

Paper title: Resource synergies for the creation of value from data assets.

Category: Development paper.

Track: Entrepreneurship.

Paper ID: 1103.

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Word count: 2209.

Abstract:

Alongside the continued use of data assets for value creation within organisations, many scholars have viewed big data analytical capabilities (BDAC) as the means by which this value creation is assured. Capabilities being an integration of several different firm resources, both tangible like technology and intangible like culture; who synergistically come together to activate one another's properties to handle and shape data assets for value creation. However, missing from the current BDAC literature stream is any means of discerning what each resource within synergies actually contributes to one another in forming data capabilities. Thus, this study divulges three different parameters in which to judge a resources contribution to capabilities; described as: (1) Direction, to indicate where influence in a bi-directional resource relationship originates and who the receiver is. (2) Reliance, to describe how dependent one resource is on another in order to contribute to data value. (3) Scale, describing how much influence a single resource has across the multiple other resources that make up a data capability. This paper aims to present how we may judge and illustrate these areas of contribution at the conference while the three part framework described is being practically studied within data driven organisations via a mixed methods approach.

1.0: Introduction.

Data in the business environment has become increasingly plentiful, diverse in variety and easier to access. Consequently, value opportunities have continued emerging for businesses in using data as an asset (Hartmann et al, 2016). Research has indicated a connection between data's application for financial and competitive performance (Reis et al, 2020). As well as the product, process and agility innovations that assures this performance (Behl, 2020).

Positive influences amongst these metrics aren't connected to firms possessing data per se. But the effective development and use of valuable insights derived from data (Ylijoki and Porras, 2019). Of course, reaching a point where insight is usable means the data where it originates must pass through a sequential process of developmental activities (Lange and Drews, 2020). With data's inherent insights becoming increasingly explicit. Such a process typically follows a value chain of multiple progressive activities. This begins with sourcing, cleaning and organisation to first ensure data's usability. Analytics are then applied to extract insights from this now workable data before applying these insights within decision making (Faroukhi et al, 2020). Use in decision making is when value is finally realised. With insights that convey solutions/opportunities being applied for financial benefit (Wheeler, 2016).

2.0: Knowledge gap in assuring data's insight development.

A common means of assuring this development process is the idea of capability theory. With capabilities described as a combination of several firm resources whose synergistic properties collectively facilitate development activities (Grover et al, 2018). For example, efficiencies in data management or analytics activities rely on interdependencies between technologies and human talent to use technology. Further, management resources are required to bring the two together. Relations between all three collectively form an infrastructure capability permitting easier access, transfer and interaction with data throughout key activities (Knauer et al, 2020). The connection between activities and capabilities can consequently be viewed as the latter's inherent resources whose synergies permit optimal environments for development throughout the former (Spanos and Prastacos, 2004). In this relationship, resources represent individual ingredients to carry out necessary activities. In turn, capabilities are the composite grouping of these resources mutual influences that allow them to do so. Like workers using technology so they may interact with data assets (Laaksonen and Peltoniemi, 2018).

Capability theory is commonly viewed as the means by which value found in data insight is assured. Resulting in the literature describing all resource deployment requirements for every activity as big data analytical capabilities (BDAC's) (Gupta and George, 2016; Shamim et al, 2018). However, literature thus far is primarily dedicated to divulging which resources form BDAC's. This has mainly been conducted by measuring potential resources against capability variables quantitatively. Findings from this perspective provide a good understanding of what resources are needed to form capabilities. But indicate little on how varying resources interact with one another to do so. Despite current studies acknowledging what is being measured are resource synergies, we lack a means of examining the effects these resources actually have on one another that constitute these synergies at a granular level.

This paper thus contributes to knowledge in a data orientation of entrepreneurship as practice. Achieved by presenting a model to judge and categorise what effects resources have on one another to form BDAC's required to extract value from data based insights, discerning a resources various contributions to value creation.

Viewing entrepreneurship as a process where resources are used in identifying and attaining opportunities for value creation (Tunstall, 2021). If required resource relations aren't present, insufficient BDAC's will fail to develop valuable insights to a state that compensates for the acquirement/deployment costs of those resources (Woroch and Strobel, 2022). This inability to align necessary resources is frequently highlighted as a principal reason for data initiative failure (Gupta and George, 2016), justifying the pursuit of this specific topic.

By deriving a model capable of identifying and categorising the effects resources have on one another to form BDAC's, it's possible to go beyond current research that simply identifies a BDAC's necessary resource configurations by establishing the relations between them that actually constitute a capability. Increasing our understanding of how to establish optimised BDAC's so as to assure developmental practices that create value (Thompson et al, 2020).

3.0: Understanding and categorising resource synergies.

The first challenge in divulging ways to judge resource synergies is of illustration. Providing a way to describe and visualise how different resources may be related in efforts to develop data. We know from practical observations of data's development that synergies are based on one resource interacting with another in order to activate respective value creation properties (Wamba et al, 2017). This makes it possible for one resource to successfully handle data for developmental purposes. While the other resources purpose is activation of the former. Like technology and employees whose technical skills activate this technology so it can be applied for developing data. This has typically been described through ideas of socio-materialism. An extension to capability theory that regard data specific synergy as relating between a material (tangible resources like technology) and social nature (how we organise and use technology via intangible resources, for example: culture, human skill, management, etc) (Orlikowski, 2007). Of course, studies also highlight synergistic relations between resources that have the same nature (Gupta and George, 2016). For example management and culture, both social in orientation, yet the former is found to activate the latter's application within value creation (Kim and Park, 2018).

Consequently, producing a model to identify/categorise resource synergies requires a way of labelling what role a resource plays in activation. Disclosing whether they are being activated through the presence of another resource so they can be applied for development purposes, or functions as the activator.

3.1: Direction.

What is absent from this activation perspective is a way to describe which resource influences which within synergies. However, a study by Hajiheydari et al (2020) utilised MICMAC analysis to review a series of resource relationships in a banks data value efforts. Findings aid in empirically discerning each resources role in these relationships. Although, only in the context of their general contributions, rather than highlighting specific relationships.

The authors reveal that some resources like management are completely **dependent** on others. While technically skilled employees are only a **driver** of other resources. A third class designates those with high driving and dependency behaviours, like data culture. Which is labelled as having a **volatile** effect; as it's connected to multiple resources simultaneously, having a different purpose in each.

These findings present a starting point in categorising resource roles by illustrating their place in synergised pairings. In viewing drivers and dependents in a capability context, its clarified

where influence in resource pairings originate and which is the receiver whose value creation properties are activated as a result. Providing this study with the first parameter in which to judge a resources contributions in forming capabilities, direction. Which can be judged based on three observable behaviours: driver, dependent and volatile. With each detailing where influence originates in a synergistic pairing and where this influence is directed towards.

3.2: Reliance.

However, in viewing two resources in a directional relationship we still lack understanding of how drivers influence a dependent, activating their value creation properties. To establish a parameter describing the underlying nature of directional relations requires an examination of more general synergy literature.

Originating in Penrose's (1959) arguments that a resource is only effective when combined. The concept of **complementarity** describes increasing effectiveness of one resource via the presence of another. However, such a pairing may not act as a necessary element for value creation. But nonetheless, increasing value creation properties in a dependent via the presence of a driver are still observed. Two resources within a complementarity synergy can thus be viewed as largely independent in their data development efforts (Kim and Mahoney, 2008); with the addition of welcome, but not fundamental, increases in a dependents properties.

This appears a different relationship from those based on total reliance. As seen in **co-specialisation**, where dependents may not display any or limited value creation properties without the presence of a driving resource (Kim and Mahoney, 2008). Some resource pairings may therefore represent a necessary pre-requisite for a dependent to exhibit any potential to assure data's development.

Ideas of complementarity and co-specialisation may not exist as two distinct phenomena however. As Jacobide et al (2006) suggest the latter is a subset of the former. With both existing on a scale of mobility determining how tied together two resources are in value creation efforts. The authors advise that synergies exhibiting high mobility will boost the dependents properties while increasingly avoiding reliance's (complimentary). Alternatively, low mobility resources are permanently joined in value creation efforts (co-specialisation). This provides a second contribution parameter: reliance. Where complimentary or co-specialised behaviours describe how subservient a dependent is on a driver in the formers value creation application.

3.3: Scale.

It's important to consider however that solely measuring bi-directional relationships between two resources risks producing misleading descriptions of a BDAC's inherent synergies. This is because any capability likely requires the presence of multiple resource pairings (Ennen and Richter, 2010). To resolve this issue when labelling resource contributions via the two parameters established, any research carried out would have to integrate various directions and reliance's captured. Illustrating an overall apparatus of the capability in question (see figure 1)

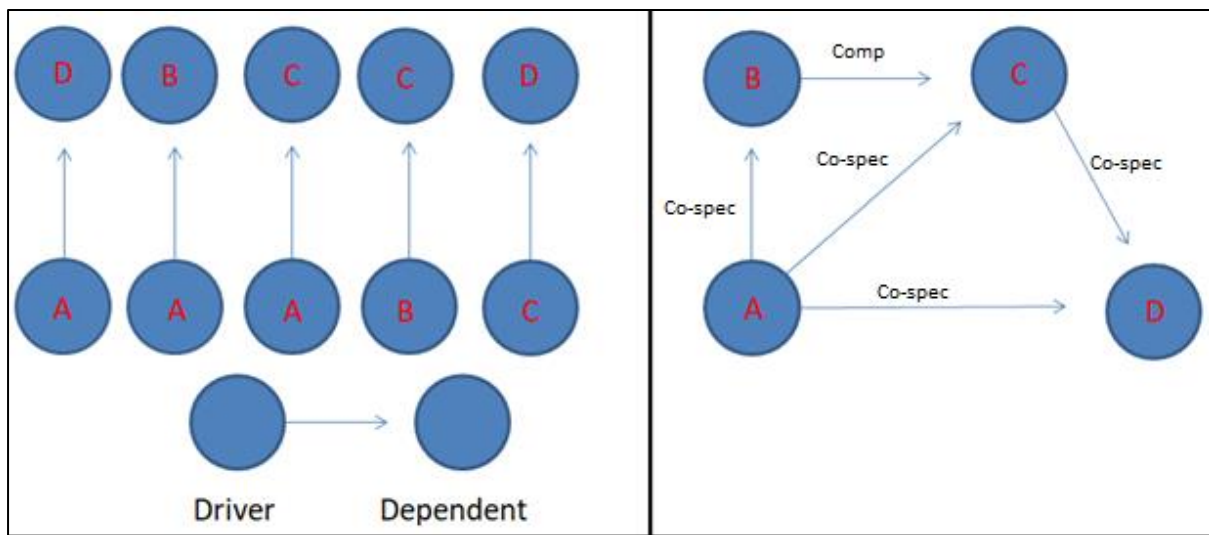


Figure 1: Individual resource pairings when combined provide the overall apparatus of a data capability.

This presents a third contribution parameter, scale. Indicating **how many directional and reliance pairings** a specific resource exhibits. Thus, providing a means of measuring the overall presence of a resource within a capability and what purpose it serves. Resource A in figure 1 for example appears to act as a driving/co-specialised linchpin of all other resources. We can derive this by simply tallying the number of directional and reliance behaviours it appears to exhibit and viewing said behaviours within a network illustration (Borgatti and Halgin, 2011).

In viewing a resources scale within a capabilities apparatus overall. We can begin to interpret their fundamental role across the different synergies that constitute a capability. As well as identify those that are fundamental to its creation. This specific parameter additionally allows reflection on the consequences of a resources absence.

4.0: Measuring synergistic contributions in research.

Now that three resource contribution parameters have been established, as a collective they may be applied to BDAC research to discern the behaviours of necessary key resources in the synergies they form amongst one another that constitute a capability. Applying all three via the interrelated contribution framework detailed in figure 2 however presents a multifaceted challenge in measuring them all simultaneously.

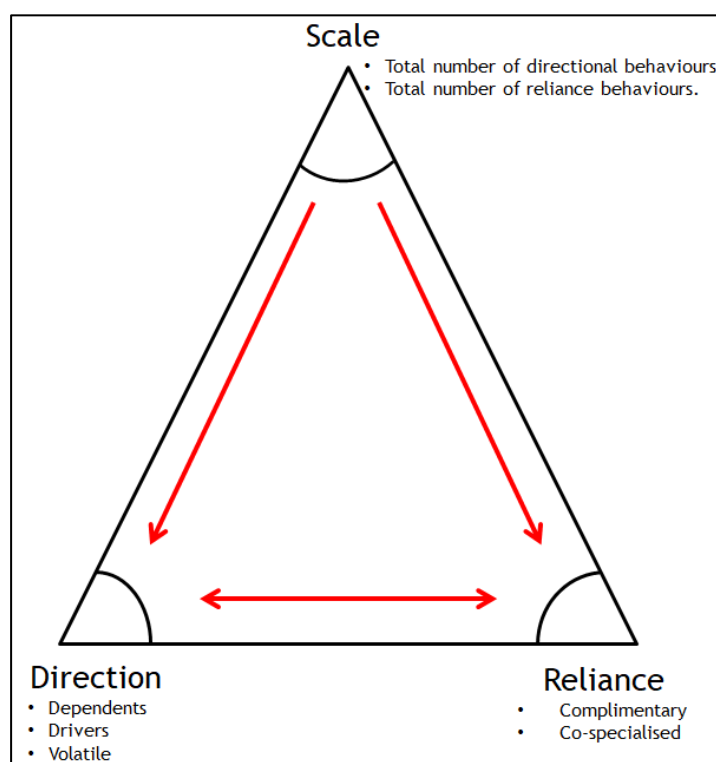


Figure 2: Resource contributions framework.

This is exacerbated by the fact that BDAC's is a broad term. Encompassing all resource deployment requirements to bring data from a raw form to the point it conveys valuable insights to be used (Gupta and George, 2016). Such an issue persists within established literature. With BDAC studies primarily quantitative nature making it difficult to discern resource behaviours the above framework describes. Primarily because of the multiple possibilities as to why they may be related within the broad capability variable they are measured against.

However, recent studies have illustrated BDAC's as a holistic phenomenon, consisting of several different capability constituents; with each addressing a different aspect of data's development. Collectively, all constituents represent an overarching BDAC (Wu et al, 2022), describing the phenomenon in its entirety. These constituents include, but are not limited to data: infrastructure, governance, analytics, visualisation, processing, decision-making and transformation capabilities (Grover et al, 2018).

To address the issue of how broad the BDAC concept is, actually applying the framework in figure 2 means forming a holistic interpretation of multiple capability constituents. Enabling a focus on where antecedents to be studied interact and what their synergies accomplish. Of course, across these different constituents the resource configurations of each and in turn each resources contribution parameters will reconfigure. Changing across constituents as each will encompass a different series of synergies (Wu et al, 2022). This further offers the chance to study how the three behaviour contributions of a specific resource differ across constituents. Detailing if it exhibits a static, unchanging role; or is more dynamic in deployment, serving multiple purposes across the different constituents that form a BDAC.

Thus, moving forward towards the conference, the author will embark on an explanatory mixed methods approach to explore the contributions of several different key resources via the above framework via a holistic BDAC interpretation. After clarifying what constituents make up a BDAC, this will involve first quantitatively clarifying the resource configurations of each constituent. This will be followed by a qualitative study discerning the behavioural contributions of each across the constituents where they are present.

5.0: Conclusion.

The above paper has addressed and established a means by which researchers examining data capabilities may describe and illustrate the various resource synergies from which they are formed. Consequently, research may now be able to examine and reflect upon the individual behaviours of resources in forming data capabilities, what capabilities they form synergies within and their propensity for change across different constituents of data development. The aim of the author is the practical study of the three resource contributions established via a mixed method approach to capitalise on these research opportunities.

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