Implementing Big Data Analytics in a Manufacturing Environment: A Theoretical Framework

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Big data analytics is one of the key technologies of "industry 4.0". McAfee and Brynjolfsson (2012) stated that a successful adoption would require the right balance between leadership, organizational culture, decision making, technology and talent. Our framework focuses on the aspects of leadership, culture and decision making, relying on the literature of complexity leadership and organizational climate. Our theoretical framework, operationalizes these constructs allowing researchers to investigate the effectiveness of the implementation of big data analytics in a manufacturing environment using a survey approach.

INTRODUCTION

The terms Industry 4.0 and the 4th industrial revolution are at the moment at every CEO's agenda in the manufacturing industry. One key technology of industry 4.0 is big data analytics. TechAmerica defines big data as follows: "big data is a term that describes large volume of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management and analysis of the information" (Federal Big Data Commission, 2012, p. 10). The use of analytics is not new, but what is so revolutionary about big data analytics? It is expected that big data analytics will allow companies to measure and therefore manage more precisely, make better predictions and more informed decisions, target more effective interventions, and also in areas that have so far been dominated by gut and intuition (McAfee & Brynjolfsson, 2012). Big data analytics is indicated to be an enabler for the advancement in manufacturing systems (Esmaeilian, Behdad, & Wang, 2016). Some examples of this advancement are additional types of value creation from big data analytics like the creation of transparency, enablement of experimentation and others (Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015).

McAfee and Brynjolfsson (2012) propose five major challenges for adoption: leadership, talent management, technology, decision making and company or organizational culture. They indicate that for companies to reap the full benefits of a transition to using big data, they will have to be able to manage the change process effectively. But the major question is how. Is there one winning combination? Is a certain challenge more important than another? In this article we will first describe the present knowledge about leadership, organizational culture and decision making in relation to big data analytics and a manufacturing environment.

We will not focus on the role and impact of technology and talent management on the adoption of big data analytics, as these two aspects are already discussed extensively by Davenport (2010) and (2014). In a second stage we will link it to the existing literature of complexity leadership and organizational climate, first from theoretical point of view and secondly from an operationalization point of view. Third it will all be combined in a theoretical model, including a survey to allow further empirical research. And finally we will describe shortly how the empirical set-up is drafted as a next step in our research

Big Data Analytics: Defining Adoption and Successful Implementation

To define success and adoption one can look at two major sources of literature. First of all the big data analytics literature. A big data project or roll-out is always done with a certain or several business benefit(s) in mind as described by Fosso Wamba et al. (2015). Therefore, if one discusses a successful implementation, one needs to go beyond the potential of one-time success or value of the project, and look at the sustained value of the change in using big data analytics throughout the organization or in certain departments or units. Ransbotham et al. (2016) state that competitive advantage can only be achieved by a sustained commitment to the role of data in decision making, having a strategic plan for analytics in alignment with the overall corporate strategy, expanding the skill set of management who use data and finally placing a high value on data. Davenport (2014) looks at a successful implementation when multiple data sources and knowledge is used for analysis and optimization, when the quality of the data is good and reliable, when one conducts data-driven experiments, when data is continuously used for decision making, when one develops analytical skills and finally one acts upon the findings.

Second major source that can help us, is the project management literature. This literature is very extensive and we will name a few contributions. For instance Joslin and Müller (2016) focus on the relationship between project governance and success, Harrington and Guimares (2005) focuses on the success of IT projects and Heckman et al. (2016) looks for instance at the relationship between change, change experience and change project performance. Therefore we will build on this part of the literature during the operationalization and link it to the big data literature mentioned before.

Big Data Analytics: Role of Leadership

Gerald Kane et al. (2016) mention change in leadership as one of the transitions of digitally maturing organizations. In their research the following skills emerge as most important to succeed as a leader in a digital workplace: having a transformative vision, including business model change; being forward looking, understanding technology, being change-oriented and openness to transparency. Kane et al. (2015), mention leading by example, implying showing support for teams and helping them to understand how their works fits into the overall business plan. They also mention listening to the internal and external environment. Vidgen et al. (2017) support this by posing that leadership is responsible for the creation of a big data and business value strategy. Kiron et al. (2011) talk about fact-driven leadership in which leaders are open to new ideas that challenge the current practices and the need for data to make decisions. Galbraight (2014) states that in order to take advantage of the opportunity of big data a shift in power will impact leadership. He describes how every organization has an establishment, a power structure with a vested interest in the status quo. The shift of power from experienced and judgmental decision makers to digital decision makers is a challenge that either current leadership can adopt or reject. But this issue plays at all organizational levels therefore another challenge of leadership will be to focus on the alignment of middle managers across the organization in support of the mission (Barton & Court, 2012). B. Brown is even most extreme by stating that in some cases and industries big data analytics could make middle management obsolete (2011). Although one needs to be careful as many others have predicted this already before, but so far it has not yet happened. McAfee and Brynjolfsson (2012) talk about muting the HiPPO or the highest-paid person's opinion. In the case of Ramco Cements by Dutta and Bose (2015) leadership's change openness and guidance are mentioned.

Big Data Analytics: Role of Organizational Culture

Lavalle, Lesser, Schockley, Hopkins and Kruschwitz (2011) name company culture as one of the most faced adoption barriers besides leadership. Schein's (2010, p. 18) generally accepted definition of culture of a group as a pattern of shared basic assumptions learned by a group as it solved its problems of external adaptation and internal integration, which has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, and feel in relation to those problems. He also states that culture can be analyzed at three different levels: artifacts, espoused beliefs and values and finally basic underlying assumptions. He defined the levels depending on the degree to which a cultural phenomenon is visible to the observer. He looks at climate as a manifestation of culture. Climate is therefore more behaviorally oriented (Patterson et al., 2005). There are for instance climates for creativity, innovation, safety… One can investigate the behavior on the level of individual, referred to as psychological climate or at an aggregate level like work group, department or organization, referred to as group, department or organizational climate (Patterson et al., 2005). As many of the terms used in literature before, when talking about culture, are more behavioral aspects, we will focus in this research on climate instead of culture.

Data Driven Climate

Kiron et al. (2011) refer to a fact- or data-driven environment. Davenport assesses a company's analytical culture as an indication for big data readiness or not (Davenport, 2014) and (Davenport et al., 2010). He defines an analytical culture as a culture that searches for the truth, that finds or identifies patterns and gets to root causes, that is as granular as possible in analysis, that seeks data and not just stories to analyze a question or issue, that values negative results as well as positive ones, that uses the results of analyses to make decisions or take actions and finally that is pragmatic about trade-offs in decision making. Janssen et al. (2017) indicate the importance of designing processes to guarantee data quality, as it is a multidimensional concept in big data describing properties of the information such as accuracy, timeliness, completeness, consistency, relevance and fitness for use. If the data quality is not monitored the quality of the decision making, later on, will also be questionable. Colegrove (2016) mentions the importance to forgive your data and to remember that perfection is a myth. Indicating that mistakes still can happen and that it is important to keep flexibility during implementation.

Cross-functional Climate or a Climate without Organizational Silos

If one looks at cooperation models in an organization in big data literature Galbraight (2014) mentions the importance of cross-functional teams, Gabel and Tokarski (2014) talk about breaking down the silos, Kane et al. (2015) see this as integration and collaboration, Fosso Wamba (2015) refer to networking, Donovan (2015) uses the term multi-disciplinary and finally Calvard (2016) speaks about interdisciplinarity.

Innovative and Entrepreneurial Climate

Another big climate aspect if one looks at big data literature is entrepreneurship. A lot of authors mention this in different ways. Donovan (2015) talks about high risk and disruption, White (2016) mentions quick experimentation, Colegrove et al. (2016) use the term piloting and Kane et al. (2016) talk about rapid experimentation and taking risks. Of course innovation and creativity are also often mentioned as for instance by Brynjolfsson and McAfee (2012) and Kane (2015). As data are able to make things like processes, value, information… more transparent (Galbraith, 2014) and visible (Berner, Graupner, & Maedche, 2014) the organizational climate should be able to cope with this.

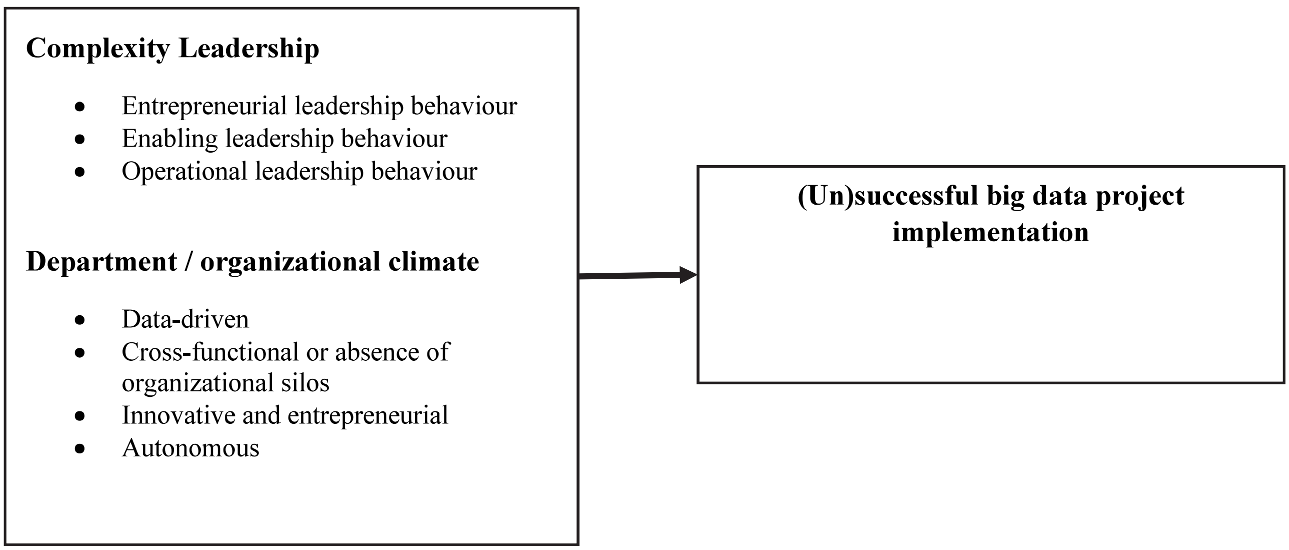
Autonomous Climate

Galbraight, (2014) mentions the following two features of big data: on the one hand the vast amount and different kinds of data, and on the other hand the real time accessibility of this data. . Predictive tools are designed to operate in real time and allow companies to influence the outcome and prevent bad outcomes before they happen. Big data increase the speed in an organization. It even allows companies to experiment with decisions based on big data and models (B. Brown, 2011). Therefore an autonomous climate will support an implementation of big data analytics as it allows companies to make decisions faster and in real-time.

Conceptual Model

Figure 1 depicts the conceptual model, drafted based on the current state of the literature.

FIGURE 1
CONCEPTUAL MODEL



OPERAZIONALIZATION

The goal of this work is the development of a survey that allows us to compare successful and unsuccessful big data analytics projects in a manufacturing environment. Based on the results from the survey it will allow us the to look at the importance and relevance of the different aspects of complexity leadership and organizational culture. To realize this, we will first have to operationalize the three main concepts: organizational culture, leadership and successful big data projects.

Successful Big Data Projects

Implementing a big data project can be compared to the implementation of projects, that are also always accompanied by change. The big data aspects add some IT flavor. Therefore, we will rely on project success literature and IT project success literature to operationalize this aspect of the framework. Joslin and Müller (2016) developed a questionnaire to measure project success along 5 dimensions: project efficiency, organizational benefits, project impact, future potential and stakeholder satisfaction.

Leadership: Complexity Leadership

Bringing big data analytics to the manufacturing floor is bringing innovation to units focused on operational tasks. Uhl-Bien et al. (2007) introduced the complexity leadership model using the concepts of complex adaptive systems (CAS), as they were convinced that leadership should not only be seen as a position and authority but an emergent, interactive dynamic. Arena and Uhl-Bien (2016) see the need for an adaptive space to link operational systems to entrepreneurial systems in order for new solutions and innovations to survive and thrive in complex environments like for instance organizations. Uhl-Bien and Arena (2017) incorporate complexity leadership behaviors in each of the systems, spaces and overlapping spaces. These behaviors create a link between the entrepreneurial and the operational system through the adaptive space. This allows them to define entrepreneurial, enabling and operational leadership, including their behaviors in order to let organizations function as complex adaptive systems in a dynamic system that are able to adapt in and evolve with a changing environment. As Uhl-Bien and Arena (2017) indicate, it could be possible that a single individual engages in all three of them. In most cases however, organizations can tap into a broad array of leaders, that excel in either one of the leadership types. It will in those case be critical to guarantee that the adaptive space is there as well as the linkages between both the entrepreneurial and operational system with the adaptive space.

So far, the complexity leadership model has not been operationalized to be used in a survey. To be able to use the complexity leadership theory, a survey is constructed based on existing literature in the field of operational, enabling and entrepreneurial leadership.

Operational Leadership

Uhl-Bien and Arena (2017) describe in their work that operational leadership has on the one side a bureaucratic focus but on the other side also a focus to realize innovation and adaptability in order to survive. The following key roles are given to illustrate this: conversion of emergent ideas to organizational systems and structures, sponsoring, aligning, executing, creating energy, creating enthusiasm, breaking down the walls that stop innovation... These roles fit very well to the concept of transformational and change leadership. In his review of complexity leadership Brown (2011) states that transformational leadership holds the strongest link to complexity leadership. Bento (2013) states that certain elements are not in contradiction with complexity theory. The big difference, as he writes, is the way both concepts look at the change to take place. Transformational leadership implies that transformations are created, complex thinking implies that transformations emerge and that leadership plays a certain role. Herold et al. (2008) look at the combination of transformational leadership and change leadership in relation to employee's commitment to change. They mention that change leadership refers to the here-and-now, focusing on the specific change at hand and how the leader is handling it from a tactical point of view. Transformational leadership refers to a longer-term relationship established between the leader and followers, built up over many interactions and having a more organizational or strategic orientation. Introducing Big data analytics is exactly the same, introducing a new technology and way of a work, a change based on an at hand project with a focus on the future. The combination of both also fits to the expected addition role described by Uhl-Bien and Arena. For that reason the scales of Herold et al. [refer] for transformational leadership and change leadership will be used to operationalize the item of operational leadership of Uhl-Bien and Arena in the survey.

Entrepreneurial Leadership

In their paper, Uhl-Bien and Arena (2017), describe the following skills for the role of entrepreneurial leader: creation and development of novelty, action oriented, quick, working with limited resources, persistent and patient, flexible and finally linking-up and conflicting. Since the concept of entrepreneurial leadership is rather clear, for the operationalization we draw from the entrepreneurial leadership literature, namely the scale developed by Renko (2015). In his measurement tool (the ENTRELEAD scale) he integrated the following key elements: innovativeness, creativity, passion and motivation, tenacity and persistence, bootstrapping, vision of the future and finally taking risks.

Enabling Leadership

Uhl-Bien and Arena (2017) refer to enabling leadership or enabling leadership capabilities needed to bridge the gap between operational leadership and entrepreneurial leadership. They not that enabling leadership helps initiate and amplify support for novelty, innovation and change. They see the following principles as part of enabling leadership: apply complexity thinking, enable adaptive space, leverage network structures, engage complexity dynamics and play in the pressures. Brokerage, leveraging adaptive tension, linking up, tags and attractors, simple rules and network closure are for them the related practices. To operationalize the concept of enabling leadership, we look at the concept of adaptive leadership. In his book Heifetz (2009) states that adaptive leadership is the practice of mobilizing people to tackle tough challenges and thrive. Heifetz summarizes the following aspects about adaptive leadership: it is about change that enables and thrives what means the orchestration of multiple stakeholders, adaptive changes are built on the past rather than jettison them what means they make the best possible use of previous wisdom and know-how therefore it is both conservative and progressive, it occurs through experimentation, it relies on diversity and it takes time. We will therefore employ certain scales from the adaptive leadership competency profile developed by Sherron (2000). In total the whole framework exists of 10 competency scales. We will employ the following ones to cover the concept of enabling leadership: influencing and motivating, Learning, envisioning, changing and effectiveness.

Climate

In climate literature one of the most extensive validated measuring tools was created by Patterson (2005). In his work he created the Organizational Climate Measure (OCM) that consists of 17 scales. Each scale consists of 5 questions that are all scored on a 5-point Likert scale. Not all 17 scales are relevant for the research at hand. Based on the literature, described earlier, 5 scales can be identified to investigate the relevance of climate in the success of big data analytics in a manufacturing environment: the quality and involvement scales to measure the data-driven climate, the integration scale to measure cross-functional climate or a climate with the absence of organizational silos, the innovation & flexibility scale to measure an innovative and entrepreneurial climate and finally the autonomy scale to measure a climate with room for autonomy and the kind of decision making climate.
Based on the aspects of literature around climate before, on top of all scales identified before one additional scale from the Patterson Organizational Climate Measure is chosen. This is typically a scale that according to literature would not be beneficial for implementing successful big data projects in a manufacturing environment. The scale of choice is tradition. It is typically a climate that does not support innovation and is therefore chosen.

METHODOLOGY

Qualitative Comparative Analysis

All different aspects of climate and complexity leadership have an impact on the final result but also interact with each other. They are interdependent. A set-theoretic approach fits well to a more systemic and holistic view of organizations like Fiss (2007) points out. Fiss (2007, p. 1191) states in his article: in studies employing complexity theory, researchers tend to see organizations as dynamic, non-linear systems, explicitly focusing on connections and the interaction of variables in creating outcomes. The method used for the research will be qualitative comparative analysis as described by Ragin (1987). It has some distinct advantages (Marx, Rihoux, & Ragin, 2014) as for instance: it emphasizes a case-based approach, it is able to link configurations of causally relevant conditions to outcomes, it is comparative and therefore is able to explore similarities and differences across comparable cases and offers a way for examining equifinality. This explains also the suitability for our research since we want to investigate the causally relevant conditions of different scales of complexity leadership and climate for a successful implementation of big data projects.

Our concepts of leadership and climate are not simple on/off concepts, either present or not. These are typical concepts that can vary along certain axes. Therefore, the original approach of qualitative comparative analysis with crisp sets is not a perfect match. But Ragin (2000) widened the methodology introducing the usage of fuzzy-set variables. This allows us to make the variables ordinal or continuous, what makes it better suited for our research.

Sample

In a first step we would like to validate our approach and set-up. In order to do this, we look at one organization, a large multinational chemical manufacturer, based in Germany, with a large production site in Belgium. On the site in Belgium about 3000 people are employed in different service functions and about 25 different manufacturing plants. In several of the plants there have been big data projects implemented over the last years, in total around 5 projects.

In a second phase, we would like to perform the actual investigation. To do this, together with a large consulting firm, we will contact their customer base that, in the last years, implemented big data projects in their organization. In total we will look for 10 to 20 different projects, each to be seen as a different case, to be in focus of the research. Ideally spread over several organizations.

Data Collection

Data will be gathered based on an online survey or questionnaire. Based on the conceptual model a survey will be composed based upon validated questions for each of the topics and from the existing body of literature. Each topic or scale composes of several questions that are rated based on a Likert-scale. The different concepts discussed in the operationalization chapter are not all rated at the same Likert scale. Some are rated at 5-point Likert scale others at 7-point Likert scale. The scaling will be adjusted in such a way that within one overarching concept i.e. project success, leadership or climate, the scales are similar. The overall score for the topic or scale will be the weighted average of the scores on all questions. As we will use fuzzy-set variables the average final scores will be changed into a continuous score between absent (=0) and fully present (=1). This is also the moment that all scores will have a similar scale whether the concept was rated against a 5-point or 7-point Likert scale.

Measures

Online questionnaires will be administered in the respondents' native language (Dutch). Questionnaires will first be translated by the researcher into Dutch and afterwards back-translated by an independent researcher, as recommended by Brislin (1980).

Use of Control Variables

We will include several demographic control variables: age, gender, education, role in organization, department (service, operations…), nationality as well as several industry control variables like sector and number of employees.

ANALYSIS

The overall analysis of the data will consist of three separate studies. In a first stage we will focus on leadership and more precise at the relative importance of each leadership dimension or the combinations of several leadership dimensions of the complexity leadership model, i.e. operational, enabling and entrepreneurial leadership. In a second study we will turn our attention to the relative importance of or combinations of each organizational climate dimension, namely data-driven, cross-functional, innovative & entrepreneurial and autonomous. The third and final study will combine both concepts leadership and climate and search for the relative importance or combinations of dimensions of both that make a big data implementation project more successful or not.

ACADEMIC, MANAGERIAL AND SOCIETAL CONTRIBUTIONS

Academic

This work will contribute to theory in three different ways. First of all, it will contribute to the literature of big data analytics by generating a better view of the importance of climate and leadership on the successful implementation of big data projects in a manufacturing environment and how both aspects interact and influence each other. It will also give a better view on how to influence both factors in order to achieve a better end result. Secondly it will further strengthen the field of complexity leadership in two ways. On the one side it combines complexity leadership with a recent digital challenge, namely big data. On the other side it enlarges body of empirical research on complexity leadership, that is still limited. And third it will contribute to enlarge the body of literature of qualitative comparative analysis, especially in a field that is suited for it like complexity leadership (Fiss, 2007).

Managerial

As a company is a complex adaptive system it is really important to know if there is only one road to a goal or whether there are several equal ways of reaching it. The results from this research will, to a certain extent, give managers a better guidance of the possible roads to implement successfully big data projects in a manufacturing environment. This research makes it a little bit more concrete, unlike the general statements found in literature so far like the 5 challenges from (McAfee & Brynjolfsson, 2012). Local subtleties and differences make often one approach work at one place and fail at another. As part of the research a survey is developed, it can later be used by managers as a tool to scan their organizations in the forefront and determine whether the conditions inside the company are ready to implement big data projects.

Societal

This work will also contribute to the value creation capabilities of organizations. Big data analytics projects are designed to generate a competitive advantage for organizations. The findings of this research will support them to access this faster or sustain it for a longer period of time.

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