DETERMINANTS OF USAGE VARIATIONS OF BUSINESS INTELLIGENCE & ANALYTICS IN ORGANIZATIONS – AN EMPIRICAL ANALYSIS

Completed Research Paper

Suresh Malladi
Stephen M. Ross School of Business
University of Michigan
701 Tappan St., Ann Arbor, MI, 48109
sureshms@umich.edu

M.S. Krishnan
Stephen M. Ross School of Business
University of Michigan
701 Tappan St. Ann Arbor, MI, 48109
mskrish@umich.edu

Abstract

While Business Intelligence & Analytics (BIA) applications are increasingly being adopted into business, there is a significant variation in using them to empower organizational business functions. There is a paucity of empirical research examining the drivers of extensive usage of BIA in organizations. Drawing on Technological-Organizational-Environmental theoretical framework, we present and test a conceptual model of factors associated with the extent of organizational usage of BIA. We find that sophistication of data-related infrastructure in firms drives usage while challenges related to data management hamper the extent of usage. 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. This study highlights the antecedents of usage and can help researchers and practitioners to understand what factors can enable firms to use BIA extensively.

Keywords: Business Intelligence, Business Analytics, IT Innovation Diffusion, Innovation Usage, Technology-Organization-Environment (TOE) Framework, IT infrastructure, Data management, Managerial Challenges, Competitive Intensity, Environmental Dynamism

Introduction

Pervasive digitization, ubiquitous connectivity and convergence of industry boundaries are rapidly replacing the firm-centric view of business with an emphasis on co-creation of value and creating personalized experiences for the customers (Prahalad and Krishnan 2008). When firms in many industries are offering similar products/ services relative to competition, business processes are becoming the last sources of differentiation to create competitive advantage (Davenport 2006). To compete in these dynamic market conditions, business processes must keep pace with the rate of change in firm strategy to respond to external changes. Firms can meet these demands and spot the changes and trends in the external environment only by continuous analysis of the real-time information which needs the ability to deeply understand and thoroughly interpret a wide variety of information (Prahalad and Krishnan 2008: 81). Compounding the scenario is the new forms of structured and unstructured information being created by old and new technologies more than ever before and the increasing challenge for firms to obtain better value from their data to gain competitive advantage (LaValle et al.2011).

In such a scenario when firms have to sift through a wealth of data to create actionable knowledge, Business Intelligence & Analytics (BIA) systems that support analytics for decision-making are being seen as a growing source of value and competitive advantage (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" and the BIA systems are enabling decision-makers to interpret organizational data to improve decision-making and optimize business functions (Davenport 2010). The technologies behind BIA have matured over the last few years and are gaining acceptance in business analytics applications, making them widely usable in business (Davenport and Harris 2007). Firms are using BIA to improve customer service, optimize pricing strategies and match best talent to job requirements etc. For example, Harrah's entertainment not only uses analytics for pricing and service promotions but also extended it to staffing decisions. Harrah's uses insights derived from data to staff right people in the right jobs and calculate the optimal number of people needed at each customer service point (Davenport et al. 2010). 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).

Despite the potential of BIA for business, industry evidence suggests that BIA usage in business is still a far cry from the hype. One reason hampering the usage is the tension between using BIA for decision-making and the rooted organizational leadership belief in gut-feel or intuition based decision-making (Zwilling 2012). Relatedly, only a few organizations are using BIA across the organization for decision-making. For example, a 2012 Harvard Business Review Analytics survey has found that only 11% of the organizations are using BIA extensively across the organization (HBR Analytics Services 2012). In addition, firms perceive unique challenges related to managing data sources, integration of BIA into business processes and talent acquisition etc., which is further hindering pervasive BIA usage (SAS Analytics and Accenture 2012). Such challenges associated with BIA imply that there could be significant differences in the ability of the firms to use them towards competitive advantage (Sabherwal and Becerra-Fernandez 2010).

Given the potential benefits and challenges that can influence value creation, it is unclear what differentiates the firms in extensively using BIA in their business functions. Why do we see post-adoption variations in the extent of BIA usage across businesses and what contextual factors influence these variations? Our literature review highlights that at least two gaps exist to supplement the extant research in the BIA subject area. First, much of the existing research informs the performance impacts of BIA based on qualitative and quantitative evidence. 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 in firms (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). Prior researchers have recognized this gap in the BIA subject area and called for empirical research grounded in theory to test the antecedents of BIA usage and value creation in organizations (Shanks and Sharma 2010). We seek to address these gaps in research and ask the research questions: What theoretical framework can be used as a guidance to understand the

BIA usage variations in organizations? Within this framework, what factors can be identified as key determinants of the BIA usage variation in organizational business activities? To better understand these questions, we developed a conceptual model for understanding BIA usage variations based on the technology-organization-environment (TOE) framework (Tornatzky and Fleischer 1990). We tested this model using survey data from 192 firms that are using BIA for business activities. The results from ordered logistic regression largely support our hypotheses and identify a set of technological and organizational enablers and inhibitors and highlight the role of competitive environment in explaining usage variation.

The contributions of this study are two-fold. First, to the best of our knowledge, this study is among the first to examine the post-adoption usage variation of BIA across a broad sample of organizations and complements the existing literature, which is largely anecdotal. Second, because industry evidence points that BIA still is in the stages of gaining awareness and acceptance, our findings inform some theoretical underpinnings and what technological, organizational and environmental characteristics can explain the differential usage of BIA in organizations.

Literature Review[1]

Innovation Diffusion Literature

According to the innovation diffusion literature, firms navigate innovation assimilation from preliminary awareness stage through the adoption and usage stages. The initial stage of awareness identifies organizational requirements and problems and locates potential innovations that can address organizational problems at hand (Rogers 1995: 391). The degree to which an innovation fits the organizational problems and can be useful to enhance a firm's performance motivates the firms to adopt selective innovations with potential benefits (Armstrong and Sambamurthy 1999). Because the adoption decision legitimizes resource allocation needed for future assimilation of the innovation, adoption stage is an important predecessor to widespread usage of technology (Cooper and Zmud 1990). However, all adoptions do not necessarily translate to widespread usage of technologies by a firm. Research has suggested that for most innovations, their extensive usage lags behind adoption (Fichman and Kemerer 1999). After its initial adoption, knowledge barriers arise because the technological and managerial knowledge required to extensively deploy the innovations is much more complex than simple awareness of the innovation and its adoption. This knowledge tends to be sticky and is acquired over a long period of time and with considerable difficulty (Cohen and Levinthal 1990; Kogut and Zander 1992). Hence this leads assimilation gaps due to the discrepancy between the knowledge and motivations of acquisition versus the knowledge and motivations related to deployment and use. These gaps further result in misalignment between the new technology and the user environment (Fichman and Kemerer 1999). For example, as Howard and Rai (1993) found in their study of assimilation of computer-aided software engineering (CASE) tools, only 6 firms out of 313 adopters have deployed these tools for broad and routine use. In a related context, Fichman and Kemerer (1999) found in their study of CASE tools diffusion that while 42% of the firms in their sample adopted these tools, only 7% of the firms could extensively use them in at least 25% of the software projects. Hence it is not mere adoption itself but the actual usage of the adopted technologies in a firm's business activities that needs to be understood as actual usage is a crucial antecedent to create value from IT investments (Devaraj and Kohli 2003; Zhu and Kraemer 2005). Usage of IT in business activities is a significant dimension of IS success and there tends to be a strong link between usage and impact (DeLone and McLean 1992). After a new IT innovation is adopted, it needs to be accepted, adapted, routinized, and extensively used in the business activities of the firm to create and sustain business value (Zhu et al. 2006). In sum, our review in the innovation diffusion stream implies that adoption and usage are two different stages in innovation diffusion that need separate examination. Relatedly, it is important to understand what actually drives the firms to use new technologies like BIA as this actual usage determines the benefits that can accrue to the adopters in the future.

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[1] This review was significantly abridged due to the page limit requirements of ICIS, 2013.

Literature on Business Intelligence & Analytics

BIA involves acquiring new insights through analyzing data and information from various sources and deploying those insights to create competitive advantage for organizations (Davenport 2006; Sabherwal and Becerra-Fernandez 2010). Firms are increasingly adopting basic BIA technologies like dashboards, adhoc query tools, interactive visualization and scorecards etc. In addition, firms are acquiring advanced BIA capabilities like advanced data visualization capabilities (sparklines, treemaps, heat maps, etc.), In-memory BI/analytics (fast analysis/what-if planning on large data sets) and social media analysis etc., to develop insights from data and use these insights for better decision-making (Chen et al. 2012). Firms are using BIA to enhance internal operational activities like business process improvement, enterprise performance management and manufacturing and total quality management etc. (Sabherwal and Becerra-Fernandez 2010). In addition, firms are using BIA for improving strategic processes related to customers, suppliers and competitors. For example, firms are leveraging advanced BIA capabilities for identifying profitable customers, tailoring offerings to individual customer preferences, to understand customer sentiments based on social network analytics and to coordinate with suppliers by real-time matching of supply and demand etc. (Davenport and Harris 2007)

Related to this gaining adoption of BIA into business, extant research in the BIA subject area has focused on how BIA adoption creates business value. These studies have improved our understanding on the value created to organizational functions and the contingent factors that can augment value creation. 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 senior executive commitment and enterprise-wide commitment to BIA are vital to realize value. Shanks and Sharma (2010) theorized that BIA technologies create first-order dynamic capabilities and these lead to second order value-creating actions that impact firm performance. They further suggested that analytics technology quality and autonomous organizational structures should be complementary to BIA investments to augment the benefits. Trkman et al. (2010) empirically 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, they suggest that strong internal IT support has a positive moderating impact on supply chain improvements.

In sum, our review in the BIA stream highlights that while the emerging literature provides qualitative and empirical evidence about the business value of BIA, to our knowledge, there is limited research in the first place to understand what contextual factors are influencing organizations to use BIA extensively in business activities. Taken together, our literature review in the innovation diffusion stream and in the BIA subject area emphasize the importance of understanding the drivers of extensive organizational usage of BIA and highlight the gap in research about understanding BIA usage determinants in organizations.

Theory and Hypotheses Development

Theoretical Background

IT innovation diffusion research has drawn on varied theoretical frameworks to explain IT adoption and usage. At the individual level, Technology Acceptance Model (TAM) (Davis 1989), the Theory of Planned Behavior (TPB) (Ajzen 1985) and Unified Theory of Acceptance and Use of technology (UTAUT) (Venkatesh et al. 2003) were used to explain the adoption and usage of IT innovations. At the organizational level, the Diffusion of Innovation Theory (Rogers 1995) and Technology-Organization-Environment (Tornatzky and Fleischer 1990) were used in isolation or combined with other theoretical perspectives like Institutional Theory (Scott 1987), the theory of the Resource Based View of the firm (Wernerfelt 1984) and Iacovou et al. (1995) model for studying diffusion of inter-organizational systems.

As we attempt to examine organizational usage of BIA, a theoretical model for BIA usage needs to take into account the specific technological, organizational, and environmental circumstances of an organization. Reviewing the literature suggests that the TOE framework (Tornatzky and Fleischer 1990) may provide a useful starting point for looking at BIA use. The Technology-Organization-Environment (TOE) framework suggests that the technological context, organizational context, and environment

context are three important factors that influence the process by which organizations adopt and implement innovations (Tornatzky and Fleisher, 1990). The Technological context relates to the technologies available to the organization and describes both the existing technologies in use and the new technologies relevant to the firm. The organizational context describes the organizational structures and processes that can facilitate or constrain innovation adoption and usage. It refers to organizational characteristics such as scope, size, and the amount of slack resources available internally etc. The environmental context encompasses external factors including industry/regulatory conditions that may influence technology adoption. It encompasses 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). TOE framework is consistent with the Roger's Diffusion of Innovation theory (Rogers 1995) in which it was emphasized that the technological characteristics, and both the internal and external characteristics of the organization are the drivers for technology diffusion.

The TOE framework has been used in earlier studies to understand new technology adoption and usage. For example, Zhu et al. (2004) drew upon TOE to study the factors that influence e-business impacts on firm performance. Chau and Tam (1997) applied the TOE framework to study open systems adoption and they suggested that one future line of research is to extend TOE to other domains and other innovations (Chau and Tam 1997:17). After reviewing the literature on TOE, we find that TOE has consistent empirical support, although specific factors within the innovation contexts may vary. Integrating TOE framework into our conceptual model can guide our research as BIA usage possesses specific characteristics in three contexts that necessitate examination. First, BIA implementations possess some unique technological characteristics that can significantly influence their usage. For example, as BIA outputs rely on quality input data, the motivation to use BIA depends on the output and this output is in turn dictated by the back-end IT infrastructure that supports quality data creation. Second, prior research suggests that capital intensive investments like BIA need some critical mass as is available in large organizations and hence studying organizational characteristics is required. In addition, specific to an information-based context as in BIA, organizational readiness in terms of information openness and transparency can be a crucial influencing factor (Davenport and Harris 2007). Third, as IT systems like BIA can effectively position the firms to react to marketplace changes, studying the influence of market characteristics like environment dynamism and if they motivate BIA usage are vital areas to examine. Hence TOE can provide theoretical guidance to develop our conceptual model.

The need for drawing upon TOE framework and reexamine the TOE factors in the context of BIA arises for at least three reasons as briefly explained here and elaborated further in the hypotheses development. First, while IT systems of the past have focused on consolidating and analyzing asynchronous stocks of data, BIA systems are well-suited to provide insights by capitalizing on real-time flow of information from a firm's value chain activities and render the capability for continuous analysis of information (Prahalad and Krishnan 2008). For example, some activities like matching supply and demand hinge on real-time monitoring rather than automated decisions (Davenport et al. 2012). Second, given the volume and velocity of both structured and unstructured information being generated in a firm's value chain and beyond, 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 the challenges posed by these demands (Iacovou et al. 1995). Third, the current data environments and the demand for new analytical capabilities may entail unique human resource requirements. Today's data context needs professionals with ability to understand the systems, interact with data, acumen to analyze information and ability to communicate effectively with executives (Davenport et al. 2012). In sum, BIA systems can provide additional opportunities contingent on new set of complementarities and can pose new challenges unique to the prevailing context that need a systematic examination.

Conceptual Model

Building on the TOE framework, we develop a conceptual model to assess the determinants of BIA usage extent in organizations. Figure 1 presents the conceptual model.
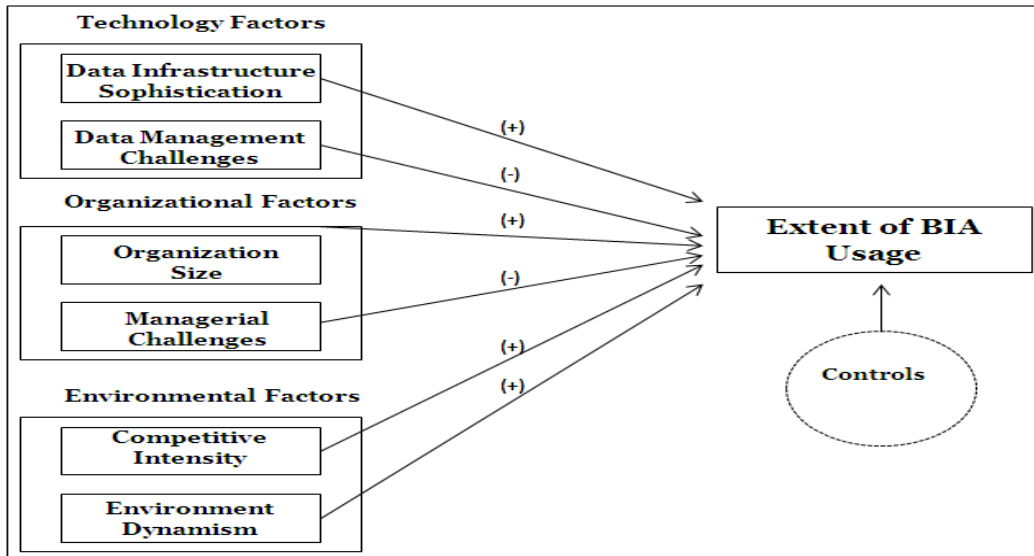
Figure 1. Conceptual Model for Extent of BIA Usage in Organizations

To suggest specific factors in the model, we considered the factors found to be significant predictors in past innovation diffusion research and complemented them with factors that reflect the unique features of BIA. First, 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 technological context. Second, research has highlighted the need for instituting strong internal data resource management practices as a precursor to IT application usage and has highlighted that lack of such capabilities can constrain benefits realization from technology implementations like BIA (Negash 2004). Hence we posit the role of challenges related to data management. Third, 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 organizational context. Fourth, 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. Accordingly, lack of such skills would be a barrier to BIA usage. Hence we include organizational managerial challenges within the organizational context. Fifth, 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. Sixth, Environment unpredictability affects the rate of innovation diffusion (Damanpour and Gopalakrishnan 1998). Greater environmental uncertainty necessitates firms to evaluate more technologies and to adopt and implement them to cope with greater information processing and information flow needs associated with such environments (Grover and Goslar 1993). Hence we include environment dynamism as a factor. In sum, we include six factors in our model drawing upon prior research and the unique requirements of the BIA context.

Hypotheses Development

Organizational IT sophistication is an important indicator of the organizational readiness for innovation adoption and use (Iacovou et al. 1995). A firm's internal IT competence determines the extent of adoption and usage of new technologies (Grover 1993). 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 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 and

existing technology infrastructure since firms that are already familiar with IT seem to show a positive attitude towards further 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).

In the BIA context, one important precursor to realize effective BIA capabilities is a deep understanding of the data sources. Data consolidation consumes 50-80% of the project resources in understanding and preparing the data (Sabherwal and Becerra-Fernandez 2010). This is further compounded by the fact that today's data sources go much beyond the structured data from the firm's transaction systems. A lot of unstructured information is being generated from across the value chain of the firms and firms need new capabilities to be able to collect, consolidate and convert data into knowledge to create actionable insights (Prahalad and Krishnan 2008). As quality data is a key to create reliable insights from BIA and that the organizational data can arise in both structured and unstructured forms through various sources, we suggest that strong data-related infrastructure in the firm establishes a foundational complementary capability on which effective BIA capabilities can be built. Hence we posit the role of strong backend data-related infrastructure as a precursor to extensive use of BIA. Put differently, we hypothesize that firms with higher levels of data-related IT infrastructure oriented towards data collection, cleansing and federation would be more likely to extensively use BIA. Hence:

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

The objective of BIA systems is to improve the timeliness and quality of inputs to the organizational decision-making process (Davenport and Harris 2007; Negash 2004). Data quality is considered to be the most important technical factor for successful BIA implementations (Sabherwal and Becerra-Fernandez 2010). Data quality plays a critical role in BIA success since poor data quality can hinder business decisions at various levels of the organization (Khatri and Brown 2010). High data quality can give users a better understanding of the decision context, increase decision-making productivity, and improve employee functioning (Seddon 1997). On the other hand, poor quality data can have significantly negative economic and social consequences in an organization (Ballou et al. 2004). Such data can result in decreased customer satisfaction, increased running costs, inefficient decision-making, lower performance and lower employee morale (Kahn et al. 2003; Redman 1998). Second, poor data quality also increases operational costs since effort is spent on detecting and correcting errors. Third, 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 and makes it difficult to build trust in the data, which may imply lack of user trust and acceptance of any initiatives based on poor data (Levitin and Redman 1998).

Given this emphasis on data quality, a firm's data environment for quality data creation significantly depends on the strength of the internal data resource management practices (Ramamurthy et al. 2008). Strong organizational data management practices help to enforce data definition standards, data integrity and security policies in organizations. In addition, strong data management practices help in 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 data management practices result 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).

BIA implementations include extracting heterogeneous data from very diverse set of resources with differing formats and semantics and then clean, transform, combine and format it before making it available for conducting the analyses. A data environment that is not properly managed is likely to suffer from problems relating to quality, reliability, integrity and standards etc. Such an environment would pose greater challenges for relying on the insights from BIA systems and leading to mistrust in the company data, which may imply a lack of user trust in initiatives using such data. In other words, this may hinder extensive usage of BIA insights in business activities. Consistent with this, we hypothesize:

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

The association between organizational size and IT innovation diffusion was well-documented in literature though the findings were mixed (Ramamurthy et al. 2008). On one hand, studies have found that large organizations enjoy resource advantages, have greater slack in resources and are better prepared to mobilize adequate financial resources to experiment with innovations (Rogers 1995). Large size creates a critical mass and the benefits of economies of scale make the costs of innovations proportionately less for large organizations. Hence size provides the incentives to innovate (Damanpour 1992; Kimberly and Evanisko 1981). The breadth of operations in large firms also makes adopted innovations often complement existing operations and become more beneficial (Geroski 2000). Large organizations also have more ability to hire professionals, such as IT knowledge professionals (Alpar and Reeves 1990). An additional perspective is that in the face of increasing size, organizations may face increasing uncertainties that demand innovative behavior and certain innovations may become necessary to subscribe as a result of increasing size (Kimberly and Evanisko 1981). However, arguments persist that large firm size is often associated with inertia and large firms tend to be less agile and flexible than small firms. The possible structural inertia associated with large firms may slow down organizational usage of new technologies and may hinder value creation (Thong and Yap 1995). Therefore, large size has also been argued to inhibit innovation adoption and usage. On the other hand, it was argued that smaller organizations tend to be more agile and productive than larger ones, particularly in their research and development endeavors, and hence are more likely to adopt innovations. Hence small organizations can be more receptive towards innovations (Frambach and Schillewaert 2002), and can be more efficient at adopting them (Yeaple 1992). However, small businesses can be constrained by inadequate financial resources and lack of in-house expertise etc. and may face more barriers to adopt and use new technologies (Ein-Dor and Segev 1978; Thong and Yap 1995).

BIA initiatives require strong internal IT-infrastructure like robust enterprise systems for collecting both structured and unstructured data from business transactions and environmental scanning and then consolidate this in internal repositories like data warehouses before creating usable knowledge out of it (Sabherwal and Becerra-Fernandez 2010). BIA adoption and usage is resource intensive in terms of both capital and special skilled labor requirements (Davenport and Harris 2007). These systems can be expensive to procure, implement and maintain; which only large organizations can afford. For example, in a related context, it was found that large organizations are more likely to implement data warehouses as they are resource intensive to procure and implement (Ramamurthy et al. 2008). Additionally, in large organizations, the potential for information silos is higher and there is a 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, we hypothesize:

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 information technology (Mata et al. 1995). IS literature has emphasized the need for organizational adaptations for technology usage including acquiring new expertise necessary to use the innovation (Fichman and Kemerer 1999) and mutually adapting new technologies and existing processes to achieve alignment and integration (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, partly due to the lack of managerial skills and know-how 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).

Achieving BIA excellence is an ongoing capability different from transaction processing. Organizations that capitalize on BIA stand apart from traditional data analysis environments by paying attention to data flows as opposed to stocks. Some activities like customer sentiment analysis are better suited for real-time monitoring of the environment and a more continuous approach to analysis and decision-making is needed rather than episodic ad-hoc analysis (Prahalad and Krishnan 2008). Managing this

transformation requires an enterprise-wide commitment to BIA and seamless integration of BIA capabilities into business processes (Davenport and Harris 2007). Further, to accommodate the transitions in terms of data volumes and analysis requirements, firms need analytical talent that is not available in most organizations as well as it needs different IT assets like more computing power than a company has ever used. These organizations rely on new class of IT talent like data scientists and product and process developers rather than data analysts. Because interacting with the data is the core skill needed from people, the new talent needs substantial and creative IT skills and should be trained to thoroughly understand products and processes within the organization (Davenport et al. 2012). When firms confront managerial challenges to accommodate such organizational adaptations associated with new technology integration and the availability of talent in the organization, it will be a significant barrier to achieve higher usage of BIA in organizations. Hence, we hypothesize that managerial challenges as defined above are a significant barrier to extensive BIA usage:

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 feels from competitors within the industry (Zhu et al. 2006). Competition leads to uncertainty in the marketplace and more intense competition is associated with higher IT use in general and innovation adoption in particular (Chau and Tam 1997; Kimberly and Evanisko 1980). Competitive pressures may make innovation adoption necessary to maintain market position (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 new 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 to outperform competition (Davenport and Harris 2007). Firms are leveraging BIA to support important distinctive capabilities that can set them apart from competition. Additionally, firms are using insights from BIA systems to build a deeper understanding of the customer preferences. Once this understanding is obtained, firms are applying this understanding to contextualize experiences per the individual customer preferences (Prahalad and Krishnan 2008). This is helping the firms to tie service delivery to personalized outcomes. Hence it is rapidly enabling the firms to move from volume-based systems that hinge on scale to cater to a segment of customers towards value-based systems that focus on creating personalized value for each customer. For example, related anecdotal evidence highlights changes in the healthcare industry as enabled by BIA where firms are using BIA to tie healthcare bills to patient outcomes. By focusing on value creation at the individual customer level, BIA systems are altering the industry structures in healthcare industry by making the firms move from emphasis on volume to an attention on individual customer experiences (Horner and Basu 2012). Hence, we hypothesize

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 boundary of the organization but are still relevant for its success (Duncan 1972). Environmental dynamism appears to be a critical dimension of a firm's external environment (Dess and Beard 1984)[2]. It involves the degree and instability of change in the firm's environment. The environment creates contingencies to which organizations respond, typically through product and process innovations. In an environment characterized by greater dynamism, top managers will experience much more uncertainty, or lack of information related to the current state of the environment and the potential impact of those developments on their firms (Milliken 1987). Hence organizations should strive to ensure compatibility with the dynamism in the environment, and such compatibility may be essential for the organization's

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[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)

long-term survival and growth (Thompson 1967). In dynamic environments, achieving such compatibility requires organizations to adapt on a continuous basis. Organizations in such environments seek to do so by developing flexibility in business processes. Ability to reconfigure business processes depends on how quickly and effectively the information systems supporting the processes can be modified. Hence greater environmental uncertainty makes it necessary for organizations to evaluate more technologies, adopt and implement them, in order to cope with greater information processing and flow requirements associated with such environments (Grover and Goslar 1993). Firms seek out ways and means to improve their IT capabilities to collect information, interpret it and act on the knowledge generated to respond to changes in the environment (Ravichandran 2000). Thus, a system that predicts, coordinates and forecasts market trends will enable the organization to react swiftly and efficiently to market changes (Wu et al. 2003).

In the BIA context, spotting new trends in dynamic environments needs thorough understanding of consumer expectations and behaviors, 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 new capabilities that can provide a glimpse of the changes and trends happening on a real-time basis which can act as weak signals of changes in the environment. Adaptive organizations have the ability to sense and interpret what may seem like noise into a meaningful course of action and translate apparent noise into meaning faster than it arrives (Haeckel 1999; Sabherwal and Becerra-Fernandez 2010). While traditional business analytics systems are asynchronous with business change, the evolving BIA systems with support from real-time connectivity and seamless data flow from the 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 revise firm strategy. For example, BIA systems are being used not only to cater to traditional consumer and seasonal demands, but also to understand the consumer dynamism in the local markets and tailor the supplier replenishment programs to suit the local community requirements (Martin 2010). Relatedly, we hypothesize that:

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

Research Design and Methodology

Data and Variable Definition

Our empirical analysis is based on data from the InformationWeek 2012 Business Intelligence, Analytics and Information Management (BIAIM) Survey. Information Week is a leading IT publication and InformationWeek surveys are reliable sources of secondary data used in previous academic studies (For example, Bharadwaj et al. 1999; Whitaker et al. 2007). These surveys target top IT managers in organizations who are in decision-making roles with sufficient overview of their firm's IT operations and investments. The 2012 BIAIM survey was conducted online in October 2011 wherein pre-qualified Information Week subscribers were sent an email invitation containing an embedded link to the survey. The respondents were business technology decision-makers at North American companies with significant decision-making authority and involvement in BIA investments in their organizations. The original dataset comprised of data collected from these decision-makers in 542 firms but only 358 respondents were allowed to complete the survey only if their firm had implemented BIA and if they had significant authority related to BIA purchase and implementation in their organizations. After dropping incomplete or duplicate 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 below.

Dependent Variable

Extent of Usage of BIA in business acitivities (BIAUsage): 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). A similar approach was used in Banker et al. (2008).

Independent Variables

Data Infrastructure Sophistication (DataInfrSophistication): 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 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 coding approach is informed by past research (Saldanha and Krishnan, 2012). The rationale in defining this variable is that IT infrastructure like data-related infrastructure mirror's an organization's historic progress with the use of IT and tends to be highly path dependent in its accumulation (Keen 1991). As our measure constitutes elements like a firm having systems in place for data warehousing, for master data management and for transforming the data etc., these systems are highly path dependent. Having these systems and capabilities needs prerequisite of specialized capabilities and coordination in terms of infrastructure for data integration and management. Relatedly, firms build sophisticated capabilities for data management before and during the implementation of such initiatives (Wixom and Watson 2001).

Data Management Challenges (DatMgmtChallenges): 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). CompIntensity is defined as the sum of the market shares of the top four market share leaders of the firm's industry (Bharadwaj et al. 1999).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).

Environment Dynamism (EnvDynamism): Informed by past research (e.g., Boyd 1995; Simerly and Li 2000), we operationalized environment dynamism 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

Control Variables

Expected Benefits (ExpBenefits): We control for expected benefits from BIA usage as higher perceived benefits may lead firms to more extensively use BIA. 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)

Manufacturing (Manuf): This variable indicates whether the firm's offering is primarily a good or a service (1 = Manufacturing, 0 = Services) (Mithas et al. 2005). This accounts for the possibility that firms in manufacturing or in service industries are more prone to use BIA due to potential differences in the need for agility to meet service needs of customers (Saldanha and Krishnan 2012).

IT orientation (Transformate): Prior research has identified three primary roles for IT in industries – automate, informate and transformate, wherein IT is primarily used respectively to automate manual tasks or to provide information for empowering the management or to fundamentally alter ways of doing business (Chatterjee et al. 2001). As done in prior research (Banker et al. 2011), we adopt Chatterjee et al.'s (2001) classification scheme and create a dummy variable that captures 'transform' IT role in the industry. Firms in industries such as airlines, financial services, advertising, information technology, telecom and media etc., were classified as using IT for transformational purposes per Chatterjee et al.'s (2001) and Banker et al.'s (2011) classification. We create this dummy variable to control for firms in such industries where IT is used for transform purposes as these firms are more likely to adopt and use new innovations faster than firms in other industries (Chatterjee et al. 2001)

Empirical Model

We developed a cross-sectional model to test our hypothesis. Our dependent variable BIAUsage is a summative index signifying the degree of usage of BIA in multiple organizational functions. We treat our dependent variable (BIAUsage) as an ordered variable. It may be argued that this variable is a count variable. But count variables indicates how many times something of similar nature has happened (Long and Freese 2003). For example, these 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 study the degree of usage of BIA in organizational functions. Hence for each firm, BIAUsage consists of 13 levels based on adoption and can take any value between zero and twelve based on usage. The categories in this variable can be ranked, but the distances between the categories are unknown. Hence 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 Banker et al. (2008) and Bardhan et al. (2007). Since the dependent variable is ordered, we use ordered logistic regression for estimation. Ordered Logistic or Ordered Probit models are used in estimation when the dependent variable is ordered (Greene 2008). We control for the expected benefits from usage as perceived benefits drive the extent of adoption and usage of innovations (Chau and Tam 1997). We control for industries using IT for transformation purposes as the firms in these industries adopt new technologies early towards strategic benefits (Banker et al. 2011). We control for firms in Hi-Tech and Telecom industries at the 3-digit NAICS level as these industries are at the forefront of BIA adoption (Accenture 2013). We also control for firms in manufacturing industries (Mithas et al. 2005).

The empirical model is as follows:

P(BIAUsage) = β0 + β1(DataInfrSophistication) + β2(DatMgmtChallenges) + β3(Size) + β4(MgrChallenges) + β5(CompIntensity) + β6 (EnvDynamism) + β7(ExpBenefits) + β8(HiITTel) + β9(Manuf) + β10(Transformate) + e

Results

Table 1 and Table 2 provide the descriptive statistics and the estimation results respectively. In Table 2, Column 2 is the results from the ordered logit regression. Column 3 is the results of the ordered probit regression, which we ran as a robustness check. For brevity, we elaborate on the results of the ordered logit estimation.

Table 1. Descriptive Statistics

#	Variables	Min	Max	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1	BIAUsage	0	12	4.97	3.23	1.00										
2	DataInfr 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**	0.26**	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	11.92	9.32	0.16**	-0.01	0.05	0.02	0.03	1.00					
7	EnvDynamism	1.00	1.041	1.02	0.01	0.06	-0.08	-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*	-0.004	0.03	-0.00	0.00	0.81**	-0.16**	0.02	1.00		
10	Manuf	0	1	0.11	0.32	-0.02	-0.06	0.06	0.08	0.007	0.08	0.61**	0.05	-0.11*	1.00	
11	Transformate	0	1	0.40	0.49	0.16**	0.06	0.02	-0.1	-0.03	0.10*	-0.14**	-0.03	0.32**	-0.33**	1.00
Significant at *10% and **5% levels																

In the ordered logit estimation, the Likelihood Ratio Chi-squre 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 (β_1 = 0.298, p<0.01) on the DataInfrSophistication variable provides **support for Hypothesis H1** that internal IT sophistication of the firms in terms of strong data-related infrastructure can enable the firms to extensively use BIA for business activities. The negative and significant coefficient (β_2 = -0.26, p<0.05) renders **support for Hypothesis H2** that firms facing challenges with respect to data resource management would be hindered from extensive usage of BIA.

We find that larger organizations are more likely to have higher usage of BIA (β_3 = 0.16, p < 0.05), **supporting Hypothesis H3**. We find **partial support for Hypothesis H4** (β_4 =-0.27, p<0.10), which posited that managerial challenges related to talent management 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 (β_5 =0.086, p<0.001).

Table 2. Empirical Estimation Results

Variable	Ordered Logit Model	Ordered Probit Model
Dependent Variable = Extent of BIA Usage		
Data Infrastructure Sophistication (*DataInfrSophistication*)	0.298*** (0.072)	0.164*** (0.04)
Data Management Challenges (*DatMgmtChallenges*)	-0.26** (0.13)	-0.155** (0.072)
Organization Size (*Size*)	0.161** (0.08)	0.098** (0.045)
Managerial Challenges (*MgrChallenges*)	-0.27* (0.162)	-0.15* (0.09)
Industry Competitive Intensity (*CompIntensity*)	0.086*** (0.03)	0.05*** (0.017)
Environment Dynamism (*EnvDynamism*)	-7.41 (16.89)	-4.13 (9.80)
Expected Benefits (*ExpBenefits*)	0.11** (0.043)	0.056** (0.025)
Hi-tech & Telecom industries (*HiITTel*)	-1.78* (1.06)	-1.12* (0.58)
Manufacturing (Manuf)	-0.02 (0.60)	-0.06 (0.34)
IT orientation (*Transformate*)	0.74** (0.30)	0.488*** (0.177)
Log Likelihood	-443.56	-443.19
LR Chi-square	62.17	62.91
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		

Our hypothesis H6 about the role of environment dynamism in driving extensive usage of BIA was not supported (p>0.10). We later discuss the potential reasons for this non-support. To quantify the effects, for example, if a firm were to increase the data infrastructure sophistication by deploying one more data management technology, the ordered log-odds of being in a higher BIA usage category would increase by 0.298 while other variables in the model are held constant. Similar interpretations can be made of other independent variables.

We conducted additional econometric checks to provide robustness to our results. As described earlier, 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. The findings not reported here for brevity purposes remain qualitatively consistent. As robustness checks for our original ordered logit regression, we tested the proportional odds assumption implicit in ordered models and a high chi-square (114.8) and high p-value (0.33) indicate that the proportional odds assumption has not been violated. The White's test (chi2 = 60.58, p=0.31) failed to reject the constant variance of the error term and hence heteroskedasticity is not a serious problem with our data. We tested for multicollinearity by running an OLS regression of the model (Long and Freese 2003). The mean (maximum) Variance Inflation Factor was 2.19(5.17) which are within suggested limits (Greene 2008), indicating that multicollinearity is not an issue. We conducted link test to check for specification errors and a statistically significant predicted value and an insignificant predicted value square suggest that meaningful predictors are included in the model with no specification error. To check for common method bias, we performed Harman's one-factor test (Podsakoff and Organ 1986). The Harman test produced four factors cumulatively accounting for 74.4% of the total variance, and the first factor accounted for only 33.46% of the variance. With no general factor accounting for more than 50% of the variance, common method bias is not problematic.

Our dependent variable 'BIAUsage' measures the extent of BIA usage in organizational business functions. To enhance the validity of this measure, we have conducted additional analysis to further investigate the information about the usage of BIA technologies in the respective organizations. We have leveraged the question asked by Information Week in the survey - *'Are you using, planning to use, or evaluating BI/analytics products from the following vendors?'.* The list of vendors included SAP, Microsoft, SAS, IBM, Micro Strategy, Information Builders, Jaspersoft and Oracle etc., who are major players in the BIA technology vendor market. We have examined the responses related to if the firm is currently using any of the vendors and tallied it against the usage of BIA in organizational business functions. For example, as the BIAUsage ranges from 0-12, one way we operationalized this analysis is that we have taken all the firms in our sample who are using BIA in all 12 business activities and then tallied them against vendors they are using. Similar procedure was repeated for firms using BIA in 11 business activities. In all the cases, we have found that these firms who responded that they are using BIA in 11 or 12 business functions are currently using services from at least one of the BIA vendors listed in the questionnaire. We believe that this analysis will provide additional robustness to our measure as it will corroborate about actually using BIA in business activities to a certain extent as the firms are using standard products from the leading vendors and are more likely to actually use them for empowering the business functions.

Supplementary Analysis

As the dependent variable 'BIAUsage' measures the usage of BIA in organizational business activities without distinguishing between internal and external orientation of business activities, we have conducted supplementary analysis to understand the usage variations related to internal-oriented and external-oriented business activities. Based on the categorization in Davenport and Harris (2007), we have classified the 12 business activities in our original dependent variable to create two variables 'BIAInternal' and 'BIAExternal'. We have classified 'Competitive Analysis', 'Customer Relationship Management', 'Sales Tracking', 'Product Development', 'Forecasting' and 'Product Marketing' broadly as external oriented activities as they relate to understanding and coordinating about the customers, suppliers and business partners. Similarly, we classified 'Business Activity Monitoring', 'Corporate governance', 'Financial analysis', 'Fraud Prevention' 'Operational process optimization' and 'Risk management' as internal-oriented activities. Running the estimations on the two new dependent variables 'BIAInternal' and 'BIAExternal' produced contrasting results in some cases in comparison to our original estimation with 'BIAUsage'. For example, our hypothesis about the Data Infrastructure Sophistication was supported in both the new estimations in line with our original estimation. However, the variables about 'Managerial Challenges' and 'Data Management Challenges' were not supported for usage in internal oriented business activities while they were strongly supported for external oriented business activities. One possible explanation for the increase in significance for 'Managerial Challenges' is that external focus of the firm requires a lot of domain knowledge to understand the complexity of the markets and map it to the organizational context. Hence the talent requirements will be much more advanced and the integration requirements will be much higher. Any managerial challenges faced in these regards will hinder the extent of BIA usage. Similarly, the Data Management Challenges variable was found to be insignificant in the estimation for internal oriented activities while it was significant for external oriented business activities. One possible reason for this contrasting result is that in the external-orientation context, both the

structural complexity and the scale of the data will be more in the external environment as firms have to negotiate higher magnitudes of structured and unstructured forms of data generating from the external environment.   For internal-oriented activities, firms may have more structured data generating coordination and integration applications like ERP. Hence it is likely that the data management challenges will be higher in the external orientation context compared to the internal orientation context

Discussion and Implications

In this paper, our objective was to build on TOE framework and understand what explains the organizational usage variations of BIA in organizations. Consistent with our hypothesis H1, an organization's internal data-related infrastructure sophistication is strongly associated with the extent of usage of BIA. This aligns with research propositions that usage and benefits from IT adoptions are contingent on the complementary investments the firms make in organizational resources (Brynjolfsson and Saunders 2010). As hypothesized in H2, we find that challenges related to data resource management may hinder BIA usage. Taken together, these two findings corroborate the technology readiness construct examined in IT innovation diffusion research and supports conceptual arguments (e.g. Sabherwal and Becerra-Fernandez 2010) that firms should first have strong systems and processes in place to collect, and consolidate data from diverse sources to be usable for BIA purposes. Hence we believe that technology readiness is a necessary precursor to BIA usage. 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 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 the role of 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 when firms face strong competition, they tend to use BIA extensively, a finding consistent with trade observations that BIA enables differentiation in the marketplace to outperform competition (Davenport and Harris 2007). However, we did not find support for H6 about the role of environment dynamism in driving extensive BIA usage. One possible explanation for this non-support is that firms in our sample may be using BIA for routine activities like business process monitoring and process optimization etc. rather than using them for value-added activities like competitive analysis and customer sentiment analysis which may align with the true spirit of BIA usage. Using BIA instead for value-added activities may provide significant results. Further investigation is needed into this aspect.

For research, first, to our knowledge, this is the first study examining the usage of BIA technologies across a broad sample of firms. Our research contributes to the IT assimilation literature and also supplements the extant anecdotal evidence and single instance case studies in BIA literature that has examined the organizational factors of 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 in the stages of gaining awareness and acceptance, our findings shed light on some theoretical underpinnings and what technological, organizational and environmental characteristics can explain the differential usage of BIA in organizations. For practice, our results offer a useful framework for managers to assess the technological conditions under which BIA should be used to better pursue business value. It is important to build backend technology competence to consolidate data before pursuing a BIA strategy. Second, our results suggest the need for ensuring that BIA is integrated into the organizational processes before expecting value from such investments. 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 in nature and do not imply causality. Future research may use longitudinal datasets which may provide additional insights about temporal ordering. Second, the use of secondary

data limits the range of variables in our analysis, though the variables chosen to analyze were guided by past research. Accordingly, our analysis investigates only a few of the potential TOE factors and there might be potentially several other variables that might affect the usage. For example, future research may include organizational culture as an organizational factor and attempt to understand how an organizational culture based on openness and information transparency may drive BIA usage. Further, our data permits building measures based on binary variables while future research may use other scales like Likert Scores for variable creation. Third, 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. Given the emerging nature of research in BIA subject area, we foresee several additional research opportunities. First, while we investigated the factors affecting extensive usage of BIA, future research may investigate adoption decisions and assimilation activities like routinization. A related area is to examine if these factors have different effects at different stages of assimilation as research has suggested that the same factors may have different effects in magnitude and direction depending on the stages of assimilation (Fichman 2000; Zhu et al. 2006). Second, research may investigate the benefits arising out of BIA for areas like customer and competitor orientation and process optimization etc. Grounding these studies in the contexts of different industry domains may have different results and implications. Third, an investigation of what complementary organizational investments can augment the benefits from BIA usage may need investigation. Fourth, while theoretical frameworks suggest that BIA usage creates first order capabilities which in turn lead to second order value-creating actions that impact firm performance, future research may systematically identify and test the mediation mechanisms that impact firm performance upon adoption and usage of BIA (Shanks and Sharma 2010).

Conclusion

In this paper, we examined how a set of technological, organizational and environmental factors may determine the extent of organizational BIA usage. To our knowledge, this study is among the first to empirically examine the factors driving the extent of organizational BIA usage. In doing so, our research contributes to the IT innovation diffusion literature by empirically validating a model of contextual factors influencing the usage of BIA, a class of technologies which are gaining prominence to create competitive advantage. Our study is a first step to respond to the calls in research to develop empirical evidence grounded in theory to understand the usage and value of BIA. Our results emphasize that in addition to the critical mass like strong data-related infrastructure or organizational size, the ability to counter data management challenges and managerial challenges related to integration talent management can determine how fast these technologies can be integrated into enterprise decision-making. In addition, our study highlights the role of competitive intensity in driving BIA usage and corroborates practitioner evidence that BIA enables differentiation in competitive markets to outperform competition.

Acknowledgments

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