PROCESS IMPROVEMENTS IN THE SECOND MACHINE AGE

A QUALITATIVE STUDY ON THE IMPACT OF BIG DATA ANALYTICS ON CONTINUAL IMPROVEMENTS

LEO WEI

VIKTOR HÖKENHAMMAR

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Process Improvements in the Second Machine Age

Abstract:
Big data analytics (BDA) is fundamentally reshaping how businesses approach and work with tasks and operations. Following rapid technological developments, and the increased ability for data processing, BDA has become increasingly ubiquitous within businesses across a plethora of industries. At the same time, many firms are still failing to realize BDA's full potential, pertaining to its ability to bolster process improvements. As such, the purpose of this paper is to explore whether BDA has a significant impact on continual process improvements, and what the nature of this impact entails. To this end, a qualitative case study has been performed, featuring a retail company possessing mature and developed BDA functions. A total of five interviews were conducted with senior staff from different business units, to explore their experiences with BDA. The findings show that BDA does have a substantially positive effect on continual improvements, in two overarching categories. Firstly, it impacts and transforms the culture within the unit, making it more data driven. Therefore, improvement initiatives are realized at a much higher rate, and the quality of said initiatives are also enhanced. Secondly, the usage of BDA enables stronger vicarious learning and knowledge sharing across business units, thereby increasing the total pool of knowledge within the organization, which facilitates stronger improvements across the board. The findings of this thesis add insights to the existing body of research relating to BDA and continual improvements, while also providing practitioners with valuable information, which can enable for a stronger, and more fruitful, cultivation of BDA.

Keywords:

Big Data Analytics, Continual Improvement, Artificial Intelligence, Automation, Business Intelligence

Authors:

Leo Wei (24363)

Viktor Hökenhammar (24505)

Supervisor:

Ingela Sölvell, PhD, Center for Advanced Studies in Leadership

Examiner:

Laurence Romani, Associate Professor, Department of Management and Organization

Bachelor Thesis
Bachelor Program in Management
Stockholm School of Economics

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1. INTRODUCTION

1.1 Background

The advent of increased information technology embeddedness in business organizations has the potential to fundamentally change practices and structures (Volkoff et al, 2007). While most large organizations have historically employed business intelligence departments, the introduction of Big Data (BD) computing and increased technological development have facilitated an exponentially growing data gathering capacity. The prospect of BD has been a focal point in both literature and the business realm since the beginning of the previous decade (Liang & Liu, 2018). The interest from companies has primarily stemmed from the prospect of increased data processing and subsequently deriving competitive advantages from these capabilities (Corea et al, 2016).

More recently, a growing number of firms have begun developing their automation, machine learning, and Artificial Intelligence (AI) capabilities (Akter et al, 2016). These capabilities serve as a natural next step in this evolution, as they transform the descriptive data points into prescriptive habits and actions, thereby significantly increasing capabilities such as decision making. The increased use of automation and prescriptive decision making has already had a profound impact on the way managers deliberate on choices (McAfee & Brynjolfsson, 2012). In contrast, managers devoid of tangible data points often make decisions based on intuition, with seniority and status often being a determining factor in selecting which opinions get heard.

Big Data Analytics (BDA) has, in its general term, most often been described as the extensive inclusion of data collection, data analysis, and predictive analysis in business processes. BDA's internal capabilities are three-fold: descriptive analytics, predictive analytics, and prescriptive analytics (Kaur Saggi & Jain, 2018). Descriptive analytics entail large-scale data mining and intake of data from a variety of human and business generated sources. Predictive analytics uses machine-learning capabilities and advanced algorithms to forecast future events, based on an extensive collection of historical data.

Finally, prescriptive analytics lays out courses of action and their contingencies, while advising action based on the previous predictive deliberation.

Today, BDA is utilized in a multitude of different industries. Within retail for example, BDA has been utilized to more accurately tailor product offerings to customers. Further, many companies are also using BDA for merchandising purposes, and to regulate inventory (Ridge et al, 2015). The development of data storing capabilities, technical advancements in AI, and the increased interconnectedness between consumers and companies has facilitated an environment conducive to the growth and adoption of BDA (Kaur Saggi & Jain, 2018). Thus, in the presiding business climate, companies view a successful implementation of BDA as a competitive advantage, one that can enhance business practices and processes across the board. This sentiment is far from unwarranted, many scholars have long since proclaimed that the proliferation of advanced analytics and AI constitute a fourth industrial revolution (Lee et al, 2014).

Thus, the ability to effectively cultivate large volumes of data has been argued to be increasingly relevant in many dynamic and rapidly developing markets and industries, where there is an enduring need for continuous improvements (Prescott, 2014). However, a large body of literature also shows that a considerable number of firms fail in realizing these supposed improvement benefits from BDA, thereby also putting into question BDA’s ability to impact continuous improvement processes (Marr, 2016; Günther et al, 2017).

1.2 Purpose and Research Question

The purpose of the study is to bridge the gap between a systems-heavy approach and management science by deeply examining how BDA alters and affects the structural landscape of continual improvement processes, and how it impacts the people working in such environments. In doing so, the study will encompass all aspects of BDA, including its descriptive, prescriptive, and predictive capabilities. Process improvement is defined as a continual effort to improve products, services, and processes in a business setting.

Furthermore, the purpose of the study is to examine whether BDA has an impact on softer, intangible, and interpersonal aspects of process improvements. To this end, a theoretical lens of organizational learning is employed, to closely examine the relation between BDA and learning, and by extension, since process improvements are repositories of past learnings, BDA's effect on process improvements can be uncovered. In an age where an increasing number of firms are seeking ways to cultivate BDA capabilities into a competitive advantage (Barton & Court, 2012), further understanding the linkage between BDA, often understood as a radical innovation, and how it influences the ability to steadily generate future incremental improvements is crucial to understand. Not only will it give managers a detailed insight into the nature of this relationship, but it can also facilitate a greater understanding of eventual pitfalls and measures needed for the optimal cultivation of BDA as a tool to improve business practices.

The research question is posited as follows:

How does big data analytics affect continual process improvements?

1.3 Delimitations

Continual process improvements are classified as improvements grounded in continual updates of current processes (Weick & Quinn 1999). As units and organizations repeatedly perform tasks over time, improvements and changes are realized. These changes are often more incremental, but in a cumulative sense, constitute significant improvements in business practices. As such, the purpose of this paper is to examine BDA's effect on continual improvement, and not to delineate its effect on any larger scale product or process innovations.

2. THEORY

In this part of the study, the authors will present previous research about the field of continual process improvements and BDA with reference to the research question. This part also includes the study´s theoretical framework – Argote and Miron-Spektor's learning cycle. The section ends with a discussion of the theoretical framework.

2.1 Previous Research

Previous research on the effects of BDA on improvement and innovation has often focused heavily on R&D (Blackburn et al, 2017; Niebel et al, 2019; Duan et al, 2020), and in doing so, more intricately analyzed the effects of BDA on new product developments and more large-scale organizational improvements. Among these, Duan et al. found that the usage of BDA leads to an increased ability for environmental scanning, which is further improved through the cementation of a data-driven culture, because of BDA usage. The increased environmental scanning enables managers to make sounder innovation decisions, which are backed by more data. However, Duan et al. solely studied the effect on product innovation, without regard for whether this effect carried over to incremental improvements and process improvements. Similarly, Zhan et al. (2017) found BDA to have a significant positive impact on product innovation. They conclude that companies benefit from incorporating BDA capabilities in their innovation processes because it accelerates the innovation journey, enhances customer connection, and facilitates the creation of an ecosystem of innovation. These three factors in summation enable companies to deliver faster innovation with increased efficiency. In the same vein, Hao et al. (2019), found that the successful implementation of BDA capabilities had a positive effect on innovation performance. However, their scope was limited, as the study did not incorporate some developments within BDA, namely the predictive capabilities involving machine learning.

In terms of BDA in relation to smaller scale incremental improvements, Wu et al. (2020), conclude that BDA usage constitutes a significant complementarity with process improvement. Furthermore, they did not find a significant relationship between process improvement and general information system capabilities. Rather, the positive effect was exclusively found related to BDA capabilities. Further, the connection of novel innovation and BDA capabilities was also found to be non-complementary, as process innovation served as the major benefactor of said capabilities. Matthias et al. (2017), argue that Big Data tools enable managers to improve operational processes because more data becomes available to deliberate upon, thereby ensuring sounder decision making. However, their study primarily focused on Big Data, meaning the descriptive part of BDA, and insufficiently on the prescriptive and predictive developments within BDA. Earlier studies have also predominantly been systems-oriented, with little emphasis placed on human experiences and perceptions of BDA. Studies examining the linkage between BDA and process improvement within management science have also been scarce. While some research concerning their relationship have been presented, their results often merely present a causal link, without delving into the core details of the impact (Matthias et al, 2017; Wu et al, 2020).

Bean (2016) insinuate that success stories of BDA-enabled innovation has been delayed. He claims that most accomplishments that derive from BDA involves operational costs savings. Some of the challenge's companies struggle with as they operationalize BDA are related to people, not technology: issues mostly concern organizational alignment, business process and adoption, and change management. Bean also argues that organizations cannot adopt BDA successfully without cultural change. According to Fountaine et al. (2019), when companies try to build an AI-powered organization, technology is not the biggest challenge, culture is. They claim that to support the adoption of AI, a company needs to align it with its culture, structure, and way of working. Otherwise, the company´s culture can contribute to resistance. Davenport (2019) claims that many companies aspire to have cultures that embrace data, analytics, and AI but few make a concerted effort to create such cultures.

2.2 Research gap

Previous research surrounding BDA and its effect on improvement has focused heavily on larger scale improvements and innovations, such as R&D and more overarching process innovations, and less so on continuous and smaller scale improvements. As such, the purpose of this paper is to study the linkage between BDA and improvements of a more continuous and incremental nature. Furthermore, in the instances where the literature does cover BDA's effect on continuous improvements, it often does so through a mechanical and systems-oriented lens, with a much smaller focus on management science. This should certainly come as no surprise, seeing as BDA, and its many endemic properties, such as machine learning and advanced neural networks, feature heavily in the wider data science literature. Therefore, as mentioned previously, the authors aim to bridge this gap, through studying the more intangible, softer, and human effects of BDA on continual improvement processes.

2.3 Theoretical Framework

In this section, the authors will present the theoretical framework of the study that the analysis and conclusion will proceed from.

2.3.1 Argote and Miron-Spektor's Learning Cycle

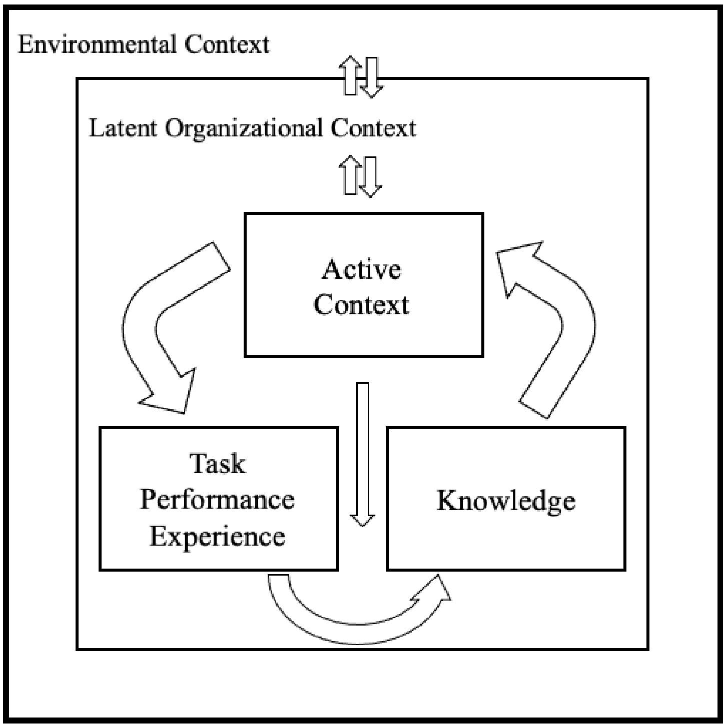

Figure 1. Argote and Miron-Spektor's learning cycle (2011), edit by Hökenhammar and Wei 2021.

Argote and Miron-Spektor's (2011) learning cycle delineates the learning and improvement process into a recurring cycle. In doing so, it presents distinct steps in the cycle, enabling an easier understanding of each step, and by extension, the entire process. The cycle can be applied to functions of varying sizes, from entire organizations to smaller business units. Starting from the onset, the entire learning process is enveloped in a wider environmental context. This context is external and pertains to factors such as customers and outside influences. Ultimately, the environmental context exists, in the scope of the model, to affect the latent context. The latent context is internal to the organization, it is also passive. Thus, it also exerts influence passively, by impacting the active context. Similarly, the active context can also impact the latent context. Concretely, the latent context embodies more interpersonal and intangible factors, such as culture and values within the designated organization or group. The active context represents the members and employees in a given organization or group, and the tools at their disposal. Within the latent context exists the core of the learning cycle. Each new lesson and impression begin with a task performance. This occurs when the active context interacts with a new task experience. Concretely, this occurs when, for example, an employee approaches a recurring task in a new way. This creates knowledge, symbolized by the bottom arrow. Knowledge can either be directly created through experience, or it can be transferred from another part of the organization, represented by the vertical arrow between the active context and the bottom knowledge arrow. This knowledge is then compartmentalized and moved to the knowledge retention stage, represented by the arrow in the upper right corner. The knowledge retained is then imposed on the active context. The active context, in a way, “stores” the retained knowledge. Finally, members generate new experiences by performing tasks, thereby beginning the cycle anew, with all previous compartmentalized knowledge.

Within the context of this paper, the model can help us understand the usage of technical tools, and their effect on the learning cycle and wider process improvements. The purpose of generating valuable knowledge from past experiences is to fundamentally improve existing practices. Thus, understanding if, and how, BDA affects different parts of the learning cycle ultimately means understanding the intricacies of BDA and process improvement.

2.3.2 Theory Discussion

The linkage between learning and improvements is well documented. A continuous improvement process requires adequate learning (Garvin, 1993). As the first stage in any improvement process, reviewing and distilling previous experiences and knowledge is crucial, in order to develop a course of action in improving existing processes. In this case, the model encompasses continual process improvements as the final stage of the learning cycle, when the active context performs a task anew, in a refined and improved manner, with the retained knowledge of previous experiences. Again, showing that improvements serve as the repository of learning. Thus, the authors find the theory to be substantially relevant, and hope this clears up any potential feeling of disconnect, since learning and process improvements can be, on a surface level, interpreted as two distinct topics.

Much confidence is placed in the chosen theoretical framework because of its viability in answering the research question. As stated previously, the authors aim to bridge the gap between the systems-heavy research and the management literature. Our goal is therefore to identify the “softer” and more intangible impact of BDA on continual improvement processes. The selected framework enables us to carry out this analysis by incorporating and capturing said criteria’s in a holistic manner. For example, factors such as culture, organizational structures, and interpersonal relations are prominently included in the delineation of the learning cycle.

While the authors believe the theoretical framework to be appropriate, as pertaining to the research question, there are nevertheless parts of the framework which should be criticized and put under scrutiny. Regarding the learning cycle, while it does a good job in conceptualizing the learning process, it does a lackluster job in accounting for some contextual factors. For example, it refrains from assigning different levels of weight, or importance, to the different stages in the cycle. Nor does it explain whether these different stages are more, or less, important, depending on contextual factors of different organizations. Further, the model also presents knowledge as a monolith, to some degree. Thus, it does not actively distinguish between different types of knowledge, such as tacit or concrete knowledge. Because of this, confusion can potentially arise when analyzing knowledge as framed by the model, because different types of knowledge creation and transfer occurs in fundamentally different ways.

However, for the purposes of this paper, these shortcomings do not impact the assessment of any potential findings, as relating to the research question. The authors have chosen to disregard weighing the effects on the different stages of the cycle; instead, the authors are exploratively trying to identify BDA’s potential impact each stage. Nor does the distinction between tacit and concrete knowledge impact the analysis, insofar as both forms contribute to improvements. Thus, the authors believe strongly that the theoretical framework is suitable in fulfilling the purpose of the study.

3. METHODOLOGY

This section will present the study´s methodological approach. To answer the research question about how the implementation and BDA affect process improvements, a qualitative case study approach was chosen (Bryman & Bell, 2018).

3.1 Research approach

The underlying philosophy of the research design will be interpretive. Since the purpose of the study is to understand how individuals and organizations assess BDA and its impact on process improvements, an interpretive philosophy enables solid elicitation of subjective perceptions and sensemaking. The study aims to describe what goes on in an organization, and the authors therefore believe the breadth this entails must account for differences in everyone's predicament and environment. Further, the research inhabits a constructivist ontological position, and in doing so, reflecting the personal social reality of respondents. To this end, a qualitative approach is deemed to be most appropriate, because the compartmentalization of experiences and viewpoints sought after would be more difficult to capture quantitatively (Ibid.).

The thesis is based on an extensive literature review in order to find an appropriate theoretical background to guide the research. Empirical data was collected with regard for previous research, which in turn facilitated the theoretical perspective. The research question was developed by theoretical and empirical insights. Thus, the study follows an abductive process so that the back-and-forth iterative nature between empirical data and theory can yield fruitful and comprehensive results, greater than any purely inductive or deductive method. The chosen approach also resulted in a deeper understanding of the different parts of the research field and enabled the authors to find a better fit for the theoretical perspective (Ibid.).

3.2 Case Study

A case study was considered an appropriate method to provide relevant in-depth data, add strength to previous research, as well as understand the complex real-life situations for employees working within BDA units (Krusenvik, 2016). With the study design, the authors could gather rich data, which later allowed for a detailed and intensive analysis. When looking for prospective companies to study, the authors sent e-mails to different organizations (see Appendix 1).

The case study is based on a retail company that possesses well-developed and mature BDA functions. The organization was chosen from the following three criteria: size, access to information, and BDA maturity. The case company fulfilled all of these criteria. Principally, its BDA maturity was very appealing since this study aims to discover and explain the effects of BDA. Thus, companies with less mature BDA functions were unattractive, since the authors were not interested in delineating any transitory effects, nor is this paper geared toward analyzing the implementation process of BDA. Finally, the availability of the case company was also a deciding factor. When scouting potential respondents, the authors encountered a high degree of desired anonymity, and in many cases, a disinterest in sharing information about the inner workings of their BDA functions. Therefore, extending the scope to study a multitude of organizations was quickly ruled out, as such a method would be much harder to accomplish, if not impossible, it would also most likely provide much shallower data. Thus, focusing on one case company in depth, and thereby also being granted much more detailed data, proved to be more fruitful.

Case studies, in general, imply some limitations, such as lack of rigor. According to Yin (2009), when conducting a case study, biased views can influence the directions of the findings and conclusions. This implies limited generalizability. When looking at just one organization, its problematic to generalize the result to other contexts (Yin, 2009; Bryman & Bell, 2018). For example, it is possible that smaller retail companies may not experience the same benefits of working with BDA as the studied company since their capabilities are not as developed and mature. Furthermore, companies within other sectors may not gain the same benefits of developing the capabilities of the studied enterprise. However, the authors believe that a case study design possesses a great learning opportunity. While the authors do not necessarily believe that the theoretical outcomes from the thesis may be directly transferrable to other organizations, the authors do believe that the outcomes can be used to understand how BDA at an organization can affect process improvements, and from this abstraction, further extrapolations and studies could be made in order to find generalizability across other industries. Further, as a large and mature retail company in a large and mature market, the authors do not believe the experiences from the case company to be vastly different from that of other similar companies in a similar context. Thus, at the very least, strong generalizability within the same context among peer organizations, of which there are many, can be assumed.

3.3 Data collection

The data collection presented under *4. EMPIRICS*, consisted of multiple semi-structured interviews with managers and employees of BDA related business units at the chosen company.

The sample of interviewees at the Company was selected to generate as much insight as possible. Five interviews were conducted during March and April 2021 (see Appendix 2). The interviews were conducted individually with managers and employees. In total, the interviewees came from two different units, allocation and sales. From each unit, the authors interviewed both the business owner, but also the product owner for the BDA product. In both of the mentioned business units, the business owner and the BDA owner work in tandem. In this constellation, the business owner is the ultimate end user of the BDA product, which the BDA owner is in charge of developing. Since the BDA function works as a support function within each unit, the authors trust it would be fruitful to interview both the business side and the more technical side, in order to gain deeper insights. Finally, the authors also interviewed the head of both these units, to gain a more general view, and to find common denominators in answers. Taken at face value, a total respondent group of five might seem a bit shallow. However, the authors believe it to be sufficient because of the depth and detail each respondent brought. Both the BDA owner and business owner are responsible for numerous employees below them. They thus comprise the top strata of each business unit. Therefore, they are able to provide substantially profound data, while also being able to act as a proxy for the numerous employees they are in charge of, thereby also encapsulating these employees' experiences. Thus, the authors believe the quality and depth of the data collected more than makes up for the seemingly small sample size.

At all times, both authors participated in the interviews. This implied two perspectives on each interview regarding what had been said. The authors believe that this approach gave a more objective view of the studied company´s BDA and process improvements. Prior to the interviews, the authors listed several questions regarding topics to cover and during the interviews the authors adapted the questionaries depending on the discussions. The interviews began with easy and open questions about the respondents' backgrounds and roles, and then progressed with more specific questions about BDA and process improvements. The inclusion of open-ended questions facilitated a coherent narrative in the line of questioning, while being flexible enough to allow for the apt digestion of eventual answers of a more personal and unexpected nature. For the interview guide, see Appendix 3.

For clarity and structure, the interviews were divided into two thematic sections, the first concerning BDA and continual process improvements, and the second about the company and its working environment. The chosen interview method enabled the authors to compare individual answers while still collecting the general group opinion. Worth mentioning is that the theoretical and empirical knowledge expanded for each interview, which increased the quality of the questions and discussions. However, several core questions remained the same in order to capture a consistent perspective of the processes.

3.4 Data Analysis

Following each interview, the empirical material was immediately transcribed, to ensure accuracy of data. After the transcripts were finished, the authors engaged in a rigorous review of the empirical data, in order to find commonalities and themes (Bryman & Bell, 2018). To ensure soundness of espoused themes, this process was done separately by both authors. In the search for different themes, the authors paid close attention to similarities, repetitions, and differences in answers. Close attention was also paid to specific industry jargon, or reiteration of key concepts. Thus, the analysis combined different measures that would ensure a rigorous and valid presentation of common themes in the data.

After the outline of general themes was finished, the authors chose relevant quotes to present. Following the iterative nature of our study design, the authors also continuously reviewed the theory in tandem with the empirical data. Thus, eventual discrepancies were dealt with, and the data was examined through the lens of the theoretical framework. Since the interviews were conducted in Swedish, quotes had to be translated into English, and subsequently, minor alterations were made to phrases, to ensure readability.

3.5 Method Discussion

To ensure transferability, descriptions of empirical findings and their extrapolations are presented in conjunction with the contextual backdrop of the organization. In many instances of the data, experiences are innately relevant to a retail context. Other times, they are heavily related to the organization's analytics-maturity. As such, the authors hope this will enable readers to more easily judge whether the findings are transferable to another context. While the authors are aware that transferability is a liability in the chosen research design, it is our hope that the efforts taken to ameliorate this problem will prove fruitful.

In terms of credibility, both authors were present during each interview, in order to ensure an affirmation of findings. Confirmatory follow up questions were also asked frequently during the interviews, to ensure the authors a correct interpretation of the interviewees position. Further, when any eventual questions arose after the fact, e-mail correspondences with the interviewees in question were held, in order to clear up any misunderstandings or outstanding questions. The aforementioned measures were also taken to bolster the confirmability of the research. Further, in order to rid the process of any partiality, the authors took turns asking different interview questions, so as to avoid any recurring instances of biased questioning. Regarding dependability, all relevant material has been stored, ranging from transcripts, notes, and the different stages in the research formulation, to ensure relevant checks can be performed.

While the authors acknowledge that the case study design does hamper the generalizability of findings, the decision to proceed with this method formulation has been thoroughly deliberated upon. Firstly, since BDA is a relatively new topic, many discrepancies exist between different organizations BDA maturity levels, insofar as they actually employ BDA solutions, which is not necessarily a given fact either. This could potentially lead to large discrepancies in data, if the study was conducted with a wide variety of organizations, since the contextual factors surrounding the level of BDA proficiency would be difficult to account for. Companies at different stages BDA maturity would potentially embody vastly different experiences, because of differences in the extent of their BDA capabilities. By choosing to study a company with a mature relationship with BDA, the authors believe it will properly represent the sought-after data, while keeping the data coherent.

Secondly, by focusing on a singular case, the authors were also able to look more thoroughly across different business units, and to find common denominators in their experience with BDA. Therefore, it is our goal to reduce the actual business practice within each unit to an unaffecting variable, which enables an isolated and more robust look at the relationship between BDA and process improvements, regardless of any underlying business context. If the study were to extend the same design to multiple cases, then, as stated previously, the contextual variances would be even larger. The difference in organizational context, combined with differences in BDA maturity, would result in substantial variance in the empirical data. It would therefore be difficult to distill the relationship between process improvements and BDA, and the authors would run the risk of having this relationship tainted by contextual factors not relevant to this study. In that case, the authors would have to reduce the scope to only study one specific business function across different organizations, in order to arrive at a conclusion of similar robustness; however, the authors believe this would further hamper generalizability.

4. EMPIRICS

In this part of the study, the answers by the respondents will be presented without the authors subjective opinions. To facilitate the reading, the authors have chosen to divide the collected data into two parts; the first part consists of BDA's effect on the culture and workplace, the second part contains BDA's effect on knowledge and learning.

Before the answers are presented, to get a bigger understanding for the effects of BDA, a short description of how the case organization employs BDA follows: The case organization employs BDA in multiple facets of their business. For example, the entirety of BDA's threefold capabilities is used in processes like procurement quantification, allocation decisions of products to stores, and balancing supplies between warehouses. In regard to more customer-facing processes, BDA is used to enhance their product recommendation engine, as well as provide more personalized marketing communication.

4.1 Cultural and Contextual Impact

The increased use of BDA can facilitate an increased awareness for improvement opportunities, through a data-driven mindset, and it can also influence the culture and workplace. The data collection regarding the effect of BDA on culture and the workplace will be divided into two parts. One part about the enthusiasm that follows from working with BDA. The other part will consist of the changes in the organizational structure and the decentralized decision-making that follows.

4.1.1 Increased Enthusiasm of Working with BDA

The use of BDA has substantial effects on the workplace culture. As respondent 1 states:

> *"For predictive analytics, when the model arrives at the same conclusion you had from the beginning; the enthusiasm increases drastically. You start asking, what is next, what can we do more? It becomes exciting. It is what IT was 20 years ago. There is a "buzz" whenever you can do predictive work without doing it manually."*

> *“More people have been aware of how powerful data can be for developing the organization and business practices, which makes them eager to learn more.”*

Along the same lines, respondent 3 claimed:

> *“When you can measure something, and see progress, everything becomes more fun. Our goal is to be able to see the progress in all forms of KPIs, and when that becomes possible, it’s fantastic.”*

The increased enthusiasm for the work, and the feeling of novelty surrounding BDA, has led to a more eager approach to improving existing products and services. Therefore, the improvement drive has become much more embedded in the culture and daily work, employees are more willing to test boundaries and experiment in different improvement endeavors. This has subsequently led to an increase in successful process improvements initiatives.

While one of the respondents felt that BDA, and its ability to increase enthusiasm among employees, led to a larger desire and yearning for process improvements, there were some caveats. Respondent 4 explains:

> *“When I was in merchandising, where there is a younger audience and younger employees, enthusiasm stemming from BDA was more palpable. So, we looked at data very intensely, and did a/b testing frequently, almost to a fault, with large enthusiasm for improvement. Whereas now, I am working in a unit where some employees have worked for the past 25 years, with clear working habits, it is therefore much harder to garner the same enthusiasm when people do not have the same data-driven mindset.”*

While present, the enthusiasm and "buzz" from BDA proliferation does not necessarily extend to most functions, to the same degree. There is also not a clear dichotomy between old and young regarding this discrepancy, as the respondent noted, it has more to do with competency and background, whether one is more data-driven and technical, or not.

The role of BDA in transforming the workplace culture is substantial. There is generally a strong enthusiasm surrounding some of these novel breakthroughs, and they seem to spur more hardy process improvements, since employees experience more enthusiasm for their work. Additionally, since BDA requires and abundance of data-points, tracking progress also provides employees with a sense of accomplishment, and a willingness to do more.

4.1.2 BDA Makes the Organization Flatter and Improvement Initiatives More Meritocratic

In the absence of BDA, respondents claimed that decision making concerning improvement were often very hierarchical. The decisions concerning potential improvement paths and initiatives were often taken based on the seniority level of the person championing it. This would often make it somewhat harder for more junior employees to suggest tweaks to existing processes, since they were often perceived to lack relevant experience.

For example, say the organization needs to decide prices for their different product offerings. Previously, in the absence of BDA, the senior staff with heaps of knowledge and experience would have used their intuition to decide the different prices of the products. The less experienced and lower ranked employees would have very little say in optimizing this process. With BDA, however, the same employees can use the available data in the organization to quantify and back up their claims. The junior employees can use BDA to gather evidence that supports their ideas and prove to the more senior staff and managers why their ideas should be considered when making decisions regarding pricing. Senior management now has a much harder time arguing against the data-proven argument since the mantra of "data does not lie" has been overarchingly cemented in the organization.

Respondent 1 from the interviewed organization describes how their unit, and by extension, the organization, became flatter and more decentralized when individuals were given the freedom to explore their opportunities with BDA:

> *"We become a more decentralized company and flatter organization when working with BDA. With BDA, we combine human ideas with data, which affects our decision making. Everyone in the organization can come with inputs and contribute to incremental improvements via BDA since each of us can present data that supports a specific vision or idea. The weight of previous experience and knowledge by managers is reduced, and we start to focus more on what the data says. Therefore, regarding rank in the organization – decision makers have to listen to less experienced employees."*

Respondent 5 continues in the same pattern:

> *"BDA changes how we as an organization work with improvements. Senior staff are more open to ideas from less experienced employees. With BDA, ideas that are supported by data will be considered to a larger extent because of the credibility that follows from data that supports a vision or idea."*

> *"With BDA, with an increased data-driven culture, if you can tell a story, describe a problem, quantify the problem, and translate it, then you can go as far as you like, the company is at your disposal. Because it is impossible to argue against such an argument. This makes process improvements very easy."*

With BDA, the decision making becomes more decentralized and flatter. Thus, BDA makes it possible for individuals at all levels in an organization to make their voices heard and to facilitate, and drive, a change.

In this respect, the implementation of BDA, and the cementation of a data-driven culture, seems to have made the realm of process improvements more meritocratic, and decision making more decentralized. More junior employees can drive change much easier since the only thing they need is the relevant data to back up any argument. By using BDA, the value of subjective opinions is decreased since the idea that "data does not lie" has become increasingly ingrained in the culture. This has enabled more sound and efficient improvements paths to surface, and the Company spends their time much more efficiently since arguments and initiatives are more data driven. It also rebalances, to some degree, the weight of seniority. So long as an employee can back up an argument, driving change can be much easier than before. At the same time, this also necessitates the increased need for strong data, and a constant need to improve available processes. According to respondent 2,

> *"With BDA the organization becomes much flatter. However, when it comes to predictive and prescriptive analytics, someone could always criticize the underlying data. This could lead to other discussions surrounding the correct answer."*

4.1.3 Summary Cultural and Contextual Impact

To sum up briefly, working with BDA and improvement changes an organization´s culture in several ways. The workplace becomes more data-driven, and the decision making of the organization becomes more decentralized since BDA enables people at all ranks to make their voices heard. Principally, this cultural change then impacts the proclivity for improvement initiatives, and the ease of implementation, culminating in a total increase in successful improvements to existing practices. Furthermore, employees become more enthusiastic and excited about their workplace because of the "buzz" that surrounds the phenomena of BDA. Subsequently, they are also more eager to test new boundaries, and to drive improvement initiatives to a larger degree.

4.2 Knowledge Sharing and Network Effects

BDA can also be used to make organization's way of working more efficient. The implementation of analytics products has led to increased interconnectedness between different business units. As such, data sharing has become much more streamlined and proficient, and information is more readily available. As respondent 3 claim:

> *"There are definitely internal network effects, the more use cases and similar products that are around us, the better decisions we make and the entire value-chain benefits. / - - - / We have gone from a silo-mindset with, say, logistics, purchasing, and sales as different functions, toward more (analytics) product-based mindset. I believe this is 100% better, and we share information much better, albeit still not perfect."*

Respondent 4 concurred:

> *"For the analytics functions, we have chosen to be very cross-functional, there are many functions and stakeholders involved, and the "tendons" are very connected, so information and knowledge sharing is definitely a benefit."*

Apart from the technical benefits of BDA, different business units have also grown closer and are now sharing knowledge and data at a much larger level. It is more natural to connect to coworkers across these boundaries, and subsequently incorporate learnings and experiences from other functions into one's own, thereby making improvement processes more proficient, as the pool of knowledge and experience grows exponentially.

Respondent 2 also mentioned some intangible effects with BDA:

> *"This is a subject that has great traction. There is a clear improvement-mindset with analytics. It feels new and cool, and many find it exciting. It is easier to engage in cross-functional work and data sharing because of the "buzz" surrounding it."*

Respondent 5 notes:

> *"We have always tried to be "omni", meaning, we want to be viewed as one company and not separated by units, however, during my first years here this was nothing more than a slogan. Today, when we set clear goals based on data from many different functions and aspects, we must work in a more cross-functional manner, because we now have the ability to share and use data at a much more efficient rate."*
>
> *"With BDA, we get a much more holistic view of the business, we can track and measure many more datapoints. This has also made the functions tighter knit. Logistics understands what e-commerce is doing, and e-commerce understands what marketing is doing. This happens because we develop a common language, by virtue of the shared data."*
>
> *"I'll give you an example, we used to send these campaign emails to customers. However, we lacked an understanding of whether this had an impact or not on actual sales. It was easy for marketing to say, "That email we sent yesterday felt great", while e-commerce would say "Actually, we sold very poorly". With BDA we can not only track these types of relationships more intricately, to measure whether it actually had an impact, but both of these functions share the same data, and thus they learn from each other more, and this leads to stronger improvements."*

In summation, network effects and knowledge sharing effects from BDA are present, and apart from the structural and technical benefits, of which are many, there are also intangible benefits. In this regard, these insights of BDA regarding the hype surrounding analytics are also congruent with the general cultural changes mentioned previously. In sum, the increased interconnectedness and ability to share knowledge more efficiently has facilitated more efficient and frequent improvements.

5. ANALYSIS

The analysis section will examine the empirical data through the lens of the theoretical framework. It begins with an analysis of the impact on the organizational context, specifically, how BDA increases enthusiasm and how BDA makes an organization flatter and improvement initiatives more meritocratic. The analysis will thereafter present how BDA can be used for knowledge sharing and network effects by making a company's way of working more efficient and increase the interconnectedness between different business units. The analysis will shed light on how BDA alters existing structures, as well as how it redefines the workplace for employees.

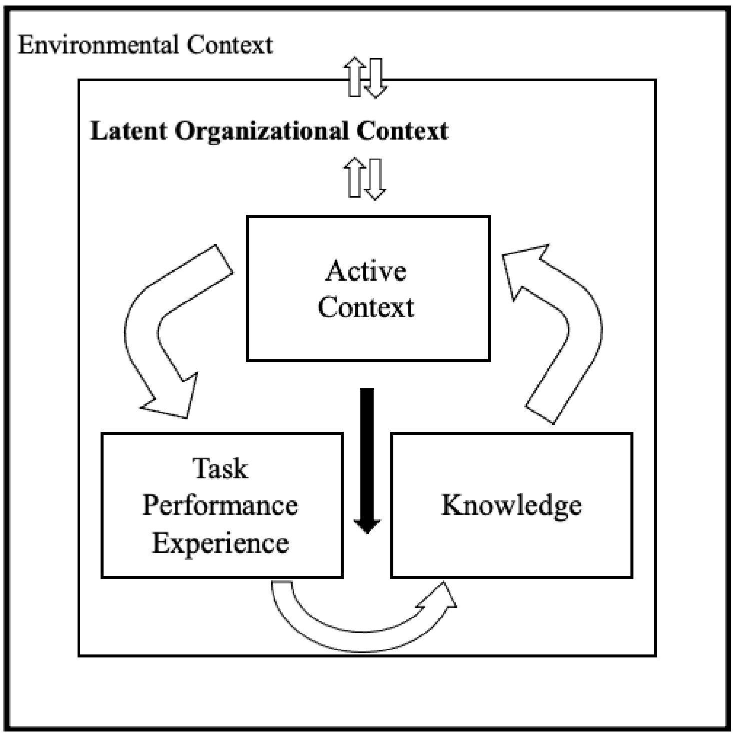

Figure 2. Argote and Miron-Spektor's learning cycle (2011), edit by Hökenhammar and Wei 2021.

5.1 Impact on the Latent Context

According to Argote and Miron-Spektor, the organizational context comprises the underlying values and cultures which envelops the business unit or organization. As such, the aforementioned cultural changes stemming from BDA can be viewed as a transformation in each business unit's latent context, and following BDA's ubiquitous use within the entire organization, also the organizations context. This change in the latent context is relevant because the entire learning and improvement cycle is situated within this context.

As the respondents have claimed, the increasingly enthusiastic and meritocratic landscape pertaining to improvements are clearly manifested cultural changes stemming from BDA. By way of the theory, this is a direct change in the latent context, which in turn affects the active context, the employees. Practically, this enables and encourages the employees to perform much hardier and efficient improvement tasks, thereby generating stronger task experience, and subsequently, more knowledge. As the first step in the learning cycle, the generation of strong knowledge and improvements are realized when the active context interacts with new task experience. As such, because of the increased data driven culture, employees have a much easier time engaging in this action, thereby driving new task improvements with BDA. Not only is there a larger absolute number of improvement initiatives, but the quality is also much higher, meaning less time is spent on supposed improvements which do not yield any actual benefit. This occurs because decisions are made based on data, and improvement initiatives which are not sufficiently corroborated by data are discarded much earlier. In sum, this enables the active context to interact more efficiently, and more often, with new task experiences, thereby creating more learning and knowledge which further leads to more improvements of existing practices.

Similarly, the general enthusiasm and "buzz" surrounding BDA, in terms of its effect on the workplace culture, can be regarded as another effect on the latent context. Thus, the ensuing context is transformed into a more ingenious and innovative one, resulting in employees becoming more enthusiastic and willing to purse different improvement endeavors in their daily work. Concretely, Argote and Miron-Spektor partially touch on this, by claiming that increased motivation and intrinsic fulfilment results in a more innovative and creative mindset. Ultimately, as derived from the empirical data, the genesis of this enthusiasm is primarily grounded in the novelty and "freshness" of BDA, but also in the ability of BDA to provide positive feedback in the form of more measurable KPI's, making improvement initiatives more gratifying. As such, when this change is understood as a cultural one, it can be viewed as a change in the latent context, which ultimately impacts the active context, similar to the aforementioned impact of a more meritocratic culture. In doing so, it achieves a similar effect in the learning cycle, as more improvement tasks are performed, more relevant knowledge and experience is created. In the end, since the active context serves as the repository of all knowledge retained, and further knowledge is created through the active context's interaction with new experiences, this increase in relevant knowledge leads to greater improvements in future processes, thereby creating a positive improvement loop.

Although the buzz surrounding BDA is noticeable, it is unclear how long-lasting it will be. If it is primarily a result of the novelty surrounding BDA, then it logically follows that this effect might not be sustained in the long run. However, if the buzz relates more to the intrinsic properties of BDA, such as the ability to easier follow up and measure KPI's, then it could conceivably have a more sustained impact. However, defining the temporal properties of the buzz is beyond the scope of this paper.

Thus, the findings show that BDA has the ability to impact process improvements in a softer and somewhat intangible manner. BDA affects the latent context, which in turn exhibits a passive influence. However, this passive influence yields tangible benefits when it carries over to the active context, insofar as it impacts the way employees view, work, and approach improvement tasks.

5.2 Impact on Knowledge Creation

The empirical data also expressed more overarching benefits of working with BDA. For example, respondents mentioned that BDA allows for increased interconnectedness between different business units in an organization. With BDA, data sharing becomes more streamlined and proficient. Thus, different functions or units can grow closer to each other and share knowledge to a bigger extent thereby making learnings from other units more proficient, as the pool of knowledge and experience grows exponentially.

According to Argote and Miron-Spektor, knowledge can be generated in two forms. Knowledge is generated whenever the active context interacts with a new task experience, this is direct first-hand knowledge generation. Knowledge can also be generated vicariously, through interaction with other members outside one's own context, this kind of knowledge is generated through knowledge sharing.

Per the empirical data, the use of BDA seems to have a substantially positive effect on the ability to efficiently share knowledge across different units, but also the willingness and proclivity for knowledge sharing among employees. Structurally, the ubiquity of BDA products in most units requires them to speak the same language. Thus, the presence of data enables different units to share information and knowledge faster and more efficiently, without having to translate it across the units. The nature of BDA heavily relies on the ability to accumulate as many data points as possible, and these network effects naturally lead to more information being shared, as more units are connected through their BDA functions. Beyond this, there is also a conscious effort within the Company to structure the makeup of the different business units into a more cross-functional constellation. This is something which has become easier with the implementation of BDA and the commonly understood language amongst employees. Moreover, employees are also more eager to communicate across units, and to share learnings, because of the hype surrounding BDA.

The increased ability for knowledge sharing has substantial implications for the learning cycle. Previously, the generation of new knowledge and improvements relied much heavier on firsthand knowledge creation. As such, this would primarily occur whenever employees interacted directly with a new task experience. However, the use of BDA has significantly increased the number of vicarious learnings, derived from other business units. Now, a business unit can learn and implement improvements in their own practices, without having to distill this knowledge from firsthand experience. The vicariously acquired knowledge begins from the creation stage and moves into the retention stage, thereby skipping the need to acquire it firsthand through an interaction between the active context and new experiences. Thus, learning is expediated to a much larger degree. This increases the total amount of knowledge in each business unit's active context, thereby exponentially increasing possible improvement avenues. Therefore, a unit will still generate knowledge from its own interaction with new task experiences, while also being able to more passively take part in relevant information and learnings from other units within the wider organization.

6. DISCUSSION AND CONCLUSION

6.1 Answer to the Research Question

The empirical data from the selected organization has been analyzed with the purpose to answer the research question: *How does big data analytics affect continual process improvements?*

Based on the analysis above, the following conclusions answer the research question. The widespread use of BDA capabilities in business processes does not merely lead to more efficient and correct business practices, by way of predictive and prescriptive tools. The use of BDA also impacts the way the organization works to refine and improve these practices. Thus, instead of merely serving as a technical solution, BDA seems to bring many ancillary and softer benefit.

One of these is BDA´s effect on the latent context. The use of BDA alters the cultural makeup of the organization, and by extension, the way its employees view process improvement tasks. To begin with, since BDA necessitates the availability of a large body of data points, this inevitably makes the units working with BDA more data driven. With this data driven mindset, the workplace becomes much more meritocratic. Instead of seniority being the deciding factor in the deliberation of potential improvement avenues, the employee with the best claim, and the necessary data to back up said claim, gets their way. This enables employees to engage in improvement tasks more frequently, with a stronger encouragement for improvement initiatives. Employees thereby engage more often in improvement tasks, experiences, and innovative alterations to existing practices, which in turn yield stronger knowledge for future improvements. This also enables the entire business unit to screen out bad improvement ideas at a much earlier stage, which is made easier with the availability of strong data.

Further, BDA also alters the context by increasing the enthusiasm among employees. As stated, employees thoroughly enjoy their work with BDA, and cite its novelty and ability for performance measurement as crucial driving factors behind this enthusiasm. With BDA, units can measure, to a much larger degree, the outcomes of their improvement initiatives. Thus, whenever improvements are deemed successful, this further increases the enthusiasm and drive to engage in further improvement tasks, thereby creating a positive feedback loop. Therefore, employees engage in more and more improvement experiences, and as stated previously, this leads to stronger learning.

Apart from this, BDA also impacts improvements processes through increased knowledge sharing among business units and employees. Normally, most improvement occurs based on knowledge gathered from first-hand experience. This can happen whenever one explores and tests a new way of working, in regard to a task or practice. However, knowledge can also be acquired vicariously, through interactions with other members, who in turn might have experienced said knowledge first-hand. In this respect, BDA seems to increase the ability for units in the organization to engage in this sort of vicarious learning. The main factor behind this effect is that the widespread use of BDA enables different business units to speak a common language, and the continued proliferation of BDA leads to more units adopting this language.

BDA also requires a large amount of data, and this sort of interconnectedness is therefore also very necessary. In doing so, insights and learnings are more easily shared across units, and the stronger connection between units enable for more vicarious learning. In short, this means that improvements become more effective, since units and employees do not have to acquire as much knowledge first-hand, but can instead tap into a larger pool of already distilled knowledge from other units. In turn, they can then incorporate the viable pieces of knowledge into their own units.

In sum, to answer the research question, BDA has several effects on an organization´s continual process improvements, and how people working in these new environments approach improvement initiatives. Not only does BDA lead to more efficient practices, through the use of BDA as a technical solution; It also leads to softer benefits, such as its effect on culture and learning, which in turn lead to stronger and more frequent incremental improvements.

6.2 Discussion

6.2.1 Research Contribution and Implications

From a theoretical standpoint, the findings of this paper contribute to the understanding of BDA's effect on continual process improvements in general, but also its overarching impact on learning specifically. As BDA and other aspects of automation and AI become more prominent and ubiquitous, they will also become more ingrained and integrated into the collective body of management studies and theories, similarly to how universally prevalent the internet, and general information technology is integrated and discussed within the literature today. From a practical standpoint, the discovered impact of BDA on process improvements can act as a benchmark to strive towards. More poignantly, it can enable managers to more effectively facilitate optimal usage of BDA in improvement endeavors. As such, with its potential for positive impact uncovered, managers can strengthen their understanding and approach to BDA, seeing as many firms are having trouble cultivating its potential to benefit improvement processes.

In terms of the cultural and contextual effect of BDA, a parallel can be drawn to Duan et al (2020). According to their study, one of the primary benefits of BDA is its ability to enhance a data-driven culture in an organization. This type of culture is defined as a pattern of behavior which strongly underscores the need for data to serve as the groundwork in any decision-making process. The principal effect of this cultural change is its impact on the ability for environmental scanning. An increased ability for environmental scanning enables organizations to better detect potential avenues for innovation, subsequently increasing the amount of successful and fruitful product innovations. In this regard, the conclusion reached by Duan et al resembles, in many respects, the findings of this paper. Similarly, the authors of this study find that the cementation of a more data driven culture, and the ensuing pivot toward more evidence-based improvement decisions, leads to stronger and more frequent improvement initiatives. The case organizations improved ability to select, choose, and find positive improvement paths closely resembles the ability for positive environmental scanning. Principally, Duan et al examined the impact of BDA on product innovation improvements, while this paper defines improvements as more incremental and small-scale. Thus, the fact that BDA seems to have a similar effect on both types of improvements, both large-scale and small-scale, shows that BDA has the ability to make improvements and innovations more effective, regardless of the size and scale of the process. The common denominator thus seems to be its impact on culture, which in turn facilitates stronger improvements and innovations of all kinds.

Gregory et al (2020), argue that the growing availability of data, and the growing use of BDA leads to stronger data network effects. This impact is different from traditional network effects because BDA does not merely exhibit network effects when the size of the network grows, it also has the ability to cultivate data on its own, with predictive and prescriptive AI capabilities. In their analysis, they claim that plenty of consumer-facing platforms, such as Facebook or Uber, experience these data network effects. As such, with each new user, the entire user base benefits, by virtue of the enlarged pool of total data that can yield beneficial insights. Similarly, this study demonstrates similar network effect gains from BDA. However, in this thesis, the BDA products are not consumer facing, instead, the end user is the business manager within each unit. The network effects experienced by the case company are therefore, for the most part, internal. Although, the end result is similar, in the sense that additional use cases in the data lead to gains in the entirety of the BDA functions. Compared to their study, the findings in this paper show that these network effects do not merely increase user value but can have an additional positive effect on improvement processes, specifically when they are internal. Likewise, per Gregory et al, these gains are not merely attributed to an increase in the network size, but also the inherent prescriptive and predictive capabilities of BDA. Additionally, these network effects also lead to stronger prescriptive and predictive capabilities, as these BDA models gain access to more datapoints, but there is also an ancillary benefit since this inevitably makes units closer knit. In turn, this leads to better knowledge sharing and stronger process improvements.

As stated, the case company has experienced many direct and indirect benefits from BDA. Principally, the cultural effects of BDA lie at the core of these benefits. Therefore, mirroring Fountaine's argument that having a culture which embraces technical solutions such as BDA is paramount in order to successfully tap into its maximum potential.

Relating to the case company, many respondents claimed that the pre-existing culture at the Company, before the advent of BDA functions, was already a relatively inclusive and meritocratic one. In this sense, BDA worked better as a means to a data-driven end, because the existing culture and values successfully facilitated the cementation of a data driven culture, which in turn led to a positive impact on improvements. With this in mind, the necessity for the right pre-existing culture could mean that a similar deployment of BDA functions in another company could yield vastly different results. Specifically, BDA on its own might not necessarily generate a data-driven and forward-thinking culture, rather it could be argued that the necessary values and groundworks must be in place to facilitate this change as well. However, the extent and importance of these pre-existing conditions cannot be derived from the findings in this paper.

In terms of extrapolating the findings from the specific case study into a larger context, some parts of the findings could be scrutinized more heavily. Indeed, within the context of the case organization, a flatter and more meritocratic workplace, as stemming from BDA, does seem incur positive effects on improvement. However, this must be put against the organizational backdrop. The case organization is a large and mature one, as such, the principal benefit of these effects could be relevant only because of its size and maturity. When inferred on a smaller and less mature company, where strict hierarchical decision making is required, a flatter organizational structure might not be beneficial. In such a scenario, a similar usage of BDA could perhaps have a detrimental effect on continual improvements. The case organization is also, as aforementioned, very mature in terms of its BDA functions. It is therefore less clear whether a company with a more unexperienced BDA function would experience the same positive benefits, since they could be a product of long-term BDA implementation, and only relevant when said company reaches a high level of BDA maturity.

6.2.2 The Study's Limitations

The study contains several limitations. Firstly, the study is based on a single theoretical framework, Argote and Miron-Spektor's (2011) learning cycle. BDA can, and has been, previously researched from different angels and the limitation of just analyzing from one perspective of learning should be considered by the reader. Further, only five respondents were interviewed. This may not be the most representative group to answer the research question. Ideally, a larger total number of respondents could have been desirable. Thus, the collected data may be skewed, which affects the answer to the research question. Thirdly, the respondents worked at the studied company at the time of the interviews and the writing of this thesis, which may imply that they have excluded classified information or left biased answers. Building on this, most of the answers given were overwhelmingly positive in describing BDA's effect on improvement. Naturally, this is not necessarily a problem, insofar as it accurately reflects a wider general consensus and reality. However, an argument could also be made that the respondents, based on their seniority levels and affiliation with the company, chose to disregard less favorable experiences and views of BDA, whether implicitly or explicitly. This could therefore have tainted some aspects of the empirical data and should be taken into account when reviewing the core findings of this paper. Finally, the study can be said to be limited by the wide definition of BDA and process improvements. BDA and process improvements are two complex concepts that may contain elements that have not been considered in this thesis.

6.2.3 Suggestions for Future Research

The purpose of this study is to reach a holistic and generalized conclusion. Thus, the propositions presented in this thesis are relevant for answering the research question. To increase specificity, further studies should explore BDA and process improvements from a less generalized perspective. To begin with, an increased sample of industries and employees from an expanded geographic area could be of interest to increase variance and reveal other effects than the proposed ones. Further studies could also examine the difference of working with and without BDA by interviewing people that have been working with the implementation stage of BDA, to deepen the understanding of the transitory effects between BDA and previous practices This could also potentially unearth major shortcomings of BDA. Additionally, future studies can also apply a closer level of detail to BDA and a specific business process, to narrow the scope of the study and hence reach a more specific conclusion. Furthermore, future research can study the post Covid-19 development of BDA and how an organization´s usage of BDA changes when historical data do not match current events to generate credible, relevant, and transferable data.

Appendices

Appendix 1. E-mail to Prospective Interviewees

To legitimize the thesis and keep the correspondence formal, all emails were sent from the email addresses provided to us by the Stockholm School of Economics.

Hi [name],

We are two bachelor students from the Stockholm School of Economics writing our Bachelor´s thesis in management, which will focus on big data analytics and process improvement.

Our perception is that there exists a gap pertaining to big data analytics and its effect on process improvement. In our study we attempt to answer how big data analytics capabilities alters the structural landscape and environment in relation to process improvement. We are interested in studying all aspects of big data analytics, including its descriptive, prescriptive, and predictive capabilities.

We are also interested in understanding more about the relation between BDA and improvement in a company like yours. We are therefore wondering; would you be willing to take part in our study and participate in an interview with us?

We would preferably like to schedule the interview for the coming weeks (9,10, or 11), however, we completely understand that you might have a busy schedule and we are therefore flexible regarding the time. Of course, we are also willing to accommodate to your needs regarding place, whether you want to conduct the interview online or in-person.

If you would like to, we are more than happy to share the findings and conclusions of our research. Our hope is that the study can contribute with interesting insights and give you the opportunity to reflect on process improvement practices within data analytics. The study is, of course, anonymous for both the interviewees and the companies as such. We would be profoundly grateful if you, or any colleague of yours, would be available.

Kind regards,
Leo Wei & Viktor Hökenhammar

Appendix 2. Interview Guide

Ethics

1. You and your employer will be anonymized.
2. We will not disclose any other participants in the study.
3. You may interrupt or leave the interview at any time without disclosing why.
4. Before we start, do you have any questions to us?

Introduction questions

1. Could you tell us a little about yourself?
2. How long have you worked at Company X?
3. Could you tell us a little bit about your role and day-to-day work?

Big Data Analytics

1. How would you define Big Data and Data Analytics?
2. How important is BDA for Company X?
3. How would you describe Company X´s way of working with BDA? What works well and what could be improved?
4. How does BDA affect your work with process improvements compared to your previous experience?
5. How does BDA affect you as a team when making decisions?
6. What are potential shortcomings of data analytics, as compared to previous practices?
7. Is the role of intuition strongly valued? If so, how do you reconcile the need for intuition with data-driven decision-making?
8. Has BDA affected the way you compartmentalize knowledge?
9. Are there any issues with BDA integration with other systems/processes?
10. How is BDA integrated in your unit?

About the Company

1. How would you describe your workplace? How is your organizational culture? How do you communicate and share information both across units and within units?
2. Has BDA impacted the culture in your unit?
3. Are incremental improvements considered a collective or individual task? Has the introduction of BDA had an effect in this respect?
4. How do your co-workers react when you perform tasks that relate to improvement?
5. Does BDA have any intangible effects on the way you view process improvements?
6. What does process improvement initiatives usually look like at Company X?
7. Has the use of BDA affected your unit’s relationship with other units? Perhaps relating to synergies or data-sharing.
8. Do you feel BDA has enabled you to better extract and incorporate learnings into your processes?
9. Do you think the proliferation of BDA necessitates competencies that you currently lack?
10. Do you consider your tasks to be easy or challenging? Why?

Ending

1. Thanks for taking the time to answer our questions.
2. Like we said in the beginning, both you as a participant and your employer will be anonymized. We will not disclose any other participants in the study.
3. Before we end, do you have any questions to us or anything you feel like you haven´t gotten the chance to say?

Appendix 3. List of interviewees and interviews

No.	Time	Date	Place
1	48 minutes	2021-03-16	Microsoft Teams
2	67 minutes	2021-03-22	Microsoft Teams
3	58 minutes	2021-03-31	Microsoft Teams
4	72 minutes	2021-04-06	Microsoft Teams
5	63 minutes	2021-04-08	Microsoft Teams

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