, Business Value, Potential Value

1. INTRODUCTION

Data own a value that companies and organisations are called to capture and exploit in economic terms to increase the level of competitiveness [1], thanks to *ad hoc* strategies, resources, and technologies [2], in fact, there is strong *hype* in the literature about investments in Big Data initiatives. In [3, 4], it is predicted that if companies would use Big Data in their innovation processes, they would save up to 20-30% on development and have time-to-market cycles that are 50-60% faster; in the public sector, Big Data would reduce the costs of administrative activities by 15-20% and thus generate a value of EUR 300 billion [2]; in the Energy and

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Transport sector, the potential is estimated at a reduction of 380 mega tonnes of CO_2, due to time and fuel savings of USD 500 billion [2]; other examples of **Big Data potential value** can be found in [5, 6, 7, 8, 9]. In industry, frameworks have been developed to assess the maturity level of Big Data management [10], in fact, despite these promising predictions, there are many examples where Big Data initiatives have failed to translate their potential value into **captured/created value**, and consequently in **business value** [6]. In [11], according to reports from 300 companies, 55% of Big Data projects remain incomplete, while several others fail to achieve their goals [12]. Gartner predicted that 60% of Big Data projects up to 2017 would not go beyond the pilot and testing phases and risk being abandoned, and another survey of 199 technology executives revealed that around 48% of organisations that invested in Big Data failed to transform data into useful information [9]. Ultimately, it is estimated that the failure rate of Big Data initiatives ranges from 50% [13] up to 85% [14, 15].
The low success rates of Big Data initiatives, found even in organisations that are leaders in their field, lead to profound reflections. It becomes legitimate to ask what are the causes and factors behind this high failure rate, and whether the discrepancy between the value generated and the expected value is due to systematic or contextual factors, thus dependent on individual initiatives.
With the aim of answering to this question, in this paper we will analyse some of the most important frameworks for capturing and creating value through Big Data, and compare them with those commonly used for IT initiatives. The objective is to identify what are the distinguishing factors that differentiate Big Data initiatives from others, so that current *business model* can be made adaptable and dynamic, in order to orchestrate and successfully manage *Big Data driven* projects and strategies.

2. BIG DATA AND IT PROJECTS FRAMEWORKS

In the literature, several frameworks designed to support business strategies can be identified in order to capture Big Data value, configure and manage the necessary resources or identify the *business value* generated by what are defined as *Big Data Initiative* [16].

Depending on the purposes and characteristics of *Big Data frameworks* identified in the literature, the following classification is proposed:

- **Big Data Value - Transformation Process**: modelling the processes of data transformation from the extraction or creation stages to its use to generate useful value for organisations; this class includes the **Big Data Value Chain**. In some models, the architecture is enriched by the analysis of the initiative's objectives and application contexts up to the measurement of the value generated.
- **Big Data Value - Creation Process**: process modelling to identify, configure and manage the resources and skills required for the development of the Big Data initiative, specialised along the different implementation phases.
- **Big Data Value - Dimensional Framework**: dimensional modelling of the *Business*

Value, which can be generated by Big Data initiatives, in order to identify all competitive and performance advantages achieved or potentially achievable.

In order to provide an overall view, in Table 1 for each identified class, the theoretical background, the models applied to Information Technology and/or data analysis projects identified as predecessors of Big Data frameworks, and the Big Data models identified in the literature are made explicit.

CLUSTER	THEORETICAL BACKGROUND	IT PROJECT FRAMEWORKS	BD PROJECT FRAMEWORKS
BDV - Transformation Process	Value chain [17], DIKW hierarchy [18], Virtual Value Chain [19] Information Value Chain [20], Process Theory [4] .	Data Value Chain as a Service [21], Linked DVC [22], Data Value Chain [23, 24]	RFIKW hierarchy [25], BD Information Value Chain [20], Big Data Value Chain [23, 24, 26, 27, 28], BDVC implementation models [16, 29, 30, 31, 32]
BDV - Creation Process	Resource-based view [33], IIRF model [34], VRIO model [9], Dynamic Capability View [35], Contingency Theory [36]	Value-based Management Framework [37], Value-creation model for value-based management [38], Information Technology value framework [39]	Big Data Analytics Framework [9], Configurational Big Data Analytics Capability Model [40], AC/TC Model [4], Conceptual Model: Digital innovation integration to promote organizations benefits [41], Inductive framework [25].
BDV - Dimensional Framework	IIRF model [34], Big Data Analytics Business Value [42]	Value Creation and Capture [43], Value-creation model for value-based management [38], IT Business Value [42, 44]	Types of value creation from Big Data [6], Conceptual framework: How value is created from BDA [9], Big Data multi-dimension value framework [45], Value creation dimensions [41].

Table 1
Classification of frameworks identified in the literature

The three classes are not a partition of the frameworks identified in the literature, but labels that highlight which aspects are modelled and specialised. For this reason, a framework can also belong to two distinct classes, as, for example, the model of Wu et al. [25] which specialises resources and, in particular, the competences required to move from one node to another in the value chain, or the Grover model [9] which includes the value dimensions within a process of creating value from Big Data starting from the resources and skills needed.

Regardless of the class of models considered, the crucial role of the *Resource Based View* (RBV) is clear. A correct configuration of resources, whether these are *Tangible, Human Skills* or *Intangible*, is a necessary condition for the creation of a competitive advantage [33, 40]. However, the adaptability required of organisations, namely the ability to evolve and scale their strategies according to changing contexts such as those in which Big Data-driven strategies are developed, has led to an evolution of RBV that is realised in the *Dynamic Capability View* (DCV) [33, 35]. Thus, the configuration of resources will dynamically change according to the initiative and the "intermediate" results obtained within the value chain, as well as the organisation itself, as can be seen in [40], in which resources are specialised according to the size of the company (SME or Large).

3. SPECIFICITIES OF BIG DATA INITIATIVES

The analysis of the frameworks in Section 2 allows to highlight the characteristic aspects in the Big Data initiatives that organisations are called upon to manage, with respect to classical software engineering or IT initiatives in general. It might be plausible that in some of these differences, reported below, may lie the causes of the high failure rate of Big Data initiatives.

a) **Randomness of the Big Data project life cycle:** in traditional software engineering, architecture design and requirements negotiation, although related, are performed at separate times. This separation of concerns is not conducive to value creation [31] and is unsuitable for Big Data contexts, in which, on the contrary, significant randomness is present, which often forces a negotiation of requirements in the process. In fact, as highlighted in the model in [4], the value creation process in Big Data projects is **probabilistic**.

   item[b)] **Uncertainty of results:** it is not possible to know the level of quality of the information in the data before analysing it, it is not even certain that the information someone intends to extract from the data is actually present in the data, or that one has sufficient technology and knowledge to ensure the success of the initiative [12]. In addition, the results of analyses may be unpredictable because they depend on *machine learning* and *deep learning* techniques. This forecasting impossibility, which does not allow the deterministic identification of data extraction and processing strategies according to the available resources, is not present in software projects, which are subject to less ambiguity in implementation strategies [12].

c) **Data, an atypical resource because shareable:** data are a resource [46], but is an exception compared to the others because it is easily shared. While an exclusive asset, such as an apple, can only be consumed once, data can be used by several actors, even simultaneously [47], as well as the knowledge derived from the analyses. In this direction, the ease whereby data could be replicated or shared among several actors in the same network becomes a competitive advantage, since analyses restricted within too specific perimeters could become limiting in that they lack information or are constrained by misleading information bias.

d) **Co-creation of value in Big Data contexts:** as can be seen in [48], in IT models, value is created by organisations and is distributed to the market, in which customers are merely "recipients of value" [49, 50]. In Big Data contexts, on the other hand, it is often directly the customers who provide the data to the organisations, who are then called upon to capture the information hidden in it. Data become a dynamic and changing resource over time, constantly being updated to generate new information value [51]. Thus, the customer or user of services goes from being a receiver of value to a **co-producer**, who participate actively in the creation of perceived value [48, 52]. This aspect will be taken into account in the model presented in Figure 1.

e) **New value generated through Big Data:** when talking about the value generated in Big Data, the analysis of massive sources of historicised or analysed data in real time, the speed with which these are collected and analysed, and their variety become the key to generating new insights for making better and faster decisions, that make the difference [48, 53, 54]. Decision support, thus, becomes a feature of the value associated with Big Data officially recognised in the literature as ROI in the implementation of the respective initiatives [36, 55]. As highlighted in [56], managers use Big Data to change their products, optimise production processes and refine their strategies.

f) **Critical obsolescence in Big Data initiatives:** time becomes an even more critical resource compared to traditional software engineering and IT initiatives, since organisations cannot prevaricate in investing in Big Data strategies if they want to remain competitive over the years [33]. At the same time, the technologies and skills required to implement Big Data initiatives are constantly evolving, and even those at the cutting edge may become obsolete over limited time periods. Finally, the information power of data is not persistent over time, but could lose its value; for these reasons, data-driven strategies must be as efficient as they are targeted and timely, in order to be able to define or consolidate in the short term a competitive advantage resulting from the initiative, which could otherwise be nullified by excessively long adoption and implementation periods.

TRADITIONAL IT PROJECTS	BIG DATA PROJECTS
Deterministic life cycle	Random life cycle
Certainty of the final result	Uncertainty of the final result
Single-use static resource	Mutable, sharable and multi-useable resource
User perceives the value generated	User co-creator of value
Operational value	Strategic value
Normal rate of obsolescence	Higher rate of obsolescence

Table 2
The main differences between traditional IT projects and Big Data projects

Among the differences between traditional IT and Big Data projects, we consider plausible that the *randomness of the Big Data project life cycle* and the *uncertainty of results* may be two determining factors of the high failure rate of Big Data initiatives. These two factors particularly involve value, described as one of the V's of Big Data [26]. Business models, to handle this form of indeterminacy, should be flexible, scalable and capable of accommodating changes in the *status quo* and then update accordingly, quantifying when the potential value changes over time, depending on the resources used and those expected to be used after an update.

4. A GENERAL FRAMEWORK FOR CONVERTING THE POTENTIAL VALUE OF BIG DATA INTO BUSINESS VALUE

Starting from the distinctive features identified in Section 3, a first generalised model is proposed below, aimed at managing uncertainties (points a and b) intrinsic to Big Data initiatives, introducing the concept of **Big Data Potential Value** into the Big Data Value Chain. The modelling, although at a high level, is intended to respond in the first instance to the new requirements accompanying Big Data projects, while at the same time preserving and integrating those business models currently used and validated over time by companies and organisations. In Figure 1 it is possible to see a representation of the model whose main points, that contributed to its creation, will be explained.

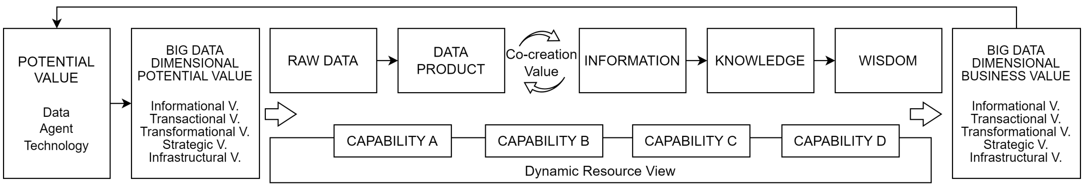

Figure 1: Model for converting the potential value of Big Data in business value

In the model, we chose to use the *Information Value Chain*, which is considered to be as representative as the Big Data Value Chain, but less constraining in terms of granularity and ordering of the different transformation processes that the data should undergo in order to generate the expected value. Instead of specialising the same architecture by dividing it into different sectors, as in the 5 use cases of the Big Data Value Chain in [27], there is a preference for greater flexibility, deferring to the project needs and the skills and creativity of the data scientists for the best possible implementation strategy [35].

The presented Information Value Chain is adapted from the RDIKW model [25], which originates from the DIKW model [18], replacing the *data format* node with the **data product** node, capable of grafting the Information Value Chain into the *Data Mesh* of [57], as already presented in [58]. The data product, in such a view, becomes a collection of data that is universally usable and agnostic with respect to a particular context or objective, in such a way as to limit the potential value inherent in the data as little as possible, while at the same time adhering to high quality standards guaranteed by the domain owner. As visible in [59], the different nodes of the chain, depending on the objectives and contexts, require specific technologies, which are constantly evolving, for the implementation of Big Data strategies. In this sense, the presented model also allows value to be created through a network of actors orchestrated by a common governance, in which the use of resources is optimised (e.g. through the Technology Mesh [58]), in such a way that the value generated is greater than the sum of the values that each actor in the network could have generated individually.

As reported in Section 2, the literature suggests that each class of frameworks identified focuses on one or more aspects of the implementation of Big Data initiatives. It is considered useful, however, to propose an initial **generalised model** in order to simultaneously include the different points of view.
From the BDV - Transformation Process, the chain of capturing value from data was taken up, meaning the transformation of data into information, knowledge and wisdom. Creation Process models engage in the transition between the different nodes of the value chain. The configuration of resources and capabilities, typical of the BDV - Creation Process, supports the capture and creation of value to move from one node to the next in the BDVC [25, 40]. Therefore, capabilities are part of the configuration of resources, which in Big Data initiatives must be dynamic and depend on multiple factors [40]. Therefore, in Figure 1, it was decided to generically represent Capability A, B, C, D to emphasise that their dynamic specialisation is necessary. From the BVD - Dimensional Frameworks we adopt a dimensional definition of value. In the proposed model, the structure in [45] has been taken as a reference, which involves the five dimensions shown in the figure (Informational, Transactional, Transformational, Strategic, Infastructural). This dimensional view is present both at the beginning, in the *Big Data Dimensional Potential Value* node, where for each dimension the value to be captured (potential) is estimated, and at the end of the chain in the *Big Data Dimensional Business Value* node, where for each dimension the value actually generated will be measured, deciding whether the initiative succeeded or failed.

Value is one of the V's of Big Data [26], however, the definitions provided often fail to fully formalise its characteristics. In the literature, it is often mentioned that there is **captured value** from Big Data and indirectly it is accepted that such value intrinsically exists in the data in the form of **potential value**. As seen, due to the factors of randomness and uncertainty (Section 3, points a and b), the expected potential value often does not turn out to be the one actually generated, a phenomenon that decrees the failure of the initiative. Furthermore, it may be limiting to think that the potential value lies solely in the data. In fact, value capture may also depend on the strategies and tools used to extract it. For these reasons, in line with the model analysis in Section 2, we propose to model potential value along three dimensions: **data, agents** and **technologies**. The "data" dimension represents the raw material, in its rough state, of the Big Data initiative, whose characteristics are well described by the V's (from which, however, "Value" is excluded). The "agents" dimension considers both human agents, such as data scientists, and "artificial agents", such as ML and DL algorithms, which contribute to the uncertainty of the outcome of the Big Data initiative, as seen in Section 3 point (b). Finally, the "technology" dimension perimeters which technologies will be used and how they will be used in the Big Data initiative, depending on the technological maturity of each of them [60, 61]. It is believed that such a specialisation could refine the measure of potential value that organisations are asked to estimate at the beginning of the initiative, thus becoming a key strategic information for estimating its feasibility.

Modelling the potential value does not reduce the randomness of the initiative, but supports awareness in its management. However, a first revelation of the value that can actually be captured from the potential value will only occur in the phases between information and knowledge, as in the ”patterning” phase of [28], or between knowledge and wisdom. In these phases, the transformations that the data have undergone in the previous phases may have inevitably altered the initial potential value inherent in them, to such an extent that this value can no longer be captured except by updating the entire value chain, as evidenced in the figure 1 by the arrow running from the ”Big Data Dimensional Business Value” node to the ”Potential Value” node. Indeed, an update of the entire chain can be considered either an improvement of the implemented process or a necessity due to the failure of the initiative itself, which either failed to estimate the potential value correctly or was unable to capture it. In both cases, it is necessary to take timely action on the implementation strategy previously adopted, considering the reasons that led to the failure of the previous one and the resources that will be needed for a new implementation.

5. CONCLUSIONS

The analysis of Big Data frameworks and their characteristics is part of an ongoing Research work aimed at systematically reviewing the literature in order to identify what should be the requirements and characteristics for a generalised Big Data project implementation and management architecture. What has emerged so far has made it possible to identify in the randomness and uncertainty of the results two possible weaknesses of Big Data initiatives.
The creation of a general model thus makes it possible to merge all those features of Big Data initiatives that are currently specialised in different models, as can be seen in Section 2. However, it is necessary to increase awareness of the value to be captured and the value created at each node of the Big Data Value Chain, in order to have visibility into the entire process. Potential value, as defined, together with a dimensional structure of business value enable the use of ad hoc techniques to adopt quantitative approaches borrowed from information theory in a dynamic context [62] and qualitative approaches aimed at studying the compatibility of relational structures, in particular preference criteria, between different representations of the system under investigation [63]. The ultimate goal of the Research conducted is to formalise the state of awareness of those who are called upon to manage the initiative, in order to provide for cyclical updates of the state of knowledge in response to randomness and uncertainty in Big Data contexts. The study of mappings (i.e., correspondences) between sets endowed with different relational structures to represent knowledge states, and specifically the extent to which such mappings preserve the relational structures, can benefit from the aforementioned methods [63], which can provide a unified, but also scalable formalism for a structural description of the different components of the present proposal. This update could lead to a redefinition of the dimensions used both to define the potential value that could be captured (Big Data Dimensional Potential Value in Figure 1), and the value that is actually generated (Big Data

Dimensional Business Value in Figure 1). In the model we are working on, this kind of structure is much more flexible than the one proposed, in fact, dimensional hierarchies can be adapted, as seen in the [45], and different weights can be used for the different dimensions, in response to the importance to the organisation of that particular generated value.
In this way the proposed enhancements will make it possible to take into account not only the *classical* risk and impact factors, but also opportunities or limitations in the updating of value recognition, exploiting the reusability of resources wherever possible. Finally, with the introduction of the concept of *data as product*, integrating the proposed model with the *Data Mesh* and the *Technology Mesh*, we have actually laid the foundations for a multi-actor approach capable of increasing the potential value of the paradigm (data, human-agent, Big Data technologies), fostering inter-company collaboration as suggested [4]. In conclusion, the model presented aims at structuring the role of human intelligence, and the richness of the relations it has with technology, and by extension with *artificial intelligence*, through the recognition of its own limits. This role, indispensable in the model, can only find in the human agent the only possible interpreter.

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