Exploratory Study of Organizational Adoption of Cloud Based Big Data Analytics

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Abstract

Consumers are increasingly using internet applications for ecommerce, mobile, social and business computing. As a result, a large amount of data is being gathered and aggregated by ISP's (Internet Service Providers). However, due to the high velocity, massive volume and highly dispersed nature of this "big data", organizations need to adopt new distributed cloud based analytics tools to access and process these data sets. Organizational benefits can result from improved estimates of market demand, identification of client preferences and business trends. Several cloud providers, such as Google, Microsoft, SAP and IBM Watson are advancing analytics tools that can be used by organizations to utilize these big data sets. Most cloud based tools offer convenient, ubiquitous and on-demand access to data sets and services. However, typical challenges include information security, integration and availability, data veracity and the need to build new IT infrastructure and capabilities within the organization. This study applies the TOE framework to identify and rank the factors that impact the adoption of such cloud based analytics tools. The TOE framework identifies three determinants of IT system adoption at the organizational level – Technology, Organization and Environment. Using a survey of medium to large sized companies in a variety of industries, this study finds that having compatible IT infrastructure components and internal firm capabilities for the secure integration of cloud based analytics data and tools and vendor support strongly facilitates the adoption of cloud based analytics, while the lack of an analytics culture and management support can hinder it.

Keywords: TOE framework, Big data, cloud computing, business analytics.

1. INTRODUCTION

Business Analytics (BA) is motivated by the capability to select and use data to facilitate decision-making and improve business processes. BA applications are defined as specialized tools for data analysis, query, and reporting that support organizational decision-making (Chaudhury, Dayal and Narasayya, 2011). With the growth of online consumer data along with the use of enterprise applications, business analytics (BA) tools have become an important option for organizations to utilize these data sets. BA applications aim at improving business decision making by supporting data-driven processes that enable knowledge workers to visualize large data sets and to make better and faster decisions by building predictive and prescriptive models using advanced mathematical techniques.

Recently, there has been a growth in the use of internet services such as mobile commerce and social computing resulting in the proliferation of consumer data collected outside organizational systems. Every minute 217 new mobile web users are added to the internet (Valerdi, 2017). Internet service providers continue to accumulate vast amounts of user data from diverse domains including retail transactions, transportation and GPS data, social interactions and consumer behavior, computer gaming, online search engines and web logs that track web site visits. This data is termed "big data" and is vast and is being generated at a high rate through the online activities of users (Gantz and

Reinsel, 2011). Big data involves situations that are characterized by the four V's – high velocity, variety, volume and veracity ("uncertainty") (Valerdi, 2017). Organizations, that can utilize this "big data" in concert with their internal enterprise data, may be able to better spot business trends, better manage risks and enhance competitiveness, thereby creating business value. For example, Coca-Cola captures information on what drinks are dispensed from their freestyle dispensers to fine-tune stocking and inventory (Kho, 2017). Also, Duetto Research offers a hotel revenue management SaaS solution that allows hotels to price rooms dynamically, based on dynamic factors such as weather and local events (Kho, 2017).

But most organizations are still grappling with how to unlock Big Data's potential. Over 80% of this big data is unstructured, consisting of textual narratives, images and non numerical values. Moreover, the big data is sparse and distributed across the internet and needs extensive processing. This is very different from the typical highly structured enterprise data generated during business transactions. The volume and high velocity of big data along with it's distributed nature makes it difficult to manage and process with traditional BI tools due to scalability issues. Exiting data warehousing and ETL (Extract, Transform and Load) tools work well with a small limited number of data sources. Beyond 25-30 data sources, data aggregation, cleaning and processing become unmanageable as the present BI tools require strict data schemas and defined storage structures to operate. A typical big data analytics application needs to access heterogeneous data from tens of thousands of internet sources and leverage objective data (e.g., observed transactions and logs) with perceptual data (e.g., survey, sentiment, voice transcript, and interview) in conjunction with various intermediate decisions and actions to predict individuals' behaviors in a variety of applications in marketing, e-commerce, security, health, and finance (Abbasi, Lau, & Brown, 2015). There is a need to harmonize various terms during data generation, translation, dissemination and adoption. As a result, new technologies and organizational capabilities are needed to integrate big data with enterprise data.

Examples of cloud based BA tools to process big data include Google's BigQuery, which allows the execution of SQL queries on Google's distributed infrastructure and Amazon Redshift, which is a hosted analytical database. Another example is a cloud based tool called Splunk (www.splunk.com), which helps to analyze distributed web logs to create interesting graphs and patterns on web site navigation. These cloud providers such as IBM Watson will play a key enabling role in nearly every facet of big data analytics (IBM, 2017). They are the most important collectors of data streams and content and also provide tools to enable big data use by other organizations through provisioning and transformation of large data pools that can be integrated with existing organizational IT infrastructure.

Regardless of the type of IT tools and chosen approach and vendor, an organization needs to invest in both human and technological resources to build the needed organizational capabilities. For exploiting a combination of internal and external data, important organizational capabilities that focus on ingesting, organizing, processing, generating and syndicating information outputs from heterogeneous data are needed. Consequently, there are calls for more research to understand "what works" and "what enables" the adoption of big data analytics tools (Abbasi, Sarker and Chiang, 2016).

Research Goals

The research goal of this study is to understand the important organizational, environmental and technological factors from the TOE framework that influence the adoption of cloud based "big data" analytics tools by organizations.

1. The study applies the TOE framework to develop and validate a research model that measures the impact of organizational, environmental and technological factors that influence the adoption of cloud based "big data" analytics tools.

2. Identification of the most important factors from the above three dimensions that impact the adoption of cloud based "big data" analytics tools.

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2. CHARACTERISTICS OF BIG DATA

Examples of big data projects are starting to emerge in diverse industries from healthcare to retail and transportation. Healthcare organizations are leveraging big data to track

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their patient's compliance with treatment regimens. Insurance companies are managing insured risk profiles using GPS data from cars. Financial applications of big data analytics include revenue and profit forecasting, prediction of loan default, fraud detection, credit scoring and identifying money laundering. Supply chain decisions are changing towards modulating demand rather than forecast based. This is particularly true in industries where the supply is perishable (e.g., airline passenger transportation) and supply chain issues have become linked to the marketing and finance decisions in pricing and promotions. Retail chains are planning and stocking stores based on classification models of their customers with granular data that can predict when and who will visit their store and what they will browse. Other examples include Netflix suggesting a movie rental based on recommendation analysis, dynamic monitoring of embedded sensors in bridges to detect real-time events and longer-term erosion, and retailers analyzing digital video streams to optimize product and display layouts and promotional spaces on a store-by-store basis.

According to Gantz and Reinsel (2011), a staggering 1.8 zettabytes of data were generated in 2011. Current estimates suggest that 1.7MB of data are generated every second by a single user leading to a cumulative daily rate of 2.5 exabytes. Companies such as Walmart, handle more than 1 million customer transactions per hour, producing 2.5 petabytes of data in a 24-hour period. Every minute, there are 98,000 tweets, 695,000 Facebook status updates, 11 million instant messages, 698,445 Google searches, 168 million emails sent over the internet (Valerdi, 2017). Facebook manages 300 million photos and 2.7 billion 'likes' per day, thus contributing 100 petabytes of data to its warehouse; and eBay has a single table of web clicks featuring more than 1 trillion rows. There was 5 exabytes of information created between the dawn of civilization through 2013, but that volume of information is now created every 2 days, and the pace is increasing' (Kirkpatrick, 2010).

A major driver of cloud based big data analytics has been the opportunity to leverage the sharply declining cost per performance level of three key information technologies: computing power, data storage, and networking bandwidth. Other benefits of using such cloud based BA tools include fast deployment of BA applications, high scalability to tackle sudden spikes in big data processing workflows and reduction in data movement across the internet by allowing the distributed processing of data on the cloud. Despite these benefits of cloud based BA tools, there are several challenges from a data lifecycle, security/privacy and aggregation perspective. There is a dearth of technical standards to curate this heterogeneous data and limited support for integrating the analytics into process workflows. Therefore, it is undesirable to force fit this data into a global schema and process the data using the traditional BI tools available currently. Typically big data is distributed and dirty with duplicate, ambiguous and missing values and needs to be processed in situ with on-demand, cloud based tools that are collocated with the distributed data sets. The nature of "big data" also leads to "data silos" due to the numerous schemas and heterogeneous sources. Much of the "big data" can also be of varying degree of reliability, conflicting and composed of narratives that require interpretation before it can be used in a business situation**.** Additionally attention must be paid to the variety of use cases from diverse business stakeholders for outputs of the analytics tools. These challenges can be addressed by establishing organizational capabilities along with the adoption of cloud based BA tools (Kho, 2017). Organizations need to perform various data tasks such as data aggregation from multiple heterogeneous sources, data cleaning and validation, data transformations, model generation, and building user interfaces for role based access to the information outputs (Ferranti, et;al., 1998). Decision making scenarios depend on the creation of models that draw on processing of aggregated internal and external data from large dynamic repositories. For structured data, predictive models, such as regression models, allow the creation of models that can facilitate business decision making. However for unstructured "big data", such as blogs and textual information, classification models are popularly used to identify patterns that create meaning.

3. RESEARCH MODEL & HYPOTHESES

Cloud based BA tools are typically adopted at the organizational level as these tools must be integrated into the organization's enterprise IT infrastructure to have the potential to impact multiple business processes and functions. Tomatzky and Fleischer (1990) developed the TOE framework, which identifies three dimensions of an organization's context that impacts it's adoption of new technology. The three dimensions include the technological factors, the organizational (internal) factors and the environmental (external) factors. According to Tomatzky and Fleischer (1990), technological factors determine what technological characteristics influence the adoption and are a combination of the new technology to be adopted along with the organization's current technology. The organizational context describes the characteristics of the organization that can facilitate or hinder the adoption of the technological innovation, such as management support and culture. The environmental context captures the characteristics of the external arena in which the organization conducts its business. The environmental factors include the industrial environment in which the organization conducts its business, influences from its competitors, regulations, business partners and any government entities that it interacts with.

Technology Influence

In the context of cloud based big data analytics applications, three technological factors of the new tools are important: relative advantage, complexity and compatibility. Tomatzky and Klein (1982) showed that both relative advantage and complexity were consistently found to be significant in the prior adoption studies they reviewed. Furthermore, these two attributes are identified as critical adoption factors in numerous prior IS research studies (Jayaraj, Rottman and Lacity, 2006; Kwon and Zmud, 1987).

Relative Advantage is defined as the degree to which the technology is perceived as better than the existing tools it supersedes (Rogers, 1995). Relative advantage is comparable to perceived usefulness in Technology Acceptance Model (TAM), and often used interchangeably in the literature. Several studies have shown that the relative advantage of a tool over existing or alternative applications is positively associated with its adoption (Agarwal and Karahanna, 2000; Keil, Beranek and Konsynski, 1995) Slyke, Belanger, Johnson and Hightower (2010) showed that relative advantage is positively related to the adoption of e-commerce. In the context of business intelligence systems, Ramamurthy examined key determinants of data warehouse (DW) adoption, and found that relative advantage has a significant positive effect on DW adoption (Ramamurthy, Sen and Sinha, 2008). This leads to the first hypothesis:

Hypothesis 1: Relative advantage will have a significant positive effect on the adoption of cloud based BA applications.

Complexity is defined as the degree to which an innovation is perceived as difficult to understand, use and manage (Rogers, 1995). Complexity is considered as an inhibitor to the adoption of the innovation. Innovations that are perceived to be complex have a lower likelihood of being "trialed", accepted and used by potential users (Agarwal and Karahanna, 2000; Gefen, Karahanna and Straub, 2003). While BI applications get more and more user-friendly, they are still complex and hard to use. It normally requires several days of training before a user can get started using the tools. According to Gartner survey, less than 30 percent of enterprise users who have access to BA tools actually use the technology due to the difficulty of use (Gartner, 2011). Another report also indicated that ease of use was the leading driver of purchasing BI tools and will accelerate as a key requirement in the future (Sallam, Richardson, Haggerty and Hostmann 2011).

Hypothesis 2: Complexity will have a significant inverse effect on the adoption of cloud based BA applications.

Big data business analytics, when integrated with enterprise data processing, offer several benefits that include improving the timeliness and quality of the decision making process, providing actionable information delivered at the right time, enabling better forecasting, helping streamline operations, reducing wasted resources and labor/inventory costs, and improving customer satisfaction (Chaudhuri, et.al., 2011; Negash, 2004; Yeoh, and Koronios, 2010). Many existing organizational technologies and tools need to be integrated with the new cloud based big data analytics tools to sustain organizational capabilities needed for big data analytics. A combination of enterprise technologies are needed to deliver the information used for making decisions. They include tools that support traditional ad hoc queries, inferential statistics, predictive analytics, simulation, and optimization, thus supporting descriptive, diagnostic, predictive, and prescriptive analytics. Therefore, for successful adoption of cloud base BA applications, it is desirable for the new technologies and existing enterprise technologies to integrate and share data assets with each other.

Hypothesis 3: Compatibility with existing IT infrastructure will have a significant positive effect on the adoption of cloud based BA applications.

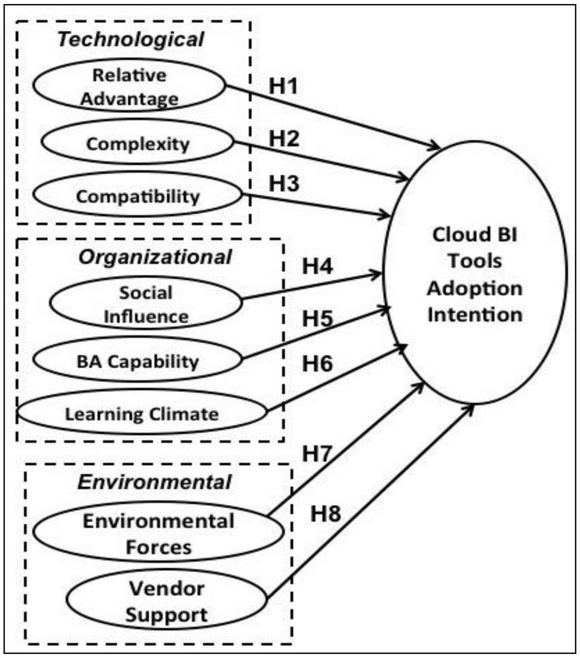

Figure 1. Research Model

Organizational Influence

Social influence on technology adoption behavior has been widely acknowledged in IS research (Karahanna and Straub, 1999; Lee, Lee and Lee, 2006; Taylot and Todd, 1995; Venkatesh and Morris, 2000). The above studies suggest that the extent to which others view technology use as valuable has positive influence on the technology experimentation and use. Social influence can emanate from a variety of sources, including co-workers, supervisors, friends, and family (Agarwal and Karahanna, 2000; Lewis, Agarwal and Sambamurthy, 2003). In working organizations, co-workers and supervisors are influential in determining technology adoption behaviors (Schmitz and Fulk, 1991). Co-workers can introduce a useful feature in an application or help them walk through steps that the worker may not be able to learn on his or her own. In addition, managers may promote technology usage as standard work practices, and encourage their subordinates to adopt and use the technology (Switzer, Nagy and Mullins, 2005).

Hypothesis 4: Social influence from referent others (co-workers & supervisors) will have a significant positive effect on the adoption of cloud based BA applications.

As important referents continue to communicate the benefits of the new tools, the existing analytics capabilities inside the organization can impact the adoption of new BI tools. In addition to business and technical expertise, analytical organizations are highly quantitative and data driven (Lawler, 2016). Therefore, analytical capabilities of the organization such as ways to acquire and manage data or prior knowledge about the development and use of models influences the adoption of the new BI applications.

Hypothesis 5: Organizational analytics capabilities will have a significant positive effect on the adoption of cloud based BA applications.

Prior research has shown that situational constraints or "surrounding conditions" are important determinants of intention to adopt and use technology (Venkatesh and Morris, 2000). In addition to the requisite skills and resource, the end user training literature suggests that organizational culture could be considered as a situational constraint that can influence adoption behavior (Egan, Yang and Bartlett, 2004; Tharenou, 2001). If an organization supports innovations and encourages employees for learning and development, employees are more willing to learn new things, discover new ways to perform their job, and apply them to their work (Noe and Schmitt, 1986). Furthermore, an organizational learning climate that promote an environment of continuous learning develops a perception that the learning curve associated with new technology adoption may be interpreted as a necessary investment to improve job performance rather than an obstacle to their existing work routines (Liang, Xue, Ki and Wei, 2010).

Hypothesis 6: Organizational learning climate will have a significant positive effect on the adoption of cloud based BA applications.

Environmental Influences

The organization's external environment has factors that place impact on the adoption of technologies. This study considers two types of factors that may influence the adoption decision of cloud based BA tools – environmental forces caused by competition, business partners and

customer behaviors and the support ecosystem created by the BA tools vendor.
Environmental forces are typically normative and coercive in nature. Normative forces are primarily from customers, business partners and industry competitors (Liu, Ke, Wei, Gu, Chen, 2010; Teo, Wei, Benbasat, 2003) Normative forces drive an organization to learn and conform to industry best practices and can influence the organization to change its business processes and adopt innovative technologies (Scott, 2003). Additionally coercive pressures from external stakeholders such as dominant business partners or intense competitors force organizations to adopt business innovations such as new technology, when it is perceived as required practices (Teo, Wei and Benbasat, 2003). Therefore, the following hypothesis is suggested:

Hypothesis 7: Environmental forces will have a significant positive effect on the adoption of cloud based BA applications.

The ecosystem created by the cloud based BA tools vendor is another environmental factor that can positively impact adoption of new tools. The vendor ecosystem refers to the existence and level of influence of external resources such as user groups, implementation consultants, tool demonstrations, trials and training opportunities for tools knowledge exchange. Vendor support also comes in the form of coordination and counseling to develop necessary strategies to plan tool adoption. Vendors can also provide access to other user organizations as case studies that can be used as reference models and examples for planning the adoption projects. Vendors also provide logistical support to answer questions about the technology and can ease the shortage of skilled personnel in the early parts of the adoption project (Fink, 1998). Vendor support could be more elaborate and extend to providing dedicated project personnel to assist the adopting organization to help the adoption of the BI tools (Sarosa and Underwood, 2005). Therefore, the following hypothesis is suggested:

Hypothesis 8: BA tools vendor support will have a significant positive effect on the adoption of BA applications.

Adoption of Cloud BA Tools
The dependent variable of the study is a five valued variable to measure the current status of the adoption of cloud based BA tools in the organization (Oliveria, Thomas and Espandel, 2014). The five items in the Cloud based BA tool adoption survey question (dependent variable) are: 1 -Not considering the adoption of cloud based BI tools, 2 - Have evaluated, but not currently planning the adoption of cloud based BA tools, 3- Currently evaluating cloud based BA tools, 4 - Finished evaluation, and currently planning the adoption of cloud based BA tools, 5 - Have already adopted cloud based BA tools.

The sources of the nine research constructs and measurement items for the survey are listed in Table 1.

Construct	Items
Relative Advantage [37]	1. Using cloud based BA application will enhance my efficiency in gathering and using relevant information 2. Using cloud based BA application will make it easier to gather and use relevant information 3. Using cloud based BA application will increase the quality of the information that I gather and use
Complexity [37]	1. There is a clear and understandable process regarding how to use cloud based BA applications 2. Using cloud based BA application will not require a lot of effort 3. Using cloud based BA application will not be difficult
IT Infrastructure Compatibility [1], [14]	1. Our existing information technologies are well integrated and share data assets with the new cloud based big data analytics tools. 2. Our organization has the skills and capabilities to successfully manage big data datasets and projects. 3. Using cloud based big data technologies will not result in any disruption in our business processes and projects.
Social Influence [28], [38], [39]	1. My manager views using BA application as an important aspect of his/her job 2. My manager is supportive of efforts to apply newly acquired skills and knowledge about BA application 3. My manager supports using BA application 4. My co-workers value using BA application
Organizational Analytics Capabilities [26]	1.Our organization has the skills and capabilities to successfully manage big data datasets 2. Our organization has successfully implemented business analytics in the past 3. Our organization is highly analytical and decision making is quantitative and data driven

Organizational Learning Climate [28]	1. My company's policies and work rules allow me to participate in training for new applications 2. My company values employee learning and development activities for supporting the adoption a new technologies 3. My company emphasizes the need for data driven, analytical approaches to decision making to their employees
Environmental Forces [31], [32], [33]	1. Our industry has forces are that are driving our organization to learn and conform to industry best practices. 2. Our business partners can influence the organization to change its business processes and adopt innovative technologies 3. We face coercive pressures from external stakeholders such as dominant business partners
BI tools vendor support [34], [35]	1. The big data tools vendor provides coordination and counseling to develop necessary strategies to plan tool adoption. 2. The vendors also provide access to other user organizations as case studies that can be used as reference models and examples 3. The Vendors provide consulting support to answer questions about the technology and ease the shortage of skilled personnel
Adoption Intention [36]	1 - Not considering the adoption of cloud based BA tools. 2 - Have evaluated, but not currently planning the adoption of cloud based BA tools. 3- Currently evaluating cloud based BA tools 4 - Finished evaluation, and currently planning the adoption of cloud based BA tools.

Table 1. Research Constructs and Measurement Items.

4. SURVEY RESULTS

A survey was conducted with a convenience sample of 30 business users representing 30 medium to large sized companies in a variety of industries. The demographics of the companies identified in the 30 completed surveys are tabulated in Table 2. Based on reported annual revenues, 21 of the 30 companies had revenues greater than $500 million. The most frequently identified industry includes manufacturing and utilities. The survey users also identified various business functions where cloud based BI tools are being used or being considered for use. The business functions most frequently identified include business activity monitoring for audits/compliance/fraud, competitive analysis, financial management and customer relationship management (CRM). Reports, scorecards, dashboards and text analytics were the leading analytics tools identified as being used or planned for usage in the 30 companies.

Partial least squares (PLS), a component-based structural equation modeling (SEM) approach, was used to test the research model. SmartPLS version 2.0 was used for the analysis. PLS works well for relatively small sample sizes and the total number of completed surveys in this study is 30. The PLS method is also recommend when the objective of the research is predicting key target constructs or identifying key driver constructs whereas a covariance-based structural equation modeling is recommended for theory testing, theory confirmation, or the comparison of alternative theories (Hair, Anderson, Tatham and Black, 2005; Chin, 1998).

Variable	**Survey Response**
Revenue	<$10 Mil -0; $10-100 Mil -9; $100-500 Mil - 5; $500 Mil-1B - 7; > $1B - 9
Industry	Manufacturing – 9; Utilities – 5; Media/Communications – 5; Financial – 4; Retail – 3; Insurance – 2; Logistics – 2;
Business Function for BA Usage *(Multiple selections allowed)*	Business Activity Audit Compliance/Fraud Monitoring – 15; Competitive Analysis – 14; Financial Mgmt. – 11; CRM – 10; Product/Offer Development – 7; Marketing – 6; Logistics/SRM - 5
Specific Cloud BA tool *(Multiple selections allowed)*	BI Reports – 21; Dashboards – 18; Business Scorecards – 12; Mobile Analytics – 9; Text Analytics – 10; Social Media – 5;

Table 2. Company Demographics

Assessment of the measurement model includes estimation of internal consistency for reliability and tests of convergent and discriminant validity for construct validity (Hair, Anderson, Tatham and Black, 2005). Internal consistency was evaluated by computing average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha (Chin, 1998; Bagozzi and Yi, 1988). As can be seen in Table 3, all the reliability measures were well above the recommended cutoff level (AVE = 0.5; CR = 0.7; Cronbach's alpha = 0.7), indicating adequate internal consistency. The successful validation of the measurement model allowed the testing of the 8 study hypotheses. All the eight hypotheses were supported at varying T-values (Table 3). By ranking the hypotheses by the T-values, the most important factors that drove cloud based BA tools were: IT infrastructure compatibility, BA vendor support and the organizational analytics capabilities. This study finds that having compatible IT infrastructure components and internal firm organizational analytics capabilities for the secure integration of cloud based analytics tools and vendor ecosystem strongly facilitate the adoption of cloud based analytics tools.

Construct	**C.A.**	**AVE**	**C.R.**	**T-Val**	**R**
Relative Advantage	.897	.708	.924	2.176	**7**
Complexity	.857	.640	.898	1.986	**8**
IT Compatibility	.878	.678	.912	6.724	**1**
Social Influence	.861	.565	.863	2.754	**6**
Org Analytics Capabilities	.887	.694	.918	4.637	**3**
Org Learning Climate	.740	.581	.785	3.765	**4**
Environment al Forces	.832	.591	.876	3.267	**5**
BI Vendor Support	.785	.622	.823	5.953	**2**

Table 3. Measurement and SEM Model Results

5. DISCUSSION

Applications of big data analytics in organizations are growing, yet realizing the potential value of these applications is proving to be challenging. Maximizing business value is dependent upon a variety of factors such as organizational analytics culture and compatibility with existing technological infrastructure (Palmer, 2013). This is one of the first studies to empirically apply the TOE framework to evaluate factors influencing adoption of cloud based BA tools using a survey research methodology. The survey results show that the presence or absence of compatible infrastructure and capabilities necessary to integrate big data cloud based tools influence the likelihood of adopting that tool. In addition to the requisite capabilities and IT infrastructure, the organizational learning climate and external forces in the organization's industry also influences adoption of cloud based BI applications (Cegielski and Farmer, 2016).

6. CONCLUSIONS

This study provides some practical implications for IT managers. When organizations adopt cloud based BA application, they should pay attention to the organization's analytics capabilities such as processes to protect the security of the data and working with data to build analytics models. An established analytics culture can drive business value from these cloud based BA tools. Integration of new cloud based technologies with existing BA infrastructure is also necessary for successful adoption. Cloud based BA tools require a new level of commitment and rigor toward managing the data lifecycle process. Additionally, big data projects must be ranked on potential for having the most business impact along with the easy availability of requisite data sets. The organizational data strategy must facilitate the integration of external and internal organizational data and the adoption of any new required tools and techniques (Kho, 2017).

Implications for Practice

The following points have practical implications for BA practitioners and organizations looking to adopt cloud based BI tools and applications:

- Similar to any other IT innovation project, planning for a BA implementation project must be initiated by identifying key business users who are motivated to adopt the new technologies and put them to use.
- BA implementations cross-functional boundaries and often do not fit well with existing organizational structures. In these environments, the organizational learning climate and social influence are important factors to consider that can support experimentation of big data resources by users (Cegielski and Farmer, 2016).
- Demonstration and experimentation can allow users to identify the usefulness of BA tools and gage the relative advantage of a BA tool. These can increase their desire to adopt.
- Environmental forces from consumers and business partners play an important role in technology adoption. It is desirable to identify and select BA tools vendors who have established and extensive ecosystem and can offer support for the chosen tool adoption.

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