# On the Adoption of Big Data Analytics: Interdependencies of Contextual Factors

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Abstract: Even though the number of papers on the adoption of big data analytics (BDA) has increased, the literature still only scratches the surface in terms of understanding the influential factors of BDA adoption. To cope with the complexity of these factors, this paper focuses on the influence of some of the most important factors regarding BDA and their interrelations. We followed the technology, organization, and environment framework (TOE framework), which is frequently used to explain the process of technology adoption, to examine the context of the decision-making process and combined it with insights from dynamic capability theory. This paper contributes to BDA research by extending the TOE framework towards a dynamic capability view. It assists in the decision-making process regarding the development of BDA capabilities by determining the most influential factors and their side effects, thereby helping to prioritize these factors and to encourage investments accordingly.

## 1 INTRODUCTION

Big data refers to large sets of structured, semi-structured or unstructured data, which are obtained from different unrelated resources; examples include sensor data and content that is extracted from social media (Malaka and Brown, 2015). As the processing of big data is beyond the abilities of conventional software tools (Manyika et al., 2011), decisions on investments in big-data-related technology must be faced. However, big data are not without benefit: As an asset, big data can "improve competitiveness, innovation and efficiencies in organizations" (Braganza et al, 2017).

The term big data analytics (BDA) covers advanced analytical techniques and technologies that operate on big data to obtain enhanced insights and improve the decision-making process (Malaka and Brown, 2015). Chen et al. (2016) understand BDA as a "unique information processing capability that brings competitive advantage to organizations" and is expected to improve performance (Kwon et al., 2014).

Deeply rooted in business intelligence (BI), BDA "reawakens" an interest in mathematics, statistics and quantitative analysis (Braganza et al., 2017), but adds some specific requirements. Because the objective of BDA is to answer highly specific questions, its solutions must be tailored to this context, which requires sound methodological skills (Debortoli et al., 2014).

Competencies on BI and BDA can be categorized into three waves, which are characterized by DBMS-based, structured content (1st wave), web-based, user generated, unstructured content (2nd wave), and mobile- and sensor-based content (3rd wave) (Chen et al., 2012). BDA capabilities can be understood as dynamic capabilities, which require a "delicate mixture of management, talent and technology" (Akter et al., 2016). As these capabilities are tailored to suit a highly specialized question (Debortoli et al. 2014), they are context-specific (Chen et al., 2016).

BDA adoption requires investments in costly technology, which is rapidly changing and offering new opportunities for information processing at increasing speeds. It requires investments in the development of analytical skills that are pinpointed to a context-specific task, and intensified data collection and storage, which are connected with issues regarding data quality, IT security, and privacy concerns. These factors are closely entangled and influence decisions on BDA adoption in different ways. The goal of this paper is to shed light on their influence on BDA adoption, to inform the decision-



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making process and to assist in prioritizing these factors and in encouraging investments accordingly.

# 2 THEORETICAL BACKGROUND

## 2.1 TOE Framework

To understand the contextual factors regarding BDA adoption, we base our work on the TOE framework. This framework identifies factors that are related to the adoption of technological innovations in the technological, organizational, and environmental contexts (Oliveira and Martins, 2011). Building upon diffusion of innovation theory (DOI), this framework is well accepted and frequently used to explain specific aspects of the adoption of BDA (Table 1).

Table 1: Some recent studies on BDA adoption based on the TOE framework (ordered by year and name).

| Reference | Focus | Research Method |
|---|---|---|
| (Debortoli et al., 2014) | Competencies and skills in BI and BDAs | Text mining of job advertisements |
| (Agrawal, 2015) | BDA adoption in firms from China and India | Data collection (106 organizations) |
| (Malaka and Brown, 2015) | Challenges of BDA adoption | Interpretive study, single-organization case study |
| (Nam et al., 2015) | Influences of perceived benefit, financial readiness, IS competence, and industrial pressure on BDA adoption | Online questionnaire survey |
| (Chen et al., 2016) | Key antecedents of organizational-level BDA usage and the effect on value creation | Survey data (161 U.S.-based companies) Domain: supply chain management |
| (Salleh and Janczewski, 2016) | Security and privacy issues related to BDA adoption | Anonymous online questionnaire survey |

Chen et al. (2016) identified two limitations of the TOE framework. The first limitation is the assumption of the model, that contextual factors directly affect the decision to adopt a technological innovation. They argue that the idealization of the decision-making process as a fully rational process cannot hold true in practice. The second limitation is that contextual factors can affect this decision in ways that are not covered by the TOE framework. Therefore, combining the TOE framework with one or more theoretical models is recommended (Low et al., 2011).

## 2.2 Dynamic Capability Theory

The TOE framework provides an overview of contextual factors of BDA adoption, but it's not the adoption of BDA as such, that provides competitive advantage. As part of the dynamic capabilities of a firm, BDA capabilities enhance the potential to improve the performance of a firm and to adapt to the challenges of turbulent environments. Therefore, we complement the TOE framework with the dynamic capability theory (DCT). DTC offers additional explanations for gaining competitive advantage out of the adoption of BDA, as several recent publications have shown (Table 2).

Table 2: Theories related to BDA adoption in some recent publications (ordered by year and name).

| Reference | Theory |
|---|---|
| (Esteves and Curto, 2013) | Decomposed Theory of Planned Behavior |
| (Debortoli et al., 2014) | Resource-Based View |
| (Akter et al., 2016) | Resource-Based View, IT Capability Theories, Concept of Sociomateriality |
| (Chen et al., 2016) | Dynamic Capability Theory |
| (Gupta and George, 2016) | Resource-Based View, Knowledge-Based View |
| (Prescott, 2016) | Resource-Based View, Dynamic Capability Theory |
| (Braganza et al., 2017) | Resource-Based View, Knowledge-Based View, Dynamic Capability Theory |
| (Côrte-Real et al., 2017) | Resource-Based View, Knowledge-Based View, Dynamic Capability Theory |
| (Gunasekaran et al., 2017) | Resource-Based View |
| (Mikalef et al., 2017) | Resource-Based View; Dynamic Capability Theory |

As an extension of the resource-based view (RBV), the DCT is closely connected to RBV. Resources refer to the tangible, intangible and human resources of a firm that, bundled together, influence the performance outcomes. Capabilities can be understood as subsets of these resources that are non-transferable, have a direct or indirect impact on the performance of a firm, and are influenced by environmental conditions (Gunasekaran et al., 2017).

Dynamic capabilities enable a firm to adapt to changing requirements (Mikalef et al., 2017). They refer to the ability to configure and reconfigure the resources of a firm to maintain competitive advantage in turbulent environments (Prescott, 2016; Côrte-Real et al., 2017). El Sawy and Pavlou (2008) identified four dimensions: sensing the environment, learning, integrating knowledge and coordinating activities. Almost all of these dimensions can be leveraged by BDA.

# 3 RESEARCH MODEL AND CONSTRUCT MEASURES

Informed by recent literature, we have identified several contextual factors that are crucial for the adoption of BDA. Information on how these factors influence the adoption of BDA and how they are interrelated can assist in prioritizing the different aspects of BDA investments. As it is impossible to cover all contextual factors that are relevant for the decision-making process, we adapted contextual factors according to previous research.

The technological context covers relative advantage, complexity and compatibility. It refers to relevant internal and external technologies (Borgman et al., 2014). The integration of internal and external data and prior IT experiences with BDA-related technologies was considered the most relevant technological factor. Thus, we posit that levels of experience with data usage from external sources, internal sources and big-data-related technology each have a significant positive effect on the adoption of BDA (H1-H3). Security and privacy issues can be obstacles to the adoption of BDA technologies; therefore, we postulate that experiences with security mechanisms have a significant positive effect on BDA adoption (H4).

The organizational context refers to descriptive measures of the organization regarding scope, size, and managerial structure (Oliveira and Martins, 2011). Successful deployment of BDA is almost impossible without the appropriate analytical skills; therefore, we posit that BDA skills have a significant positive effect on the adoption of BDA (H5). In the telecom industry, Bughin (2016) found evidence that a good part of the returns could be explained by the capabilities to effectively manage big data projects; thus, we postulate that management support has a significant positive effect on BDA adoption (H6).

As dynamic capabilities enable a firm to evolve according to the requirements of a changing environment, market pressure (H7) is expected to have a positive impact on BDA adoption. Competitive pressure is an important external driver for the adoption of innovations (Agrawal, 2015); therefore, we postulate that competitive pressure to use BDA has a significant positive effect on BDA adoption (H8). With these hypotheses, we intend to confirm the results of previous research and extend the previous research to an analysis of the factors' interrelated effects. As gaining competitive advantage is at the core of developing dynamic capabilities, we postulate that BDA adoption will have a positive effect on market performance (H9).

Where possible, constructs were adapted from existing research.

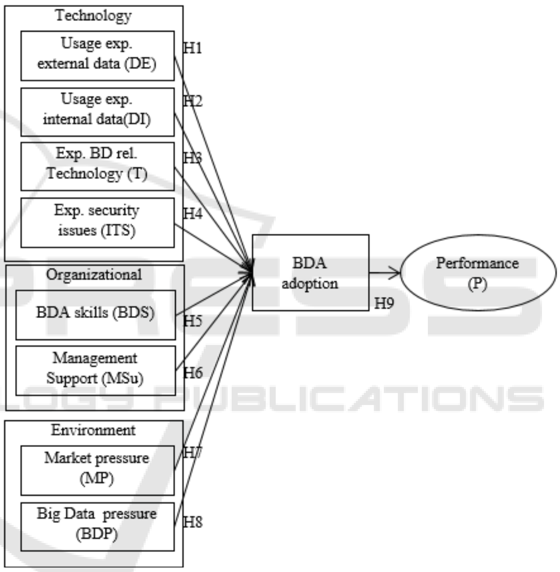


Figure 1: Research model.

The research model covers technological factors that are relevant for assessing experiences with data from external or internal sources and with big data technology. We follow the argument of Kwon et al. (2014) that "expanded IT capability in data management and utilization is expected to become a virtuous force in furthering adoption of new data-related IT capability" (e.g., BDA). As privacy and security issues can affect the (perceived) complexity (Borgman et al. 2014), these were included, according to Salleh and Janczewski (2016).

Big data capabilities cover tangible resources (e.g., technology, data and financial resources), human skills (e.g., technical skills and managerial skills) and intangible resources (e.g., organizational learning and data-drive culture) (Mikalef et al. 2017).

Table 3: Technology Context: Constructs.

| |
|---|
| Usage experience with data from external sources (Kwon et al., 2014):<br>To predict demand;<br>To facilitate understanding of market conditions;<br>To facilitate understanding of customer demands;<br>Quality and reliability evaluation of external (data) (N);<br>Usage of social media data (N). |
| Usage experience with data from internal sources (Gupta and George, 2016):<br>Integration of data from multiple internal data sources into a data warehouse;<br>Access to very large, unstructured, or fast-moving data for analysis;<br>Analysis of Cookies, Logfiles, App-data (N);<br>Analysis of sensor data (N); |
| Experience with big-data-related technology (Gupta and George, 2016):<br>Parallel computing approaches;<br>Different visualization tools;<br>Cloud-based services for data processing and analysis;<br>Open-source software for big data analytics;<br>New forms of data storage;<br>Near-real-time or real-time analysis (N);<br>Event-driven decision automation (N); |
| Privacy and security (Salleh and Janczewski, 2016):<br>Security requirements for BDA are compatible with existing information security infrastructure.<br>Information security mechanisms for BDA are compatible with existing systems (A); |

(A) adapted, (N) new

Debortoli et al. (2014) observed that a big data project is often more comparable to a research project, as it requires better methodological skills than traditional BI and requires some learning intensity (Gupta and George, 2016). As capabilities cannot provide competitive advantage by themselves, management plays a crucial role in capacity building, by structuring and orchestrating resources (Gunasekaran et al., 2017).

Table 4: Organizational Context: Constructs.

| |
|---|
| BDA skills: (Gupta and George, 2016)<br>Providing BDA training for employees;<br>Hiring new employees with BDA skills;<br>Using external experts to bring in BDA expertise (N);<br>Suitable education or work experience of BDA staff (A). |
| Management Support: (Gupta and George, 2016)<br>Having a good sense of where to apply BDA (A);<br>Having clear expectations related to the outcomes and benefits of BDA (A). |

(A) adapted, (N) new

Côrte-Real et al. (2017) used the construct “market pressure” and two other items to measure organizational agility. These items are market-driven; thus, they are environmental contextual factors. As the readiness of competitors to deploy BDA is expected to influence BDA adoption (Chen et al., 2016), Big Data pressure is included in the environmental context using constructs that were adapted from Agrawal (2015).

Table 5: Environmental Context: Constructs.

| |
|---|
| Market pressure: (Côrte-Real et al., 2017)<br>Necessity of responding to changes in consumer demand (A);<br>Necessity of reacting to new product or service launches by competitors;<br>Necessity of adopting new technologies to produce better, faster, cheaper products and services (due to market demands); |
| Big Data pressure (Agrawal, 2015):<br>Perceived competition intensity to implement BDA (A);<br>Risk of competitive disadvantage if BDA is not adopted. (A) |

(A) adapted, (N) new

Because the dynamic capabilities are orchestrated to gain competitive advantage, measurement of the market performance has been included in the model. Since this advantage will not materialize immediately, the time since the adoption of BDA was required as additional information (Gupta and George, 2016).

Table 6: Market Performance: Construct.

| |
|---|
| Market Performance (Gupta and George, 2016):<br>Time needed to introduce new products or services into the market compared to competitors;<br>Success rate of new product or services launches compared to competitors;<br>Market share compared to competitors (A). |

(A) adapted, (N) new

## 4 DATA ANALYSIS AND RESULTS

To test our hypotheses, we conducted an anonymous online survey, addressing the top management of German companies. The addresses were acquired using the Hoppenstedt database. 138 German companies took part in this survey, which had been pre-tested in a pilot study. After data sets with missing values on BDA usage were filtered out, 46 data sets from organizations of different sizes (turnover from 0-1 million Euros up to 1000 million Euros per year) remained for further analysis. According to their answers, 30% belong to the 1st wave of BI and BDA competencies, 46% to the 2nd wave, and 24% to the 3rd.

1-5 Likert scales were used to measure DI, DE, ITS, BDS, MSu, MP, BDP and P. T is a measure, that covers six widespread big data technologies, which were adopted from Gupta and George (2016). For our analysis, we used IBM SPSS Statistics 25.

Cronbach's alpha was used to assess the reliability of scales. A confirmatory factor analysis was conducted for deleting items that did not contribute strongly to the scales. All items of each final scale loaded on a single factor. With the exception of ITS and DI, all cronbach's alpha coefficients are above 0.80 which are excellent values. DI with 0.707 is a commonly acceptable value (Hair et al. 2006). Hair et al. (2006) argued that Cronbach's alpha values may decrease to .60 and still be acceptable, especially in exploratory studies. Thus, we accept the cronbach's alpha of 0.652 for ITS. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy meets the minimum criteria of 0.5 and Bartlett's test of sphericity is significant for each construct (Field 2013). Table 7 lists the Cronbach's Alpha scores, KMO values and Barlett's test significance levels for DI, DE, ITS, BDS, MSu, BDP, MP and P.

Table 7: Cronbach's Alpha scores, KMO values and Barlett's test significance levels.

| Construct | Cronbach's Alpha | KMO | Barlett's test |
|---|---|---|---|
| DI | .707 | .500 | Sign (0.001) |
| DE | .884 | .846 | Sign (0.000) |
| ITS | .652 | .500 | Sign (0.004) |
| BDS | .900 | .822 | Sign (0.000) |
| MSu | .951 | .500 | Sign (0.000) |
| BDP | .891 | .500 | Sign (0.000) |
| MP | .816 | .687 | Sign (0.000) |
| P | .833 | .692 | Sign (0.000) |

BDA adoption was measured as a dichotomous variable, which resulted in two groups: BDA adopters and BDA non-adopters. Therefore, a t-test analysis (independent sample test) was conducted to test hypotheses H1-H9 (Figure 1). The t-test assesses whether the means of two groups are significantly different from each other.

There is sufficient evidence to suggest that the values of DE, DI, T, ITS, BDS, MSu, and BDP are higher in organizations that adopt BDA than in those that do not (Table 8 and 9). Thus, H1-H6 and H8 are supported, but H7 is not supported.

Table 8: Group statistics.

| | BDA | Mean | Std. Dev | Std. Error Mean |
|---|---|---|---|---|
| DE | no | 2.8389 | .93580 | .19102 |
| | yes | 3.6147 | 1.26142 | .30594 |
| DI | no | 2.1818 | 1.17053 | .24956 |
| | yes | 3.2941 | 1.43678 | .34847 |
| T | no | 2.3750 | 1.31256 | .26793 |
| | yes | 4.3125 | 1.81544 | .45386 |
| ITS | no | 2.7105 | 1.03166 | .23668 |
| | yes | 3.6563 | .87023 | .21756 |
| BDS | no | 2.1146 | 1.26901 | .25904 |
| | yes | 3.7396 | .96555 | .24139 |
| MSu | no | 2.5455 | 1.46311 | .31194 |
| | yes | 3.5938 | .98689 | .24672 |
| MP | no | 3.5797 | 1.03581 | .21598 |
| | yes | 3.6979 | .98924 | .24731 |
| BDP | no | 2.5750 | 1.19511 | .26723 |
| | yes | 3.9688 | 1.10255 | .27564 |
| P | no | 2.9091 | 1.23091 | .26243 |
| | yes | 3.2083 | 1.25831 | .31458 |

The hypothesis that BDA adoption has a positive effect on market performance (H9) could not be supported either.

Table 9: Independent Sample Test.

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | |
|---|---|---|---|---|---|
| | | F | Sig. | t | Sig. (2-tailed) |
| DE | EVA | 1.740 | .195 | -2.263 | .029 |
| | EVNA | | | -2.151 | .040 |
| DI | EVA | .641 | .428 | -2.665 | .011 |
| | EVNA | | | -2.595 | .014 |
| T | EVA | 3.491 | .069 | -3.921 | .000 |
| | EVNA | | | -3.676 | .001 |
| ITS | EVA | .324 | .573 | -2.898 | .007 |
| | EVNA | | | -2.942 | .006 |
| BDS | EVA | 3.236 | .080 | -4.345 | .000 |
| | EVNA | | | -4.589 | .000 |
| MSu | EVA | 4.252 | .046 | -2.480 | .018 |
| | EVNA | | | -2.636 | .012 |
| MP | EVA | .011 | .916 | -.357 | .723 |
| | EVNA | | | -.360 | .721 |
| BDP | EVA | .687 | .413 | -3.597 | .001 |
| | EVNA | | | -3.630 | .001 |
| P | EVA | .103 | .750 | -.733 | .468 |
| | EVNA | | | -.730 | .470 |

(EVA) Equal variances assumed, (EVNA) Equal variances not assumed

It is a remarkable result that technology is not among the most important internal factors that influence BDA adoption, but BDA skills and usage of internal data are. Among the environmental factors, competitor pressure has a stronger impact on BDA adoption than market pressure.

Table 10 represents the correlations of the constructs. There are significant relationships between MSu and DE, DI, BDS, BDP and ITS, with p (2-tailed) < 0.01. The strongest significant relationships are those between BDS and MSu (r = 0.747), DI and MSu (r = 0.673) and BDP and MSu (r = 0.597), with p (2-tailed) < 0.01. It is interesting to note that BDP is strongly and significantly related to DI (r = 0.750) and to BDS (r = 0.714), and DI is also strongly and significantly related to BDS (r = 0.657), with p (2-tailed) < 0.01.

The correlations indicate that the perceived competition intensity to implement BDA and the risk of competitive disadvantage are highly correlated with learning activities regarding BDA skills and usage of internal data.

Table 10: Pearson Correlations.

| | DE | DI | BDS | MP | BDP | ITS | MSu |
|---|---|---|---|---|---|---|---|
| T | .457** | .425** | .560** | .049 | .435** | .410* | .273 |
| DE | | .617** | .589** | .223 | .549** | .369* | .415** |
| DI | | | .657** | .377* | .750** | .289 | .673** |
| BDS | | | | .198 | .714** | .510** | .747** |
| MP | | | | | .351* | .120 | .119 |
| BDP | | | | | | .507** | .597** |
| ITS | | | | | | | .446** |

**Correlation is significant at the 0.01 level (2-tailed)
*Correlation is significant at the 0.05 level (2-tailed)

Competitive pressure has a stronger effect on BDA adoption than market pressure and has a strong correlation to management support. That competitive pressure to use BDA is positively associated with management support is further confirmation of the results of Chen et al. (2016).

Correlations of MSu with BDS, DI, ITS, DE and T indicate strong differences, the strongest being the one with BDS, followed by the correlation with internal data usage. Taking the three waves of BI and BDA competencies into consideration, it is reasonable that internal data usage has a higher correlation with MSu than external data usage. That there is no strong correlation between technology and MSu indicates that technology is not fueling the expectations that are related to BDA in the same way as BDA skills or data usage.

Developing new knowledge and skills is fundamental for exploiting the potential of BDA, which results in improved operational capabilities (El Sawy and Pavlou 2008). Gupta and George (2016) emphasize that the development of firm-specific BDA capabilities will not be rewarding if "an organization lacks learning intensity". They identified the need to adopt a culture where "decisions are made based on people's opinions." The strong correlation between BDA skills and management supports can be explained by this kind of a culture: having a clear expectation on where to apply BDA and what outcomes and benefits to expect could indicate that management is well advised.

# 5 CONCLUSIONS

The main focus of this work was on highlighting the entanglement of the contextual factors. Enriching the TOE framework with insights from dynamic capabilities provided additional information on how the BDA capabilities are orchestrated according to a specific task to be accomplished by BDA.

As the sample size is too small to provide strong evidence, most of this paper is argumentative. The results of the survey are used as indications; however, a more extensive survey is required to confirm the results. Nonetheless, as the argument is in line with previous research, it contributes to the discussion on interrelated effects regarding the contextual factors of BDA.

We identified BDA skills and internal data usage as the most influential factors, both of which have a strong correlation to management support. This gives skill development high priority in regard to channeling BDA investments.

That perceived competition intensity to implement BDA and the risk of competitive disadvantage (if BDA is not adopted) have a strong effect on BDA adoption, does not come as a surprise. However, we did expect the market pressure to have some influence on BDA adoption. As the lack of influence was rather unexpected, further research is necessary to confirm the results or to adopt constructs and variables.

We could not find evidence for a link between BDA adoption and firm performance, but we expect that the time since adoption would need to be taken into consideration. Due to missing values, we had to omit the time since BDA adoption from our analysis. As a positive influence on market performance would be a sustained effect, one explanation for this could be the recency of BDA investments. Assessing this relationship over an extended period of time could be an interesting direction for further research.

The lack of a significant effect is in line with the results of Chae, Koh et al. (2014), who could not confirm a relationship between IT capabilities and firm performance. We follow their suggestion to further investigate constructs and variables that take into consideration that the role of IT has changed over time (Chae et al. 2014).

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