Adoption of Business Intelligence & Analytics in Organizations – An Empirical Study of Antecedents

Completed Research Paper

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ABSTRACT

Although Business Intelligence & Analytics (BIA) systems are increasingly seen as a source of competitive advantage, limited research, to our knowledge, has examined the factors driving their organizational adoption. Drawing on Technology-Organization-Environment framework, we present a theoretical model of factors associated with the extent of organizational adoption of BIA technologies and test it with a large cross-sectional sample. We find that an organization’s perceived benefits, technology sophistication in terms of data infrastructure and organization size are positively associated with the extent of BIA adoption. In addition, we find that firms in knowledge-intensive industries are likely to more extensively adopt BIA and the lack of industry standards hinders adoption. This study can inform researchers and practitioners on the enabling conditions in organizations that drive the adoption of BIA technologies.

Keywords

Business Analytics, Business Intelligence, Technology-Organization-Environment (TOE) Framework, Technology Innovation Adoption, Antecedents, Knowledge Intensity, IT Infrastructure, Data Management, Organization Size, Industry Standards

INTRODUCTION

Pervasive digitization and ubiquitous connectivity are enabling the firms to go beyond firm boundaries and work with customers and business partners to co-create value (Prahalad and Krishnan, 2008). As firms in many industries are largely offering similar products/services, business processes become crucial to create differentiation (Davenport, 2006). Firms need to identify the business processes that create a distinctive capability and apply extensive data and analysis to support these processes (Davenport and Harris, 2007). However, new forms of structured and unstructured information generating not only from a firm’s transactions but in its interactions with customers and partners or as created by technologies like Radio Frequency Identification (RFID) is leading to large data volumes that a firm has to deal with (LaValle, Lesser, Shockley, Hopkins and Kruchwitz, 2011). This implies that firms need new capabilities/tools to consolidate and understand the data and create valuable knowledge/insights out of it to empower decision-making in support of the distinctive capabilities.

Business Intelligence & Analytics (BIA) systems that support analytics for decision-making are becoming a growing source of value and competitive advantage (LaValle et al., 2011). Defined as “the broad use of data and quantitative analysis for decision-making within organizations”, BIA-based systems are enabling decision-makers to interpret organizational data to enhance decision-making and improve business functions (Davenport, 2010). The technologies behind BIA have matured over the last few years, making them widely usable in business (Davenport and Harris, 2007). Firms are using BIA to enhance customer service, optimize pricing and improve supply chains etc. For example, United Parcel Service not only uses IT to provide transparency to the customers on their shipment status, but also uses analytics effectively to track customer usage patterns and complaints to predict customer attrition (Davenport, 2006).

Despite the potential benefits, there is limited empirical research, to our knowledge, on what factors influence the organizational adoption of BIA. Research has attempted to improve our understanding on the business value of BIA and the enablers of value creation but limited attention was paid to understand the drivers of BIA adoption. Our study attempts to

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1 IDC, a leading IT analyst firm, has estimated that the BIA market grew by 14% in 2011 and is projected to reach $50.7bn by 2016 (Taft, 2012).
contribute to BIA research by studying the factors driving the differential adoption of BIA in organizations. Building on the Technology-Organization-Environment (TOE) framework, we study how technological, organizational and environmental contextual factors are associated with organizational BIA adoption. Relatedly, we ask the research question: How do the contextual technological, organizational and environmental characteristics of an organization drive the extent of BIA adoption?

This study has two primary contributions among others. First, it is among the first, to our knowledge, to develop and empirically validate a theoretical model of the extent of organizational adoption of BIA technologies. In doing so, we contribute to the IT Innovation Adoption literature by examining the adoption characteristics of a new class of technologies. Second, using a large cross-sectional sample to validate our model provides findings that are better generalizable than anecdotal evidence and case studies.

LITERATURE OVERVIEW (ABBREVIATED)²

BIA involves acquiring new insights through analyzing data and information from various sources and using those insights to create competitive differentiation (Davenport, 2006; Sabherwal and Becerra-Fernandez, 2010). Firms are increasingly adopting BIA technologies like dashboards, adhoc query and interactive visualization etc. to develop insights from data and use these insights for decision-making (Chen, Chiang and Storey, 2012). Extant research on BIA has focused on how BIA adoption creates business value. For example, Davenport (2006) presented qualitative evidence on how analytics-based insights can improve areas like customer service, supply chain management (SCM) and pricing etc. and suggested that firm’s executive commitment and enterprise-wide analytics focus are vital to realize value. Shanks and Sharma (2011) theorized that BIA technologies create first-order dynamic capabilities which lead to second order value-creating actions that impact firm performance. They further suggested that analytics technology quality and autonomous organizational structures augment the benefits. Trkman, McCormack, Oliveira and Ladeira (2010) empirically investigated the impact of BIA on supply chain performance and found that using analytics in plan, source, make and deliver areas of SCM has led to improvements in SCM. Additionally, they evidenced the positive moderating impact of strong IT support on supply chain improvements.

While the literature has attempted to improve our understanding on the business value of BIA, there is limited research, to our knowledge, to understand what contextual factors influence organizations to adopt BIA in the first place. Our study attempts to address this gap by developing a theoretical model to understand the contextual factors influencing BIA adoption. Consequently, we ask the research question: What technological, organizational and environmental factors influence the extent of organizational BIA adoption?

THEORY AND HYPOTHESES

A theoretical model of adoption needs to consider the specific technological, organizational, and environmental circumstances of an organization (Zhu, Kraemer and Xu, 2006). Reviewing the literature suggests that the Technology-Organization-Environment framework may provide appropriate guidance. The TOE framework suggests that the process by which a firm adopts and implements technological innovations is influenced by the technological, organizational and environmental contexts (Tornatzky and Fleisher, 1990). The technological context relates to the technologies available to the organization. However, the degree of relevance among available technologies depends on the potential benefits received (Chau and Tam, 1997). The organizational context describes the organizational characteristics i.e. the organizational structures and processes that facilitate or constrain innovation adoption. The environmental context encompasses external factors including industry/regulatory conditions that may influence technology adoption. These three contexts present constraints and opportunities for technological innovation (Tornatzky and Fleisher, 1990: p. 154).

We adopt the TOE framework to study the contextual factors that can influence organizational BIA adoption. TOE framework can provide appropriate guidance as BIA systems possess technological characteristics and their adoption depends on organizational characteristics like internal technology competence to derive value. In addition, as BIA technologies are maturing, environmental factors should be analyzed to understand how BIA market conditions influence adoption. Consistent with the definition of TOE framework and the emphasis placed on the context surrounding its three elements, we hypothesize that (1) perceived benefits (technological) (2) organization size & organizational readiness in terms of data infrastructure

² This review was significantly abbreviated to comply with AMCIS length restrictions
sophistication (organizational) and (3) industry knowledge intensity and lack of industry standards (environmental) may determine the extent of BIA adoption.

To consider specific factors to investigate, we include factors cited in literature and factors unique to BIA. Perceived benefits were a significant predictor of innovation adoption (Chau and Tam 1997). Hence we consider it under technological factors. Firm size was frequently found to have significant influence on adoption (Damanpour, 1991). BIA requires strong financial resources and robust backend infrastructure to consolidate information towards analysis (Sabherwal and Becerra-Fernandez, 2010). Hence we hypothesize the role of size and strong data-related IT infrastructure in the organizational context. With emerging technologies, lack of industry standards hinders adoption (Whitaker, Mithas and Krishnan, 2007). With BIA vendor market still maturing, we consider standards as an environmental factor. As BIA technologies help to process information and convert it into actionable insights, they can be advantageous to firms in knowledge-intensive industries to create knowledge from plethora of information. Hence we consider industry knowledge intensity as a factor (Saldanha and Krishnan, 2012).

Reexamining IT adoption factors in the context of BIA arises for at least two reasons. First, unlike the IT systems of the past which thrive on asynchronous data stocks, BIA facilitates working on real-time information and renders the capability for continuous analysis (Prahalad and Krishnan 2008). Second, given the volume and velocity of information being generated, the existing IT infrastructure may be inadequate and scaling the existing technologies may be insufficient. Firms may need strong financial and technical resources to match the new demands (Iacovou, Benbasat and Dexter, 1995). In sum, BIA systems can create additional opportunities contingent on organizational complementarities and pose new challenges unique to the context that need a systematic examination.

Hypotheses

BIA adoption creates competitive advantage to organizations and the emerging literature is systematically investigating the theoretical propositions (Davenport and Harris, 2007). How useful these technologies are as perceived by the organizations assumes greater significance when the potential of these relatively new technologies is unproven. In such a case, organizations rely on perceived benefits from these technologies that drive adoption. Perceived benefits are the gains or improvements derived from adopting these technologies. They differ from awareness as awareness is concerned with the reception of information about BIA, while perceived benefits capture the extent of agreement with claimed benefits (Chau and Tam, 1997). For example, perceived benefits highlight if the adoption of BIA has provided differential benefits to business functions upon adoption. Thus perceived benefits drive the decision on the extent of BIA adoption. Consistent with this discussion, we hypothesize:

\[ H1: \text{The organization's higher perceived benefits of BIA technologies are positively associated with the extent of BIA adoption.} \]

The association between organizational size and IT adoptions had mixed findings in literature (Ramamurthy, Sen and Sinha, 2008). Large organizations have greater slack in resources and are better prepared to mobilize adequate financial resources to experiment with innovations. The benefits of economies of scale make the costs of innovations proportionately less for large organizations and impose relatively lesser burden (Damanpour, 1991). The breadth of operations in large firms also makes adopted innovations often complement existing operations and become more beneficial (Geroski, 2000). However, small businesses may be more innovative and may adopt innovations faster but are constrained by lack of financial resources and in-house expertise etc. and hence face more barriers to technology adoption (Thong and Yap, 1995).

BIA requires strong IT-infrastructure to collect structured and unstructured data from business transactions and environmental scanning and consolidate this data in internal repositories like data-warehouses to create usable knowledge out of it. BIA adoption is resource-intensive in terms of capital and skilled labor and can be expensive to implement and integrate; which large organizations can afford. For example, related research has found that only large organizations are likely to implement data warehouses as they are resource-intensive to implement (Ramamurthy et al., 2008). Hence:

\[ H2: \text{Large Organizational Size is positively associated with the extent of BIA adoption} \]

Technology adoption should be based on a firm’s technological strengths (Grover, 1993) Organizational IT sophistication is indicates the organizational readiness for innovation adoption (Iacovou et al., 1995). Internal IT sophistication helps to assess
the level of support for using IT towards organizational objectives. On the other hand, the absence of required internal IT resources presents a barrier to adopt and use new technologies (Taylor and Todd, 1995).

In the BIA context, creating quality data is an important antecedent to create effective BIA-based insights. Data consolidation consumes 50-80% of the project resources in understanding and preparing the data (Sabherwal and Becerra-Fernandez, 2010). As quality data is key to create reliable insights from BIA and the organizational data can arise in both structured and unstructured forms through various sources, firms with highly sophisticated data-related IT infrastructure oriented towards data collection, cleansing and federation would be more likely to adopt BIA. Hence:

**H3: Higher sophistication of organizational data-related infrastructure is positively associated with the extent of BIA adoption**

Information systems facilitate use of a common language by standardizing data elements and data structures (Goodhue, Wybo and Kirsch, 1992). Data standards make it easy to communicate and organize information and enable common interpretation. Standards are vital for managing data quality, which is important as firms increasingly rely on data-driven technologies (Parssian, Sarkar, and Jacob, 2004). Lack of data standards is a significant barrier for technology adoption and delays the returns from IT investments (Whitaker et al., 2007).

As BIA creates insights based on information collected from within and beyond the organization and uses different tools for consolidation and presentation, we argue that industry standards have important implications. First, standard-compliant applications can share data and enable less redundancy towards better data quality. Standard interfaces among the tools create better data integration and enable better decision making (Ross, 2003). Second, organizations may switch BIA tools or supporting infrastructure due to the inadequacy of existing tools or due to advanced functionality in others (Sabherwal and Becerra-Fernandez, 2010). Compliance to industry standards promotes interoperability among data tools and provides the scope to integrate data across different sources. Put differently, lack of industry standards would diminish the advantages by forcing vendor lock-in or by hindering the ability to combine disparate data sources and formats and might negatively impact adoption. Hence:

**H4: The lack of industry standards is negatively associated with the extent of BIA adoption**

Organizations in information-intensive sectors are more likely to adopt IT innovations (Yap, 1990). The need for adopting IT innovations is influenced by the inherent information and knowledge intensity in the firm’s products and services (Porter and Millar, 1985). Knowledge has become the core strategic asset of an organization (Eriksson and Dickson, 2000). The firm’s ability to absorb and exploit knowledge from various sources is becoming a major determinant of technology adoption. Further, the speed of new knowledge creation and knowledge transfer across firm boundaries is becoming crucial for firm success in volatile environments (El Sawy, Malhotra, Gosain and Young, 1999). Thus, organizational success depends on the ability to gather, maintain, and disseminate knowledge. BIA technologies and its supporting infrastructure have emerged as a valuable tool to collect and convert large volumes of information into actionable insights for decision-making (Sabherwal and Becerra-Fernandez, 2010). These tools can be more valuable and relevant for firms in knowledge-intensive industries to act on the abundance of information, structure it and create actionable insights out of it. Hence:

**H5: Higher Industry knowledge intensity is positively associated with the extent of BIA adoption**

**METHODOLOGY**

Data for our study comes from the InformationWeek 2012 Business Intelligence, Analytics and Information Management Survey conducted in October 2011 to gather information from 542 firms across North America.³ 358 respondents completed the survey based on implementing BIA in their organization. After dropping incomplete/duplicate observations and removing outliers per Cook’s distance, (Long and Freese, 2003), the final sample comprised of data from 229 firms. Relevant survey questions are provided in Appendix A.

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³ InformationWeek is a reliable data source used in several previous academic studies (For example, Whitaker et al., 2007)
Variables Definition

Dependent Variable

Extent of Adoption of BIA (BIAExtent): This 8-item summative index represents the BIA technologies like Alerts, Dashboards and Embedded BI etc., used within the organization. A complete list is provided in Appendix A. These representative technologies are consistent with BIA technologies currently being used extensively in organizations (Chen et al., 2012). Respondents were asked if each technology is being ‘used extensively’ or ‘on a limited basis’ or ‘planned use’ or ‘No current/planned use’. As we study the extent of adoption, consistent with prior research, we coded the technology use as ‘1’ if it is ‘Used Extensively’ and ‘0’ otherwise (Saldanha and Krishnan, 2012).

Independent Variables

Perceived benefits (PercBenefits): A 12-item summative index representing the current usage of early-generation BI or plans to utilize new-generation BIA for competitive analysis, corporate governance etc. A complete list of benefits forming the index is furnished in Appendix A. Each item within the index was coded ‘1’ if the organization is using or plans to use BIA for that activity and ‘0’ otherwise. The summative measure was formed by adding the binary responses for 12 items to capture the extent of agreement with claimed benefits (Chau and Tam, 1997).

Organization Size (Size): Size in terms of the annual revenues. Informed by research, we have used seven point bracketed variable indicating annual firm revenues (in millions) (1 - less than $6, 2 - $6–$49.9, 3 - $50–$99.9, 4 - $100–$499.9, 5 - $500–$999.9, 6 - $1,000–$4,999, 7 - $5,000 or more) (Whitaker et al., 2007)

Data Infrastructure Sophistication (DataInfr): A 7-item summative measure capturing number of technologies like data cleansing tools, data federation software etc. used for data consolidation. The complete list was provided in Appendix A. Each item within the index was coded as ‘1’ if the organization implemented that technology and ‘0’ otherwise (Saldanha and Krishnan, 2012)

Lack of Industry Standards (Standards): A binary variable capturing whether lack of industry standards are perceived as a challenge. It was coded as ‘1’ if so and ‘0’ otherwise (Whitaker et al., 2007).

Industry Knowledge Intensity (IndKnowInt): Measured as the ratio of scientists and engineers to the total employment (Allen, 2001; Ha and Howitt, 2007). National Science Foundation (NSF) provides these ratios at 3-digit NAICS industry level and at the ‘size of the company’ level. As our data comprise some industries not covered by NAICS classification (eg. Government), we have adopted latest 2009 NSF data at the ‘size of the company level’ i.e. ratio of scientists and engineers to total employees in firms bracketed under different firm sizes. This is an industry-level metric based on firm sizes aggregated across industries rather than industry type.

Control Variables

IT Capital Intensity (ITCapInt): Firms in IT-intensive industries may be more likely to adopt BIA. As we do not have the IT-capital data at the firm level, we control for IT capital intensity at 3-digit NAICS industry level. Using industry level variables when firm level variables are unavailable is consistent with prior research (Schilling and Phelps, 2007). We have created a binary variable as ‘1’ for firms in IT-intensive industries and ‘0’ otherwise. Industry IT-capital intensity is measured as the ratio of the share of IT-capital to total capital (Jorgenson, Ho, Samuels and Stiroh, 2007).

Manufacturing (Manuf): This binary represents whether the firm offers goods or services (1= Manufacturing,0=Services) (Saldanha and Krishnan, 2012).

EMPIRICAL MODEL

As our dependent variable (BIAExtent) is ordered, we use cross-sectional ordered logistic regression for estimation. Ordered Logistic or Ordered Probit models are used for ordered dependent variables (Greene, 2008). While BIAExtent can be argued as a count variable, count variables indicate how many times something of similar nature has happened and each item in the
index may have equal impact weight (Long and Freese 2003). As we study the BIA adoption extent, BIAExtent corresponds to adoption degree and consists of 8 levels taking any value from 0-7. The categories in this variable can be ranked, but the distances between them are unknown. Hence the weight of each item in the index may not be same as in the count variable (Greene 2008). A similar approach was used in past research (Banker, Bardhan and Chen, 2008). The empirical model is as follows:

\[
\text{Ordered Logit(BIAExtent)} = \beta_0 + \beta_1(\text{PercBenefits}) + \beta_2(\text{Size}) + \beta_3(\text{DataInfr}) + \beta_4(\text{Standards}) + \beta_5(\text{IndKnowInt}) + \beta_6(\text{ITcapInt}) + \beta_7(\text{Manuf}) + e
\]

**RESULTS**

Descriptive statistics and empirical results are in Table 1 and Table 2 respectively.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>S.D</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>BIAExtent</td>
<td>2.26</td>
<td>1.7</td>
<td>0</td>
<td>7</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PercBenefits</td>
<td>5.04</td>
<td>3.22</td>
<td>0</td>
<td>12</td>
<td>0.46*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>4.53</td>
<td>1.90</td>
<td>1</td>
<td>7</td>
<td>0.21*</td>
<td>0.16*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DataInfr</td>
<td>1.85</td>
<td>1.74</td>
<td>0</td>
<td>7</td>
<td>0.43*</td>
<td>0.38*</td>
<td>0.25*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standards</td>
<td>0.14</td>
<td>0.38</td>
<td>0</td>
<td>1</td>
<td>-0.06</td>
<td>0.09</td>
<td>-0.17*</td>
<td>0.02</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IndKnowInt</td>
<td>78.16</td>
<td>28.5</td>
<td>55</td>
<td>164</td>
<td>0.03</td>
<td>-0.03</td>
<td>-0.35*</td>
<td>-0.09</td>
<td>0.04</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IndCapInt</td>
<td>0.89</td>
<td>0.30</td>
<td>0</td>
<td>1</td>
<td>-0.06</td>
<td>0.06</td>
<td>-0.08</td>
<td>0.06</td>
<td>0.002</td>
<td>-0.03</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Manuf</td>
<td>0.15</td>
<td>0.36</td>
<td>0</td>
<td>1</td>
<td>0.12*</td>
<td>-0.03</td>
<td>0.09</td>
<td>-0.05</td>
<td>0.01</td>
<td>-0.001</td>
<td>-0.23*</td>
<td>1</td>
</tr>
</tbody>
</table>

N = 229, *indicates significance at 5% level

<table>
<thead>
<tr>
<th>Dependent Variable = BIAExtent (Extent of BIA Adoption)</th>
<th>Ordered Logit Model</th>
<th>Ordered Probit Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>PercBenefits (Perceived Benefits)</td>
<td>0.255*** (0.044)</td>
<td>0.148*** (0.025)</td>
</tr>
<tr>
<td>Size (Organization Size)</td>
<td>0.171*** (0.075)</td>
<td>0.100*** (0.044)</td>
</tr>
<tr>
<td>DataInfr (Data Infrastructure Sophistication)</td>
<td>0.342*** (0.077)</td>
<td>0.194*** (0.043)</td>
</tr>
<tr>
<td>Standards (Lack of Industry Standards)</td>
<td>-0.914*** (0.035)</td>
<td>-0.572*** (0.207)</td>
</tr>
<tr>
<td>IndKnowInt (Industry Knowledge Intensity)</td>
<td>0.014** (0.006)</td>
<td>0.008*** (0.005)</td>
</tr>
<tr>
<td>ITCapInt (IT Capital Intensity)</td>
<td>-0.618 (0.296)</td>
<td>-0.356 (0.235)</td>
</tr>
<tr>
<td>Manuf (Manufacturing)</td>
<td>0.625* (0.329)</td>
<td>0.358* (0.195)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-372.70 (373.91)</td>
<td></td>
</tr>
<tr>
<td>Likelihood Ratio</td>
<td>102.99 (102.38)</td>
<td></td>
</tr>
<tr>
<td>Prob &gt; Chi-Sqr</td>
<td>0.0000 (0.0000)</td>
<td></td>
</tr>
<tr>
<td>Pseudo R-square</td>
<td>0.1214 (0.1209)</td>
<td></td>
</tr>
<tr>
<td>Observations (N)</td>
<td>229</td>
<td>229</td>
</tr>
</tbody>
</table>

Table 1. Descriptive Statistics

Table 2. Empirical Estimation

In Table 2, Column 2 presents the results of ordered logistic regression. The positive and significant coefficient on PercBenefits ($\beta_1 = 0.255, p<0.01$) supports Hypothesis 1 that higher perceived benefits can drive the extent of BIA adoption. The coefficient on Size is positive and significant at 2% significance level ($\beta_2 = 0.171, p<0.03$) suggesting that larger organizations are more likely to adopt BIA to a higher extent, supporting Hypothesis 2. We find support for Hypothesis 3 in Table 2, Column 3 presents results of ordered probit regression which we ran as a robustness check and for which the results are qualitatively similar. For the sake of brevity, we explain the results of ordered logit regression from Column 2.

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5 In Table 2, Column 3 presents results of ordered probit regression which we ran as a robustness check and for which the results are qualitatively similar. For the sake of brevity, we explain the results of ordered logit regression from Column 2.
about data-infrastructure sophistication suggesting that firms with strong backend data-consolidation infrastructure are likely to adopt BIA extensively. The negative and significant coefficient on Standards variable ($\beta_4 = -0.914$, $p<0.01$) supports Hypothesis 4 and suggests that lack of industry standards hinders the extent of BIA adoption. Finally, firms in knowledge-intensive industries are more likely to extensively adopt BIA technologies ($\beta_5 = 0.014$, $p<0.05$) supporting Hypothesis 5.

**Econometric Robustness Checks**

In the original estimation, high chi-square (38.21) and high p-value (0.6380) indicate that the proportional odds assumption has not been violated. White’s test for heteroskedasticity ($p=0.14$, chi2=40.75) suggests that heteroskedasticity is not a serious problem. We tested for multicollinearity by computing variance inflation factors (VIF) and condition indices. The mean(maximum) VIF was 1.19(1.40) and the condition number was 18.51, both within the prescribed limits, suggesting that multicollinearity is not an issue (Greene, 2008). The link test to check for specification errors produced significant linear predicted value ($p=0.007$) and insignificant linear predicted value squared($p=0.846$) suggesting no specification error (Long and Freese, 2003). The Harman’s one factor test produced four principal components together accounting for 72% of the total variation with the first component accounting for 26% of the variation (Podsakoff and Organ, 1986). With no general factor accounting for over 50% of the variation, common method bias is not problematic. We estimated the model as a count model using Poisson count and negative binomial regressions. The results not reported here for brevity purposes remain qualitatively consistent.

**DISCUSSION AND IMPLICATIONS**

The result about perceived benefits highlights the relation between the extent of agreement with the claimed benefits and the extent of BIA adoption (Chau and Tam, 1997). The results of organization size and organizational readiness in terms of sophisticated data-related infrastructure suggest the importance of critical mass needed in organizations to justify investments in BIA which is capital and skill intensive (Kimberly and Evanisko, 1981). The finding about the organizational data-infrastructure sophistication particularly highlights the complementarity between internal data management capabilities and BIA adoption and suggests that these may be inseparable to derive quality insights from BIA.

For researchers, first, to our knowledge, this study is one of the first to empirically examine the contextual factors driving organizational BIA adoption and the large data sample may provide better generalizability of findings that go beyond anecdotal evidence and case studies. Second, our study contributes to the IT innovation adoption literature by developing and validating a theoretical model of BIA adoption, a major set of innovations that can redefine competition (Davenport, 2006). Third, while anecdotal evidence emphasizes that industry standards are important for these technologies to permeate, this study empirically validates the relation between lack of standards and its negative implications for BIA adoption. Our finding extends prior research on how standards and interoperability drive adoption and suggests that BIA adoption may be impacted by the same concerns about lack of standards as was with some prior IT innovations (Saldanha and Krishnan, 2012; Whitaker et al., 2007).

For managers, our results highlight the role of organizational strengths like strong internal IT infrastructure that are imperative before adopting BIA. The role of standards may also prompt managers to evaluate how easy or difficult it will be to create an internal capability that helps collect and process information from disparate sources and then convert it into useful knowledge/insights.

**LIMITATIONS AND FUTURE RESEARCH OPPORTUNITIES**

This study has three primary limitations. First, because of cross-sectional sample, our findings are associational in nature and do not imply causality. Second, using secondary data limits the range of variables chosen, though the variables chosen were guided by past research. Third, the survey allowed capturing information only from BIA adopters and this hindered analyzing information about non-adopters.

As BIA research is emerging, we foresee several research opportunities. For example, first, while we investigated the factors affecting adoption, future research may investigate diffusion and assimilation factors. Researching new generation of advanced analytics emerging in the recent past is another area. Second, researchers may empirically investigate the benefits of BIA for areas like customer orientation and process optimization etc. Third, an investigation of complementary organizational investments to enhance the benefits from BIA needs investigation.
CONCLUSION
In this paper, we examined how technological, organizational and environmental factors may determine the extent of BIA adoption. To our knowledge, this study is among the first to empirically examine the factors driving the extent of organizational BIA adoption. It contributes to the IT innovations adoption literature by empirically validating a model of contextual factors influencing the adoption of BIA, a specific class of technologies gaining prominence to create competitive advantage. Our results emphasize that in addition to the critical mass of the organizations like data-related infrastructure or size, the emergence of industry standards and industry knowledge intensity can influence BIA adoption towards data-driven decision-making.

ACKNOWLEDGMENTS
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REFERENCES


## APPENDIX A – RELEVANT SURVEY QUESTIONS

Table 3 below describes relevant survey questions used in the study.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Relevant InformationWeek Survey Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>BIAExtent (Extent of BIA Technology Adoption)</td>
<td>Which of the following technologies are used extensively to share BI analytic insights within your organization? • Alerts (e-mail, SMS, etc. for exceptions thresholds) • Dashboards (drillable interactive data visualization interfaces) • Embedded BI (charts data visualizations within business apps or portals) • Mobile (smartphone or tablet-based) dashboards/data visualizations • Query and analysis software (e.g., in-memory what-if planning, OLAP cubes, etc.) • Reports (formatted PDF/HTML sent by e-mail or accessed online) • Scorecards (comparing performance to pre-defined goals) • Spreadsheets/Microsoft Excel</td>
</tr>
<tr>
<td>PercBenefits (Perceived Benefits)</td>
<td>How do you currently utilize or plan to business intelligence analytics? • Business activity monitoring • Competitive analysis • Corporate governance • Customer relationship management • Financial analysis • Forecasting • Fraud prevention • Operational process optimization • Product development • Product marketing • Risk management • Sales tracking</td>
</tr>
<tr>
<td>Size (Organization Size)</td>
<td>For research classification purposes only, which of the following dollar ranges includes the annual revenue of your entire organization? • Less than $6 million • $6 million to $49.9 million • $50 million to $99.9 million • $100 million to $499.9 million • $500 million to $999.9 million • $1 billion to $4.9 billion • $5 billion or more • Government non-profit • Don’t know/decline to say</td>
</tr>
<tr>
<td>DataInf (Data Infrastructure Sophistication)</td>
<td>Which of the following systems technologies used within your organization? • Data cleaning/data quality tools • Data federation software • Data integration software (ETL) • Document imaging/capture (scanning and optical character recognition) • On-premise data mart(s)/data warehouse(s) • On-premise document record repository • Master data management (MDM)/systems software</td>
</tr>
<tr>
<td>Standards (Lack of Standards)</td>
<td>What are the barriers to adopting BI analytics products enterprise-wide? • Lack of industry standards</td>
</tr>
</tbody>
</table>

Table 3. Relevant Survey Questions