Determinants of Usage Variations of Business Intelligence & Analytics in Organizations – An Empirical Analysis

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Abstract

While Business Intelligence & Analytics (BIA) applications are increasingly being adopted into business, significant variation exists in using them to empower business activities and there is limited empirical research examining the drivers of extensive usage of BIA in organizations. Building on Technological-Organizational-Environmental framework, we present and empirically test a conceptual model of factors associated with the extent of BIA usage. We find that sophistication of data-related infrastructure in firms drives usage while data management challenges hamper the usage extent. Further, we find that large organizations have a higher propensity to use BIA in business functions while managerial challenges related to integration and talent management prevent extensive usage. Finally, we find that industry competitive intensity influences usage extent. Drawing on a large sample, this study highlights the antecedents of BIA usage and can help researchers and practitioners to understand what factors can enable firms to use BIA extensively.

Introduction

As firms in many industries are offering similar products/services relative to competition, business processes are becoming the last sources of competitive differentiation (Davenport 2006). Business processes must keep pace with the rate of change in firm strategy to respond to external dynamics. Firms can meet these demands and spot the changes in external environment only by continuous analysis of real-time information which needs the ability to deeply understand and thoroughly interpret a wide variety of information (Prahalad and Krishnan 2008). The structured and unstructured information being created by old and new technologies more than ever before is further increasing the challenge for firms to obtain better value from data to create actionable insights and gain competitive advantage (LaValle et al.2011). In such a scenario, Business Intelligence & Analytics (BIA) based systems that support analytics for decision-making are being seen as a growing source of value (Davenport 2006; LaValle et al. 2011). BIA is defined as "the broad use of data and quantitative analysis and fact-based management for decision-making within organizations" (Davenport 2010). BIA-based systems are enabling decision-makers to interpret organizational data to enhance decision-making and improve business activities. BIA technologies have matured over the last few years, making them widely usable in business functions to improve customer service, optimize pricing and match talent to job requirements etc. (Davenport and Harris 2007). For example, Harrah's entertainment uses BIA insights not only for pricing and service promotions but also to staff right people in right jobs and deploy optimal number of people at each customer service point (Davenport et al. 2010).

Despite the potential, industry evidence suggests that only a small percentage of adopting firms are extensively using BIA across the organization. One reason hampering extensive usage is the tension between using BIA vs. the rooted leadership belief in gut-feel or intuition towards decisions (Zwilling 2012). For example, a 2012 Harvard Business Analytics survey found that only 11% of the adopting firms are using BIA extensively across business activities (HBR Analytics 2012). Additionally, firms perceive unique challenges in managing data, integrating BIA into business processes and acquiring talent etc., which hinders pervasive usage (SAS Analytics and Accenture 2012). Such challenges imply that there can be differences in firms' ability to use BIA towards competitive advantage (Sabherwal and Becerra-Fernandez 2010). Relatedly, it is unclear what differentiates firms in extensively using BIA in business activities. Our literature review highlights that at least two gaps exist to supplement the extant BIA research. First, much of the existing research presents qualitative and quantitative evidence on the performance impacts of BIA. While this is important to establish the business value of BIA, we need a better understanding of actual usage – *'the missing link'* identified in past research as an important antecedent to accelerate value creation (Devaraj and Kohli 2003). Second, the lack of empirical evidence on actual usage of new innovations in general may be in part due to the lack of theory to guide empirical research (Benbasat and Weber 1996). Research has particularly recognized this gap in the BIA stream and called for empirical research grounded in theory to test the antecedents of BIA usage and value creation (Shanks et al. 2010). We seek to address these gaps in research and ask the questions: *What theoretical framework can be used as a guidance to understand BIA usage variations in firm's business activities? Within this framework, what factors can be identified as key determinants of BIA usage variation?* To better understand the questions, we developed a conceptual model based on the technology-organization-environment (TOE) framework (Tornatzky and Fleischer 1990). The results from ordered logistic regression using data from 192 firms largely supports our hypotheses and identify the differential role of a set of technological and organizational enablers and inhibitors and highlight the role of competitive environment in explaining BIA usage variation in firms.

Literature Review[1]

Innovation Diffusion Literature: The degree to which an innovation fits the firm's problems and can enhance firm performance motivates the firms to adopt selective innovations (Armstrong and Sambamurthy 1999). Because the adoption decision legitimizes resource allocation for future assimilation, adoption stage is

[1] This review was significantly abridged due to page limit requirements. An additional sub-section in this review which we did not include due to length restrictions is about what prior studies have informed regarding "usage" in other IT implementation contexts and what are the specifics of BIA that justify a separate study on BIA usage. However, the next section on 'Theory and Hypotheses development' addresses this concern to a major extent by describing in the context of TOE framework why BIA needs a separate examination and why a reexamination of factors is needed.

an important predecessor to widespread usage (Cooper and Zmud 1990). However, all adoptions do not necessarily translate into widespread usage and extensive usage lags behind adoption for most innovations (Fichman and Kemerer 1999). The technological and managerial knowledge required to use the innovations is much more complex than simple awareness of the innovation or its adoption. This knowledge tends to be sticky and is acquired over a long period of time with considerable difficulty (Cohen and Levinthal 1990; Kogut and Zander 1992). Hence this leads to assimilation gaps due to the difference between the knowledge and motivations of adoption versus the knowledge and motivations of usage. These gaps result in misalignment between the adopted new technology and the user environment (Fichman and Kemerer 1999). For example, as Howard and Rai (1993) found in studying the assimilation of computer-aided software engineering (CASE) tools, only 6 firms out of 313 adopters have deployed these tools for broad and routine usage. Hence it is not mere adoption but usage that needs to be understood as actual usage is a crucial antecedent to create value from IT investments (Devaraj and Kohli 2003). Using IT in business activities is a major dimension of IS success and there tends to be a strong link between usage and impact (DeLone and McLean 1992). The adopted technologies need to be accepted, adapted, routinized, and extensively used to create and sustain value (Zhu et al. 2006). In sum, our review in this stream implies that adoption and usage are two different stages in IT innovation diffusion that need separate examination. Further, understanding what actually drives firms to use technologies is important as actual usage is crucial to realize value.

Literature on BIA: BIA involves acquiring new insights through analyzing data from various sources and deploying those insights to create competitive advantage (Davenport 2006). Firms are increasingly adopting basic BIA technologies like dashboards, adhoc query tools and interactive visualization etc., and are acquiring advanced BIA capabilities like advanced data visualization (e.g. treemaps and heat maps), In-memory BI/analytics (fast analysis/what-if planning on large data sets) and social media analysis etc., to develop insights from data (Chen et al. 2010). The BIA insights are being used to enhance internal operational activities like business process improvement, enterprise performance management and quality management etc. (Sabherwal and Becerra-Fernandez 2010). In addition, firms are using BIA for improving strategic processes related to customers like personalization of offerings or to coordinate with suppliers as in the case of real-time matching of supply and demand (Davenport and Harris 2007). Our review in the BIA stream as summarized Table 1 highlights that the emerging literature has focused on theoretical insights or qualitative and empirical evidence about the business value of BIA and enabling mechanisms. However, to our knowledge, limited research exists in the first place to understand what contextual factors influence firms to use BIA extensively in business activities. Taken together, our literature review in innovation diffusion and BIA research streams emphasizes the importance of understanding the determinants of extensive usage of BIA in firm's business activities and highlights the gap in research about understanding these determinants.

Theory and Hypotheses Development

IT innovation diffusion research has drawn on varied theoretical frameworks to explain IT adoption and usage. Specifically at the firm level, the Diffusion of Innovation (DOI) Theory (Rogers 1995) and Technology-Organization-Environment (Tornatzky and Fleischer 1990) were used in isolation or combined with other perspectives like Institutional Theory (Scott 1987). As we examine organizational usage of BIA, a theoretical model needs to consider the specific technological, organizational, and environmental circumstances of an organization (Zhu and Kraemer 2005). Reviewing the literature suggests that the Technology-Organization-Environment (TOE) framework (Tornatzky and Fleischer 1990) may provide appropriate guidance for examining BIA usage. The TOE framework suggests that the technological, organizational and environment contexts are three important areas that influence the process by which organizations adopt and implement innovations (Tornatzky and Fleisher, 1990). The Technological context relates to the extant technologies in use and relevant new technologies and technical skills available for the firm. The Organizational context relates to organizational structures and processes that influence innovation adoption and usage and refers to characteristics such as scope and size etc. The Environmental context is the arena in which the firm conducts its business – its industry, competitors, Government etc. These three contexts present constraints and opportunities for technological innovation (Tornatzky and Fleisher, 1990: p. 154). The TOE framework is consistent with the Roger's DOI theory (Rogers 1995) which emphasizes that the technological characteristics and both the internal and external characteristics of the organization are the drivers for technology diffusion (Zhu et al. 2006).

The TOE framework has been used in research to understand technology adoption and usage. For example, Zhu et al. (2004) drew upon TOE to study the factors influencing e-business usage on firm performance. Chau and Tam (1997) applied the TOE framework to study open systems adoption and they suggested that future research can extend TOE to other innovation domains (Chau and Tam 1997:17). Based on literature review on TOE framework, we find that TOE framework found consistent empirical support, although specific factors examined varied based on innovation contexts. Integrating TOE framework into our conceptual model can guide our research as BIA usage possesses specific characteristics in three contexts that need examination. For example, in Technological context, extensive BIA usage may be motivated by quality insights from BIA systems which in turn depend on backend systems that support quality data creation. Hence the three TOE elements may provide theoretical guidance to develop our conceptual model.

The need for reexamining the TOE factors in the BIA context arises for at least three reasons. First, while IT systems of the past have focused on consolidating and analyzing asynchronous data, BIA systems can render the capability for continuous analysis of information and create insights by capitalizing on real-time information (Prahalad and Krishnan 2008). For example, activities like matching supply and demand hinge on real-time monitoring rather than on automated decisions (Davenport et al. 2012). Second, given the volume and velocity of both structured and unstructured information being generated, the existing IT infrastructure of the firms may be insufficient to handle the data flows and scaling the existing technologies may be insufficient to meet the data demands. Hence firms may need strong financial and new technical resources to address these demands (Iacovou et al. 1995). Third, current data environments and the demand for new analytical capabilities may entail unique human resource requirements needing professionals who can understand the systems, interact with data, analyze information and communicate insights with executives (Davenport et al. 2012). In sum, BIA systems can create opportunities contingent on new set of complementarities and can pose unique new challenges that need a systematic examination.

Conceptual Model: Building on the TOE framework, we develop a conceptual model to assess the determinants of the extent of BIA usage. Figure 1 presents the model. To suggest the factors in the model, we draw upon factors found to be significant predictors in past innovation diffusion research and complemented them with factors that reflect the unique features of BIA. Table 2 describes the six factors we identified and the rationale for including them as informed by past research or the unique features of BIA.

Hypotheses Development

Organizational IT sophistication helps to assess the level of support for using IT towards organizational objectives (Grover 1993). It determines the organizational readiness towards the extent of adoption and usage of new technologies (Iacovou et al. 1995). On the other hand, the absence of required internal IT resources could present a barrier to adopt and effectively use new technologies (Taylor and Todd 1995). Additionally, new technology use is significantly contingent on complementary resources like existing technology infrastructure since firms that are already familiar with IT show a positive attitude towards future IT extensions (Neo 1988). Technology infrastructure is an important foundational capability to establish a platform on which other capabilities can be built (Zhu et al. 2006). Specific to BIA context, a deep understanding and consolidation of the data sources is salient to realize effective BIA capabilities. Data consolidation consumes 50-80% of the project resources in understanding and preparing data (Sabherwal and Becerra-Fernandez 2010). This is further compounded by today's data sources that go beyond the structured data from firm's transactions. A lot of unstructured information is being generated from across the value chain and beyond. Firms need new capabilities to collect, consolidate and convert data into knowledge to create actionable insights (Prahalad and Krishnan 2008). As quality data is vital to create reliable insights from BIA and that the organizational data can arise in structured and unstructured forms, we suggest that robust data-related infrastructure establishes a foundational complementary capability on which effective BIA capabilities can be built. Put differently, we propose that firms with sophisticated data-related infrastructure oriented towards data collection, cleansing and federation would be more likely to extensively use BIA.

H1: Higher internal data-related infrastructure sophistication of the firm is positively associated with the extent of BIA usage in organizational business activities

Data quality is considered the most important technical factor for successful BIA implementations since high data quality can give users a better understanding of the decision context, increase decision-making productivity, and improve employee functioning (Sabherwal and Becerra-Fernandez 2010; Seddon 1997). On the other hand, poor quality data can result in increased operational costs in detecting and correcting errors, decreased customer satisfaction, inefficient decision-making, lower performance and lower employee morale (Ballou et al. 2004; Kahn et al. 2003; Redman 1998). Further, since data implicitly defines common terms in an enterprise, data is a significant contributor to organizational culture. Poor data quality negatively affects the organizational culture by making it difficult to build trust in data and can lead to lack of user acceptance of any initiatives based on such data (Levitin and Redman 1998). Given this emphasis on data quality, a firm's data environment for quality data creation significantly depends on the sophistication of internal data management capability (DMC) (Ramamurthy et al. 2008). Sophisticated DMC helps to enforce data definition standards, data integrity and security policies. In addition, sophisticated DMC helps effective mining of organizational data to create taxonomies (Sabherwal and Becerra-Fernandez 2010). These taxonomies enable identifying the critical knowledge areas used to describe and catalog organizational knowledge and competency subject areas. On the other hand, poorly organized DMC results in important information being locked in a variety of systems, makes it difficult to consolidate information and to interpret and share data across IT applications (Goodhue et al. 1988). Specific to BIA context, BIA implementations involve extracting heterogeneous data with differing formats and semantics from diverse sources and then clean, transform, combine and format it before making it available for analysis. A data environment that is not properly managed is likely to suffer from problems related to quality, reliability, integrity and standards etc. It would pose challenges in terms of mistrust in the data and in relying on and acceptance of insights from BIA systems using that data. In other words, this may hinder extensive usage of BIA in business activities. Hence

H2: Higher challenges with respect to data management are negatively associated with the extent of BIA usage in organizational business activities

The findings about the association between organization size and IT innovation diffusion in literature were mixed (Ramamurthy et al. 2008). On one hand, it was argued that large organizations possess resource advantages, greater slack in resources and flexibility to mobilize financial resources to experiment with innovations (Rogers 1995). Size creates a critical mass and the benefits of economies of scale make the costs of innovations proportionately less to provide incentives to innovate (Kimberly and Evanisko 1980). The breadth of operations also makes adopted innovations often complement existing operations and become more beneficial (Geroski 2000). Large firms also have more ability to hire professionals with specialized skills such as IT expertise (Alpar and Reeves 1990). However, large size has also been argued to inhibit adoption and usage of new technologies as large firms tend to be less agile and flexible than small firms due to possible structural inertia, the force that hinders organizational change (Thong and Yap 1995). On the other hand, smaller firms tend to be more agile and productive than larger ones, particularly in research and development endeavors, and hence small firms can be more receptive towards innovations and efficient at adopting them (Yeaple 1992). However, small firms can be constrained by inadequate financial resources and lack of expertise etc. and face more barriers to adopt and use new technologies (Ein-Dor and Segev 1978; Thong and Yap 1995). In BIA context, BIA initiatives require robust internal IT-infrastructure like enterprise systems for collecting structured and unstructured data from business transactions and environmental scanning and then consolidating this in repositories before creating usable knowledge (Sabherwal and Becerra-Fernandez 2010). BIA adoption and usage is resource intensive in terms of both capital and skilled labor requirements (Davenport and Harris 2007). For example, in a related context, large organizations were found to be more likely to implement data warehouses as they are resource intensive

(Ramamurthy et al. 2008). Additionally, in large organizations, the potential for information silos is higher with greater difficulty in finding and using information (Grudin 2006). BIA implementations can become enablers of efficient information processing by increasing information integration and information transparency in such silo-ed contexts and can provide the incentive to adopt and use BIA extensively. Hence:

H3: Large Organizational Size is positively associated with the extent of BIA usage in organizational business activities

The ability to blend managerial and IT skills lies at the heart of firms' ability to assimilate IT (Mata et al. 1995). Technology usage needs organizational adaptations including acquiring new expertise necessary to use the innovation and harmonizing new technologies and existing processes to achieve alignment and integration (Fichman and Kemerer 1999; Straub and Watson 2001). However, extensive usage of new technologies brings about unique challenges with regard to such adaptations (Chatterjee et al. 2002). Not all firms can effectively manage organizational adaptations due to the lack of managerial skills and knowledge for change management (Roberts et al. 2003). Firms face organizational challenges during new technology assimilation due to management issues such as lack of integration of technology into business processes and lack of skilled technical people and experienced trained users etc. (Zhu et al. 2006). Specific to BIA, achieving BIA excellence is an ongoing capability different from transaction processing. Capitalizing on BIA needs paying attention to data flows unlike traditional data analysis which draws upon data stocks (Davenport et al. 2012). Some activities like customer sentiment analysis need real-time monitoring and a more continuous approach to analysis and decision-making rather than episodic ad-hoc analysis (Prahalad and Krishnan 2008). Managing this transformation requires seamless integration of BIA capabilities into business processes (Davenport and Harris 2007). Further, to accommodate the transitions in data volumes and analysis requirements, firms need new talent and different IT assets like systems with more computing power that is not available in most organizations (McAfee and Brynjolfsson 2012). Firms need new class of talent like data scientists and product and process developers rather than data analysts. Because interacting with the data is the core skill needed, the new talent needs substantial and creative IT skills and should be trained to thoroughly understand the firm's products and processes (Davenport et al. 2012). When firms confront managerial challenges to accommodate such adaptations associated with technology integration and talent management, it can significantly hamper higher usage of BIA in organizational activities. Hence:

H4: ***Managerial challenges related to integration management and talent management are negatively related to the extent of BIA usage in organizational business activities***

Competitive intensity refers to the degree of pressure that the company faces from competitors within the industry (Zhu et al. 2006). Competition leads to uncertainty in the market and intense competition is associated with higher IT use in general and innovation adoption in particular to maintain market position (Kimberly and Evanisko 1980; Robertson and Gatingnon 1986). Further, competitive intensity accelerates innovation diffusion as firms attempt to alter the rules of competition, affect the industry structure, and leverage new ways to outperform rivals, thus changing the competitive landscape (Porter and Millar 1985). Firms try to achieve this by rapidly adopting and integrating innovations and making changes in the internal business processes to make the processes more efficient (Porter 1991). In the BIA context, BIA offers new means of competing through data-driven decision-making to predict trends and changes in the environment and adjust business strategy accordingly (Davenport and Harris 2007). Firms are leveraging BIA insights to support important distinctive capabilities that can differentiate them from competition. Additionally, firms are using BIA insights to build a deeper understanding of customer preferences and then apply this understanding to contextualize experiences per the individual preferences (Prahalad and Krishnan 2008). This is enabling the firms to tie service delivery to personalized outcomes and move from volume-based systems that hinge on scale to serve a segment of customers towards value-based systems that focus on creating personalized value. For example, anecdotal evidence highlights changes in healthcare industry where firms are using BIA insights to tie healthcare bills to individual patient outcomes. By facilitating to change the focus to create personalized value to each customer, BIA systems are altering the industry structures in industries like healthcare by making the firms move from emphasizing on volume to an attention on individual experiences and thereby differentiate service from competition (Horner and Basu 2012). Hence:

H5: Higher industry competitive intensity is positively associated with the extent of BIA usage in organizational business activities

An organization's environment is defined as those physical and social factors that are outside the firm boundary but are still relevant for its success (Duncan 1972). Environmental dynamism, the degree and instability of change in a firm's environment, appears to be a critical dimension of a firm's success (Dess and Beard 1984).[2] In dynamic environments, managers will experience much more uncertainty, or lack of information related to the current state of the environment and the potential impact of the developments on their firms (Milliken 1987). Hence organizations strive to ensure compatibility with the dynamism towards long-term survival and growth (Thompson 1967). Achieving such compatibility requires organizations to adapt on a continuous basis and firms seek to do so by developing flexibility in business processes. Ability to reconfigure business processes depends on how quickly and effectively the IT systems supporting the processes can be modified (Prahalad and Krishnan 2008). Hence greater environmental dynamism makes it necessary for organizations to evaluate more technologies, adopt and implement them, in order to cope with greater information processing requirements associated with such environments (Grover and Goslar 1993). Firms seek IT capabilities to collect information, interpret it and act on the knowledge generated to respond to environmental dynamism (Ravichandran 2000). In other words, firms seek out systems that predict, coordinate and forecast market trends that will enable to react swiftly and efficiently to market changes (Wu et al. 2003). In the BIA context, spotting the trends and changes needs a thorough understanding of consumer expectations and behaviors, of technological changes developing in the environment and the nature of the supply chain and opportunities for improving supply chain performance (Prahalad and Krishnan 2008). Firms need capabilities that can provide a glimpse of the changes happening on a real-time basis which can act as weak signals of the environmental changes. While traditional business intelligence systems are asynchronous with business change, the evolving BIA systems with support from real-time connectivity

[2] Organizational environment includes factors beyond a firm and its industry and constitutes technologies, regulatory bodies, economic factors and social and political dynamics (Albright 2004)

and seamless data flow from backend infrastructure can provide the capability for continuous analysis of real-time information to quickly spot opportunities and anomalies in a firm's external environment and swiftly revise firm response. For example, BIA systems are being used not only to support changes in traditional consumer and seasonal demands, but also to understand the consumer dynamism in the local markets and tailor the supplier replenishment programs to swiftly adjust to the local requirements (Martin 2010). Hence:

H6: Higher environmental dynamism is positively associated with the extent of BIA usage in organizational business activities

Research Design and Methodology

Data were drawn from InformationWeek 2012 Business Intelligence, Analytics and Information Management Survey. InformationWeek surveys are reliable sources used in academic research (for example, Bharadwaj et al. 1999). The original dataset comprised of data from 542 firms out of which only 358 firms were allowed to complete the survey for implementing BIA technologies. After dropping incomplete observations and removing outliers per Cook's distance (Long and Freese 2003), the final sample comprised of data from 192 firms. The variables are described in Table 3. We developed a cross-sectional model to test our hypothesis. Our dependent variable *BIAUsage* is an ordered variable and is a summative index signifying the extent of BIA usage in organizational business activities. It may be argued that this variable is a count variable. But count variables indicate how many times something of similar nature has happened (Long and Freese 2003). For example, count models are used to study number of patents and number of products etc. and each patent or product is considered to have an equal impact weight in additive count variable. In this study, we examine the extent of BIA usage. Hence for each firm, *BIAUsage* consists of 13 levels and can take any value between zero and twelve based on usage in varied business activities. The categories in this variable can be ranked, but the distances between the categories are unknown. The weight of each item in the index may not be same as in the count variable (Greene 2008). Hence we treat the dependent variable as ordered. A similar measurement approach was used in Bardhan et al. (2007) and Banker et al. (2008). Since the dependent variable is ordered, we use ordered logistic regression for estimation (Greene 2008). Informed by past research, we control for expected benefits from usage and for firms in industries using IT for transformation purposes as these two factors drive earlier adoption and broad usage of new technologies (Banker et al. 2011; Chau and Tam 1997). Further, we control for firms in Hi-Tech and Telecom industries, industries at the forefront of BIA adoption (Accenture 2013). The empirical model is:

P(BIAUsage) = β0 + β1(DataInfrSophistication) + β2(DatMgmtChallenges) + β3(Size) + β4(MgrChallenges) + β5(CompIntensity) + β6 (EnvDynamism) + β7(ExpBenefits) + β8(HiITTel) + β9(Transformate) + e

Results

Table 4 and Table 5 provide the descriptive statistics and the estimation results respectively. In Table 5, Column 3 is the results of the ordered probit regression, which we ran as a robustness check. For brevity, we explain the results of the ordered logistic estimation in Column 2. The Likelihood Ratio Chi-square value of 62.17 ($p<0.001$) indicates that we can reject the null hypothesis that the coefficients of the model are jointly zero. The positive and significant coefficient ($\beta_1 = 0.298$, $p<0.01$) on *DataInfrSophistication* variable provides ***support for H1*** that robust data-related infrastructure can enable the firms to extensively use BIA for business activities. The negative and significant coefficient ($\beta_2 = -0.261$, $p<0.05$) renders ***support for H2*** that data management challenges would hinder extensive BIA usage. We find that larger organizations are more likely to have extensive usage of BIA ($\beta3 = 0.17$, $p < 0.05$), ***supporting H3***. We find ***partial support for H4*** ($\beta4 = -0.27$, $p<0.10$), which posited that managerial challenges related to talent and integration management are likely to constrain extensive BIA usage. ***Consistent with H5***, we find that firms in highly competitive industries are more likely to extensively use BIA ($\beta5 = 0.09$, $p<0.001$). Hypothesis H6 about impact of environment dynamism on BIA usage was not supported ($p>0.10$). We later discuss the potential reasons for this non-support. Table 6 describes econometric checks conducted to provide robustness to our results.

Discussion and Implications

Consistent with H1, an organization's data-related infrastructure sophistication is strongly associated with the extent of BIA usage. This aligns with research propositions that usage and benefits from IT adoptions are contingent on complementary investments the firms make in organizational resources (Brynjolfsson and Saunders 2010). As hypothesized in H2, we find that challenges related to data management may hinder BIA usage. Taken together, these two findings corroborate the technology readiness construct examined in IT innovation diffusion research and support conceptual arguments (e.g. Sabherwal and Becerra-Fernandez 2010) that firms should first have robust systems and processes in place to collect and consolidate data from diverse sources to be usable for BIA purposes. The support for H3 about organization size suggests the role of critical mass in driving the usage of BIA. In addition, as informed by research, the potential for information silos is higher in large organizations and initiatives like BIA may provide incentives by enabling information integration and information transparency and bring forth the information hitherto confined to silos (Grudin 2006). The support for H4 about managerial challenges marks the importance of seamless integration of BIA into a firm's business processes and of responding to the unique talent requirements of BIA. This alerts the need for building necessary managerial skills for efficient usage of innovations like BIA. The support for H5 about competitive intensity suggests that competitive pressure increases a firm's motivation to seek new technologies to maintain competitive advantage (Iacovou et al. 1995). We find that firms facing strong competition tend to use BIA extensively, a finding consistent with industry observations that firms are using BIA to understand business opportunities and refine firm response in the wake of increasing competition (LaValle et al.2011). However, H6 about the role of environment dynamism was not supported. One possible explanation for this non-support is that firms in our sample may be using BIA for routine tasks like business process monitoring and process optimization etc. rather than for strategic activities like competitive analysis and customer orientation which may align with the true spirit of BIA usage. Using BIA instead for strategic activities may provide different results. Further investigation is needed into this aspect.

For research, first, to our knowledge, this study is among the first to empirically examine the drivers of BIA usage across a large sample of firms. It contributes to the IT assimilation literature and also supplements the extant anecdotal evidence in BIA literature that has examined the factors driving BIA usage. Second, we have demonstrated the usefulness of the TOE framework for identifying factors affecting BIA usage based on relevant factors from past research and extant context. As BIA is still gaining acceptance, our findings shed light on some theoretical underpinnings and what TOE characteristics can explain the differential usage of BIA. For managers, first, our results offer a useful framework to assess the technological conditions under which BIA should be deployed to realize better value. Second, our results suggest the need for addressing challenges related to BIA integration into organizational processes before expecting value. In addition, managers should recognize that BIA usage entails unique human resource requirements and acquiring right talent should be of primary importance before embarking on these investments.

Limitations and Future Research Opportunities

This study has three primary limitations among others. First, due to the cross-sectional sample, our findings are associational and do not imply causality. Future research may use longitudinal datasets which provide insights about temporal ordering. Second, though InformationWeek randomly selects the respondents, the data is not from a pure random sample and this may limit the full generalizability of our findings. Third, use of secondary data limits the range of variables analyzed, though the variables chosen were guided by past research. There might be potentially several other variables that might affect BIA usage. For example, future research may examine how an organizational culture based on openness and information transparency may drive BIA usage. Further, research may also investigate factors driving BIA adoption and assimilation. Additional opportunities to pursue include what complementary investments can augment the benefits and examining and testing the mediation mechanisms that impact firm performance upon usage of BIA.

Conclusion

Our study is a step to develop empirical evidence grounded in theory to understand the contextual factors driving the usage of BIA-based systems, a class of technologies gaining prominence to create competitive advantage. Our results emphasize that in addition to critical mass in firms like data-related infrastructure or size, addressing data management challenges and managerial challenges of integration and talent management can determine how fast these technologies can permeate and empower enterprise decision-making. Further, our study highlights the role of competitive intensity in driving BIA usage and aligns with anecdotal evidence that BIA is being seen as a valuable enabler to differentiate and outperform competition.

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Figures and Tables

Figure 1. Conceptual Model for Extent of BIA Usage in Organizations

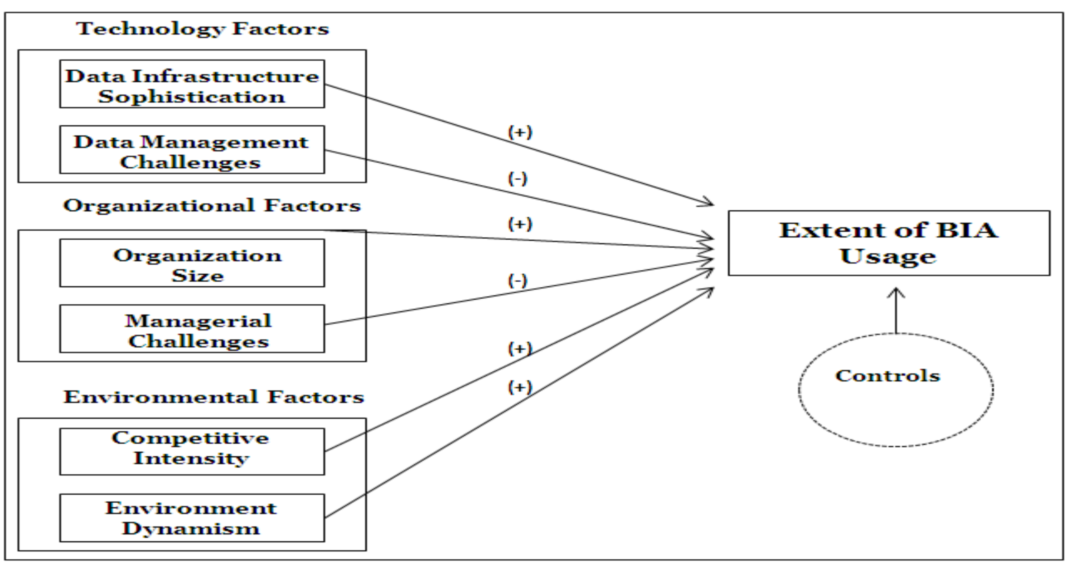

Table 1. A Brief Review of Literature on BIA

Study Title	Study Type	Description/Findings
Davenport, T.H. 2006. Competing on Analytics," *Harvard Business Review* (84:1), pp. 99-107.	Qualitative	Analytics based insights can improve areas like customer service, supply chain management (SCM) and pricing etc. and a firm's senior executive commitment and enterprise-wide commitment to BIA are vital to realize value.
Trkman, P., McCormack, K., Valadares de Oliveira, M.P., and Bronzo Ladeira, M. 2010. "The impact of business analytics on supply chain performance," *Decision Support Systems*, 49, pp. 318-327.	Empirical	Investigated the impact of BIA on supply chain performance and found that using BIA insights in plan, source, make and deliver areas of supply chain management have led to improvements in supply chain performance. Additionally, it was found that strong internal IT sophistication has a positive moderating impact on supply chain improvements.
Chen, H., Chiang, R. H. L. and Storey, V. C. 2010. "Business intelligence research," *MIS Quarterly* (34:1), pp. 201-203.	Theoretical	Proposed a framework that identifies the evolution, applications, and emerging research areas of BI&A. Three major evolutions of BIA - BI&A 1.0, BI&A 2.0, and BI&A 3.0 are defined and described in terms of their key characteristics and capabilities. This study further analyzed the current research in BIA and the challenges and opportunities associated with BIA research
LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S., and Kruschwitz, N. 2011. "Big Data, Analytics and the Path from Insights to Value," Sloan Management Review, (52:2), pp.21-31.	Qualitative	Top performing organizations are twice as likely to apply BIA. The biggest challenges to BIA implementations are managerial and cultural.
Shanks, G., and Sharma, R. 2011. "Creating Value from Business Analytics Systems: The Impact of Strategy," in *Proceedings of 15th Pacific Asia Conference on Information Systems (PACIS)*, Brisbane	Theoretical propositions tested with case study based qualitative evidence	Business analytics capabilities lead to organizational benefits in terms of creating value, competitive advantage and innovation. However, a firm's strategy in terms of IT architecture can have a moderating role in enabling business analytics capabilities to create value
McAfee, A., and Brynjolfsson, E. 2012. "Big Data: The Management Revolution," Harvard Business Review (90:10), pp. 60-68	Qualitative	Working with big data and analytics needs leadership that can propagate the vision about data-driven decision making, new talent like data scientists and computer scientists who can work with volumes of data, IT capabilities that can handle the volume and velocity of information and an organizational culture that can foster cross-functional cooperation towards data interpretation and problem solving.

Table 2. Rationale for including specific factors in the conceptual model

Context	Factor	Rationale
Technological	Data-related IT infrastructure sophistication	Innovation diffusion literature highlights the role of technical readiness in the usage of innovations (Iacovou et al. 1995). BIA specifically requires strong backend IT infrastructure to collect and consolidate information towards analysis (Sabherwal and Becerra-Fernandez 2010). Hence we hypothesize the role of data-related IT infrastructure sophistication in the Technology context.
Technological	Challenges related to data resource management	Research has highlighted the need for instituting strong internal data management capabilities as a precursor to IT usage and has highlighted that lack of such capabilities can constrain benefits realization from technology implementations like BIA (Negash 2004). Hence we include challenges related to data management as a factor in the Technology context
Organizational	Organization Size	Firm size was frequently analyzed in innovation literature as a determinant of innovation adoption and usage (Damanpour 1992). IS literature specifically found significant linkage between firm size and IT adoption and usage (Gurbaxani and Whang 1991). Hence we posit the role of firm size in the Organization context.
Organizational	Managerial Challenges related to integration management and talent management	BIA requires organizational adaptation in terms of integrating BIA capabilities into organizational business processes (Prahalad and Krishnan 2008; Straub and Watson 2001). In addition, BIA implementations need special expertise to assist in complex data processing requirements of the firms (Davenport et al. 2010). These two requirements demand firms to possess relevant managerial skills. Lack of such skills would be a significant barrier to BIA usage. Hence we include organizational managerial challenges within the Organization context.
Environmental	Competitive Intensity	Research has consistently suggested the significant effect of competition on innovation diffusion as competition makes innovation adoption necessary to maintain market position (Chau and Tam 1997; Rogers 1995). Hence we examine competition intensity in the Environment context.
Environmental	Environmental Dynamism	Environment unpredictability affects the rate of innovation diffusion (Damanpour and Gopalakrishnan 1998). Greater environmental uncertainty necessitates firms to evaluate more technologies as well as to adopt and implement them to cope with greater information processing and information flow requirements associated with such environments (Grover and Goslar 1993). Hence we include environment dynamism as a factor in the Environment context.

Table 3. Variable Description

Variable	Description
Dependent Variable	
Extent of BIA Usage (*BIAExtent*)	An ordered variable indicating the extent of usage of BIA for business activities. Survey respondents were asked *"How do you currently utilize business intelligence/analytics? Select all that apply"* and were given 12 options - - 'Business activity monitoring', 'Competitive analysis', 'Corporate governance', 'Customer relationship management', 'Financial analysis', 'Forecasting', 'Fraud prevention', 'Operational process optimization', 'Product development', 'Product marketing', 'Risk management' and 'Sales tracking'. We created a summative index of binaries from 12 elements wherein each element represents if

	BIA is being used for that respective business activity (1=yes; 0=no). Similar measurement approach was used in Bardhan et al. (2007) and Banker et al. (2008).
Independent Variables	
Data Infrastructure Sophistication *(DataInfr Sophistication)*	This 10-item summative measure captures number of data-related technologies used for data consolidation. The respondents were asked *"Which of the following systems/technologies are used within your organization? Select all that apply"* and the options included 'Complex event processing technology', 'Hadoop or other non-relational ("NoSQL") processing platforms', 'High-scale data mart/data warehouse systems supporting massively parallel processing', 'Data cleansing/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' and 'Master data management (MDM) systems/software'. Each item was coded as '1' if the organization has implemented a particular technology and '0' otherwise. This approach is informed by past research (Saldanha and Krishnan, 2012).
Data Management Challenges (*DatMgmt Challenges*):	This 4-item summative measure corresponds to question – *"What are your organization's biggest impediments to success related to information management?"* and the options included challenges related to – 'Extracting data/transactional information from paper-based forms and documents', 'Integrating data (e.g., extract, transform, load or data federation)', 'Maintaining reliable and responsive data marts/warehouses', 'Organizing and maintaining data models and/or taxonomies'. Each item within the index was coded as '1' if the organization has faced a particular challenge and '0' otherwise.
Organization Size (*Size*)	Size in terms of annual revenues. Consistent with prior research, we used seven point bracketed variable indicating annual firm revenues (amounts 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)
Managerial Challenges - *MgrChallenges*	This 3-item summative index captures the challenges related to talent management and integration of BIA into organizational systems and processes. The respondents were asked *'What are the barriers to adopting BI/analytics enterprise-wide?'* The options included – 'BI/analytics talent is too expensive to hire', 'Training internal staff too time-intensive and costly' and 'Cannot provide seamless data/application/business process integration'. Each item was coded as '1' if the organization has faced a particular challenge and '0' otherwise.
Industry Competitive Intensity (*CompIntensity*)	Competitive intensity of a firm's industry is measured using the four-firm concentration ratio, a commonly used inverse measure for competition (Melville et al. 2007; Porter and Sakakibara 2004). Competitive Intensity is defined as the sum of the market shares of the top four market share leaders of the firm's industry. We use the concentration ratio data provided by the U.S. Census Bureau at the most detailed North American Industry Classification System (NAICS) level for the most recently available year 2007. This is consistent with Bharadwaj et al. (1999)
Environment Dynamism (*EnvDynamism*)	Environment Dynamism is operationalized as the standardized variation in industry-level sales revenue over the last 5 years. We regressed annual industry sales data over 5 years for each industry at the 3-digit NAICS industry level against time and divided the standard error of the beta coefficient of the time variable by the average annual sales revenue for each industry to obtain the industry-level index of environmental dynamism. This operationalization is Informed by past research (e.g., Boyd 1995; Simerly and Li 2000).

Control Variables	
Expected Benefits (*ExpBenefits*)	We control for expected benefits from BIA usage as higher perceived benefits may lead firms to adopt BIA and use it more extensively (Chau and Tam 1997). This 13-item summative index captures the current goals of the organization for implementing BIA. We created binaries to represent each of the 13 elements in response to the question – *"What are your company's current goals for implementing BI/analytics solutions? Please select all that apply."* The options included - 'Analyze customer data to increase sales', 'Analyze customer data to retain customers', 'Enable real-time information', 'Expand BI to more people in the organization', 'Improve business planning', 'Integrate BI with productivity applications such as Microsoft Office', 'Measure and manage performance', 'Monitor and share business performance metrics', 'Obtain better visibility into business processes', 'Predict customer behavior or fraud', 'provide business reporting tools', 'share information with executives', 'speed production/development cycle times'. We created the summative index based on the 13 binary elements (1=yes; 0=no) for each expected benefit.
Hi-tech & Telecom industries (*HiITTel*)	This indicator variable represents whether the firm is in Hi-Tech Industries or Telecom (1=HiITTel; 0=other). We control for the firms in these two industries as firms in these two industries are at the forefront of BIA adoption and usage (Accenture 2013)
IT orientation (*Transformate*)	As in prior research (i.e. Banker et al. 2011), we adopt Chatterjee et al.'s (2001) classification scheme and use a dummy variable (1=Transformate; 0= otherwise) to capture industries where firms in the industry are using IT for 'transformation' purposes. Firms in such industries adopt and use new innovations faster than in other industries (Chatterjee et al. 2001)

Table 4. Descriptive Statistics

#	Variables	Min	Max	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1	BIAUsage	0	12	4.97	3.23	1.00									
2	DataIntr Sophistication	0	10	2.08	2.05	0.37**	1.00								
3	DatMgmt Challenges	0	4	1.38	1.17	-0.02	0.07	1.00							
4	Size	1	7	4.44	1.88	0.14**	0.20**	0.08	1.00						
5	MgrChallenges	0	3	1.04	0.83	-0.18**	-0.15**	-0.12**	-0.13**	1.00					
6	CompIntensity	3.5	56.2	11.99	9.14	0.16**	-0.01	0.05	0.02	0.02	1.00				
7	EnvDynamism	1.00	1.041	1.02	0.01	0.06	-0.1	-0.03	0.19**	0.04	0.13**	1.00			
8	ExpBenefits	0	13	6.49	3.34	0.25**	0.19**	0.32**	0.11*	-0.20**	0.03	0.10*	1.00		
9	HiITTel	0	1	0.08	0.27	0.10*	-0.003	0.03	-0.00	0.00	0.80**	-0.16**	0.02	1.00	
10	Transformate	0	1	0.46	0.49	0.16**	0.06	0.02	-0.1	-0.03	0.09	-0.14**	0.03	0.32**	1.00
Significant at *10% and **5% levels															

<u>**Table 5. Empirical Estimation Results**</u>

Dependent Variable = Extent of BIA Usage		
Variable	**Ordered Logit Model**	**Ordered Probit Model**
Data Infrastructure Sophistication (*DataInfrSophistication*)	0.298*** (0.072)	0.164*** (0.04)
Data Management Challenges (*DatMgmtChallenges*)	-0.261** (0.128)	-0.157** (0.072)
Organization Size (*Size*)	0.168** (0.076)	0.099** (0.045)
Managerial Challenges (*MgrChallenges*)	-0.27* (0.161)	-0.15* (0.089)
Industry Competitive Intensity (*CompIntensity*)	0.086*** (0.03)	0.05*** (0.016)
Environment Dynamism (*EnvDynamism*)	-7.71 (13.08)	-5.19 (7.45)
Expected Benefits (*ExpBenefits*)	0.11*** (0.042)	0.057** (0.025)
Hi-tech & Telecom industries (*HiITTel*)	-1.78* (1.04)	-1.138** (0.568)
IT orientation (*Transformate*)	0.737*** (0.288)	0.497*** (0.168)
Log Likelihood	-443.56	-443.20
LR Chi-square	62.17	62.88
Prob > Chi-square	0.0000	0.0000
McFadden's pseudo R-square	0.07	0.07
Observations	192	192
Standard Errors are in parentheses. Significant at *10%, **5% and ***1% levels		

Table 6. Econometric Robustness Checks

Testing For	Test	Results	Explanation
Sensitivity of results to Count based Models	Poisson Count Regression & Negative Binomial Regression	The findings not reported here for brevity purposes remain qualitatively consistent with original estimation.	As it may be argued that the model can also be estimated as a count model, to test the sensitivity of the results, we estimated our model using the Poisson count and negative binomial regression models.
Sensitivity of results to ordered probit Estimation	Ordered Probit Estimation	Results presented in Column 3 of Table 5 were qualitatively similar to the main ordered logit estimation	As our dependent variable is ordered, ordered logit or ordered probit estimation models are appropriate (Greene 2008). As we estimated our main model using ordered logit estimation, we ran an ordered probit estimation as a sensitivity check.
Proportional Odds Assumption	Wolfe and Gould's test	A high chi-square value (37.80) and high p-value (15.50)	Proportional Odds Assumption has not been violated
Heteroskedasticity	White's test	High chi-square (60.35) and high p-value (p=0.151)	Heteroskedasticity is not a serious problem with our data
Specification Test	Link Test	A significant linear predicted value and an insignificant linear predicted value squared	Failed to reject the assumption that the model was specified correctly and indicates that meaningful predictors were chosen.
Reliability of survey measures	-	-	As our model used summative measures, tests for the reliability of survey measures are not applicable in our study (Jarvis et al. 2003).[1]
Common method bias	Harman's one factor test	The Harman test produced four factors cumulatively accounting for 81.06% of the total variance, and the first factor accounted for only 32.77% of the variance.	With no general factor accounting for more than 50% of the variance, common method bias is not problematic.
Multicollinearity	We tested for multicollinearity by running an OLS regression of the model and calculating Variance Inflation Factor (VIF).[2]	Highest VIF = 4.92 Mean VIF = 1.48	Multicollinearity is not problematic as the VIF value is within the prescribed limit of 10 (Greene 2008). [3]

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