Supporting End-User Business Computing with "Big Data"

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Abstract

Consumers are increasingly using internet applications ("apps") for ecommerce, mobile and business computing. As a result, a large amount of transactional 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", businesses need to build new data processing capabilities and adopt and train users on new distributed cloud based analytics tools to access and process these big data sets. Several SaaS (Software as a Service) providers, such as Google, Microsoft, SAS and IBM 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 a shared pool of configurable computing resources such as data sets, networks, servers, storage, applications and services. Positive business benefits of using "big data" can result from a variety of improvements in business management activities. These business improvements include better business visibility through multi dimensional visualizations of very large data sets, generating accurate rules and models to estimate market demand, faster identification of client preferences and business trends. However, typical challenges include information security, availability, data veracity (correctness and cleansing) and the need to build new IT infrastructure, capabilities and skill sets within the organization. This paper identifies a new model for end user business computing— from data governance to self service computing —that is integral in working with "big data" and is very distinct from traditional enterprise business applications. The contributions of this paper is to define a EUC (end user computing) model that allows improved planning, implementation and support for end user business computing with "big data".

1. Introduction

Business intelligence is motivated by the capability to select and use data to facilitate decision-making and improve business processes (Negash, 2004). BI applications are defined as specialized tools for data analysis, query, and reporting that support organizational decision-making (Chaudhuri, Dayal & Narasayya, 2011). Modern organizations generate enormous amounts of operational data that contain valuable patterns, relationships and business information. With the growth of online business databases and the use of enterprise applications, business intelligence (BI) tools have become an important option for manipulating these data sets. BI applications aim at improving business decision making by implementing data-driven decision making processes that enable knowledge workers to make better and faster decisions. The most advanced component of business intelligence is analytics, which includes building predictive and prescriptive models using advanced mathematical techniques. The adoption of business analytics is an increasingly high priority for organizations to gather insights for how their business can make better decisions enabling positive business results. Choosing the business technologies and data analytics tools are an important step to implement an architecture to analyze large amounts of data from several sources in the businesses organizations and is often referred to as Big Data. Companies seek to leverage this data from transaction systems and automated business processes to support "fact-based" decision-making (Lusting, 2010). Decision based on fact enables a company's data to become a valuable resource. The payoff is clear. According to a joint study by MIT Sloan Management Review and IBM Institute of Business Value, organizations that excel in analytics often outperform those who are just beginning to adopt analytics by a factor of three to one. And top performers are 5.4 times more likely to use an analytic approach over intuition and gut instinct when making decisions.

2. Business Analytics – Types and Uses

Analytics is organized into three independent categories for analyzing data or a dataset. Data analytics focuses on collecting information from business data to provide insightful knowledge for operations or performance. Business analytics uses this information to develop ways to improve the business. The basic understanding of business analytics (BA) is a collection of data related to its business and uses three categories to produce a decision for the business to make structural changes, fix operational issues, and increase financial performance.

- **Descriptive Analytics:** A set of technologies and processes that use data to understand and analyze business performance.
- **Predictive Analytics:** The extensive use of data and mathematical techniques to uncover explanatory and predictive models of business performance representing the inherit relationship between data inputs and outputs/outcomes.
- **Prescriptive Analytics:** A set of mathematical techniques that computationally determine a set of high-value alternative actions or decisions given a complex set of objectives, requirements, and constraints, with the goal of improving business performance.

Descriptive analysis is used to establish statistics that can be put into outputs like charts and graphs with measures for items such as mean, median, and standard deviation to identify trends by categorizing, characterizing, consolidating and classifying the data (Lusting, 2010). This can provide a general idea of information in the dataset from the past for useful analysis. It does not provide the ability to use the data to predict what the trends or relationships are to the business.

Predictive analysis can take the descriptive data a step farther and build a data model to use for predictive task like future trends, root causes, what will happen now, and data mining for additional relationships found in a dataset. Predictive analytics uses the understanding of the past to make "predictions" about the future and includes the use of data and information in the descriptive analysis activity.

The next stage of business analytics is the prescription analysis phase which is used to optimize decision-making to show companies what actions to take to maximize profitable growth, given their business constraints. This phase is the third and includes the descriptive and predictive analysis phases. The models created in this third phase use optimization and simulation algorithms to provide advice on possible outcomes and answer: "What should we do?". This analysis helps identity business situations that need an action plan and defined path to move forward to help business improvements and performance.

Examples can help us understand the implementation of business analysis using the three phases and how it results in an outcome that is useful. To demonstrate a real world example the Department of Orthopedic Surgery at Denmark's Lillebaelt Hospital had an issue with a resource-intensive, manual journal audit process that checked random samples of the patient journals for quarterly audits. The issue was that they used random samples for the audits that did not provide enough information for mistakes made and the quality control time was consuming and inefficient ("Unleashing the value"). Chief Surgeon Sten Larsen stated "This meant that we had registered faulty or too few diagnoses or treatments. For example, when a patient with a thigh-bone fracture caught pneumonia during hospitalization, the pneumonia and the treatment of it were too often not registered." ("Unleashing the value"). Clearly a solution was needed to improve this. This was accomplished by implementing a product named SAS Text Analytics. The errors were significantly reduced and also helped improve error detection as the journal audits were automated using the text analysis tool. This is a good example of descriptive analysis of examining past data and finding valuable insights.

Another example is Siemens a large global company for many products including trains. Using Business analytics is changing the maintenance operations and procedures they perform to keep the trains operating efficiently. Where incident driven events and scheduled visual inspections previously were used to determine train component replacements Siemens has moved on to more cost-effective, condition-based, predictive maintenance model. The status of equipment and components is measured by remote monitoring of diagnostic sensor data; data which is also used to analyze patterns and trends ("The Internet of Trains", 2015). Siemens used TeraData a large data analytics vendor to implement a solutions using Teradata Aster Discovery Platform's analytic tools. Using the tools predictive analysis capabilities along with the sensor data provided faster lower cost method to replace failed components and help prevent incidents before they can happen. This also provides a key train safety benefit to the business.

Prescriptive analysis is deterministic to find out what should be done by an organization from post descriptive and predictive data analysis activities. This final BA phase results in analysis modeling to create new information for business decisions. Southern States Cooperative is currently a large farmer-owned cooperative in the United States. Their prescriptive analytics project was a classic, direct marketing optimization situation. Southern States team's goals were to better target, produce and maximize profits from direct marketing initiatives (Underwood, 2015). A significant challenge for the project was an inability to unify customer and marketing data across multiple sources in addition to relying on Excel for data modeling which was taking too long. Excel also did not provide the required analytical capabilities. The solution was to adopt optimization data models using analytic tool Alteryx which is an analytics software company. The project used a proof of concept test that took only two days to complete by breaking down the data models into four parts including a probability model of catalog use, a revenue model to assess the incremental gross margin, an estimate of expected gross margin percentage for each customer, and an optimization module to assist direct marketing managers in selecting the mailing list and catalog items. This enabled multiple algorithms to be input into Alteryx to find a solution for the prescriptive analytic joint optimization issue. Some optimization variables defined by this task were a subset of possible merchandise items that “matched” the target market segment of the catalog, a subset of target market customers that have an expected positive return, and expected contribution dollars associated with a positive response. This resulted in the models creating a new direct mailing campaign in 2013 with a redemption rate of 10% and an ROI of +59%. Additionally over the last quarter of 2013 eight direct mailer campaigns (all modeled) were done with an average marketing ROI of 186% (Underwood, 2015). Time and resources had been significantly reduced using these technologies and the tools from Alteryx resulting in meaningful business improvements. The above examples show how business analytics are a real value to companies and organizations. The economic pressures of any business are increasingly making business analytics a necessity to remain competitive, drive down costs, add efficiency, create improvements, and increase profits. For most businesses it's not the question of if they adopt business analytics but when and how.

3. Big Data Analytics

Recently, there has been a growth in the use of internet services such as mobile commerce and social computing resulting in the proliferation of user data collected outside the "traditional" organizational systems. 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 patterns and web logs that tracks web site visits.

This data is vast and is growing at a high rate. "Big data" is the name that refers to this data being generated and collected by internet service providers based on the online activities of users. According to Gantz & Reinsel (2011), a staggering 1.8ZB (zettabytes) of data was generated in 2011. Current estimates suggest that 1.7MB of data is generated every second by a single user leading to a daily collective rate of 2.5EB (exabytes). Companies such as Walmart, handle more than 1 million customer transactions per hour, producing 2.5PB (petabytes) of data in a 24-hour period. 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 2003, but that volume of information is now created every 2 days, and the pace is increasing' (Kirkpatrick, 2010). In fact 90% of all digital data has been created in the last 2 years – the period between 2013-2015.

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 typically highly structured enterprise data generated during business operations. As a result new tools and technologies and organizational capabilities are needed to integrate big data with enterprise data (Liu, et.al., 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. Moore's Law has continued to operate on raw computing power, with the cost per million transistors declining from $222 per million transistors in 1992 to $0.06 per million transistors in 2012. Data storage costs have followed a similar path, decreasing from $569 per gigabyte of storage in 1992 to $0.03 per gigabyte in 2012. Data transmission costs have also declined, from $1,245 per 1,000 megabits per second (Mbps) in 1999 to $23 per 1,000 Mbps in 2012 (Hagel, Brown, Samoylova, & Lui, 2013). Other benefits of using cloud based BI tools include fast deployment of BI 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.

Organizations, who 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. Examples of such big data projects are starting to emerge in diverse industries from healthcare to retail and transportation. Healthcare organizations are leveraging big data to track their patient’s compliance with treatment regimens. Insurance companies are managing insured risk profiles using GPS data from cars and lifestyle choices. Financial applications of big data analytics include revenue and profit forecasting, prediction of loan default, fraud detection, credit scoring and even identifying money laundering. In the domain of mobile commerce, the concepts of “local offers” are being made based on a person’s local presence. Supply chain decisions are changing from being forecast based to one of modulating demand. This is particularly visible 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 actual store shoppers, which 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.

4. Organizational Challenges of “Big Data”

Despite these benefits of cloud based BI tools, there are several challenges from a data security/privacy and aggregation perspective. 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 BI tools. 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. 2010). 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. Regardless of the approach, the organization needs to invest in both human and technological resources to build the needed 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.

Current literature shows that end users have been reluctant to accept analytics models into their practice, systems that they viewed as reducing their autonomy or interfering with their decision making. The differentiation among business functions and the lack of common goals creates a resistance towards adoption and use of organization-wide big data models and analytics based systems among practitioners in various organizational forms. Yet the interdependence of these functions are needed to improve business outcomes. This calls for the use of systems to share big data, perform more thorough models and research analytics interactions. Investments in training, certifications and standardization of skills and processes to implement big data analytics in complex functionally structured organizations can help in adoption of end user analytics systems. model holds that greater differentiation (specialization) of practice leads to fewer common goals among practitioners and a less favorable view of interdependence. Coupled with that is a divergent view of the role of technology among clinicians (originating from the clinician's values, training or experience. All this leads to significant conflict based on power and politics when a decision about big data systems specification, implementation or adoption needs to be taken. A study to compare these forces among different organizations to understand the forces of power and influence and how they fit into each of the above three types, holds promise to explain adoption challenges that should be addressed in implementing big data analytics systems.

5. Technical Challenges of "Big Data"

Big data is definitely a big opportunity but also a source of consternation for organizations – both business managers and IT departments. IT architectures and business processes and business models need to evolve as big data applications are adopted in a company's infrastructure. The volume and high rate of creation 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 use strict data schemas and defined storage structures to operate. A typical big data analytics application may need to access heterogeneous data from thousands of ISPs' servers. To address the heterogeneity and distributed nature of big data, clustered environments like storage grids are needed, which are radically different from the converged and virtualized IT environments driving most organizations' enterprise applications.

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. Examples of cloud based BI 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.

The nature of "big data" also leads to "data silos" due to the numerous schemas and heterogeneous sources of the "big data". 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. There is a need to harmonize various terms during data generation, translation, dissemination and adoption. However, 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. Big data will inject high-velocity requirements associated with capture and analysis, as well as results/predictive reporting into business applications. With big data, IT capability is best organized around the specific opportunity rather than merely a set of shared services that are traditionally the popular approach to enterprise IT.

6. Towards An End User Model

6.1 Data Collection

A paper based survey was performed at a local SAP user group meeting. The sample was drawn from the attendees of a BI workshop offered at the meeting on the SAP Business Objects tool and represents a convenience sample. The author introduced the survey, and invited the attendees to take some time to complete the survey at the end of the workshop. Participation was entirely voluntary and the respondents were asked to indicate their assessment of the magnitude for each item on a scale of 1-5 (strongly disagree, disagree, neutral, agree and strongly agree). A total of 90 completed surveys (out of approximately 125 surveys distributed) were collected and analyzed for this study. Four demographic questions, their years of job experience, BI application usage experience, job title and their industry of work were asked. The respondents had different functional responsibilities ranging from sales/marketing, IT, logistic, accounting, finance, service, production, HR and in different levels: operational, managerial, strategic, and executive. The respondents represented different business functions in different industries, such as insurance, logistics, manufacturing, energy, and healthcare.

The user acceptance of information systems are supported by four different set of potential determinants (technology, individual difference, social influence, and situational constraints). Agrawal suggested that, to better understand individual acceptance of information technologies, a variety of factors including individual difference, beliefs and attitudes, social influence, managerial interventions, and situational influence should be examined. Diffusion of Innovation Theory (DOI) serves as a fundamental theoretical base of innovation adoption research in many disciplines, including sociology, communications, marketing, education, etc. DOI is a useful theory for studying a variety of IT innovations. DOI argues that innovation characteristics, such as relative advantage, compatibility, complexity, trialability and observability influence an individual's decision whether to accept or reject IT innovations. Additionally, compatibility, relative advantage and complexity are consistently found to be significant factors in user's intentions to adopt IT innovations.

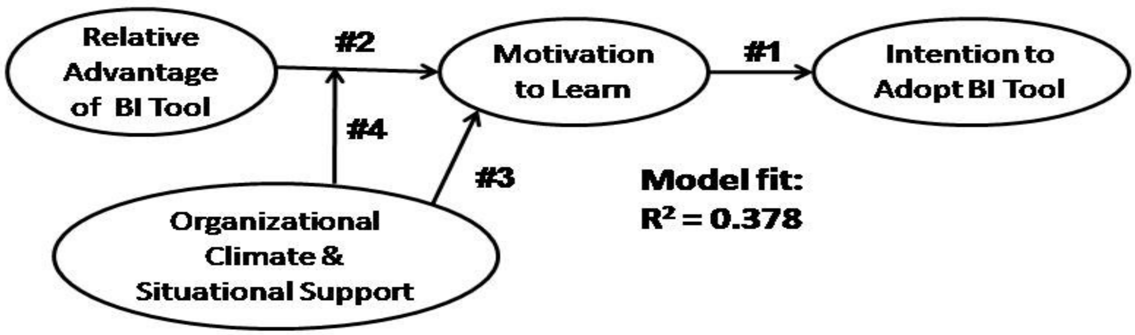

Figure 1: Empirical Model fitted to survey data using PLS-Graph

Motivation theory has also been used often to understand individuals' IT adoption. Motivation theory suggests that individual behavior is determined by two fundamental types of motivation: extrinsic (utilitarian) motivation and intrinsic (hedonic) motivation. Extrinsic motivation refers to performing an activity because it is perceived to be instrumental in achieving valued outcomes that are distant from the activity itself, such as improving job performance, pay, or promotion. Intrinsic motivation refers to performing an activity for no apparent reinforcement other than the process of performing the activity per se. In the context of technology adoption, extrinsic motivation emphasizes an individual's personal gain associated with a technology use. Extrinsic motivation has been found as significant predictors of technology adoption. Especially, extrinsic motivation plays as a dominant predictor of utilitarian technology adoption. Since BI applications can be considered as utilitarian technologies that aim to provide instrumental values to users, such as improving job performance, we expect that extrinsic motivation would influence individual technology acceptance. On the other hand, intrinsic motivation emphasizes the importance of having an enjoyable and playful technology experience. In addition to the extrinsic motivation, intrinsic motivation has been found as an important predictor of technology adoption. Just like other technologies, if individuals perceive that using BI application is enjoyable and intuitive, they may be willing to adopt the BI application.

Axiom #1: ***Motivation to Learn has a significant positive effect on the Intention to Adopt BI applications.***

6.2 What is Relative Advantage?

Relative Advantage is defined as the degree to which the innovation is perceived as better than the idea it supersedes (Rogers: Diffusion of Innovations). BI applications can offer several benefits that include improving timeliness and quality of 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. Several studies have shown that perceived advantage of an innovation over existing or alternative products/processes is positively associated with information system adoption and have indicated that relative advantage is positively related to the adoption of a knowledge-based system.

Axiom #2: ***Relative advantage has a significant positive effect on motivation to learn BI applications.***

6.3 Organizational Climate and Support

Previous research has shown that situational constraints are important determinants of intention to use technology. Typically, the concept of situational constraints has been operationalized using the perceived behaviors control construct in the theory of planned behavior. According to the theory of planned behavior, the presence or absence of requisite skills, resources necessary to perform a behavior can influence the likelihood of performing that behavior. In the context of technology adoption, individuals may not be willing to adopt a technology if they believe that they do not have skills or resources necessary to use that technology. Situational constraints have been widely studied in the training literature. In addition to the requisite skills and resource, the training literature suggests that organizational learning climate could be considered as a situational constraint that can influence behavior. If an organization encourages employees for learning and development, employees are more willing to learn new things and apply them to their work.

> **Axiom #3:** ***Organizational learning climate and support has a significant positive influence on Individual Motivation to Learn a BI application.***
>
> **Axiom #4:** ***Organizational learning climate and support boosts the relationship between Relative Advantage and Motivation to Learn BI applications.***

7. Conclusions

In the digital universe, it is now possible to run factories from afar, tap vast stores of social networking traffic for meaning, analyze customers in efficient ways that were impossible even a few years ago, and create smart cities, buildings, and homes. But this requires sifting through the data in the digital universe to identify the ones that matter and creating organizational value out of them. Applications of big data analytics have not even come close to exhausting the possibilities, nor has the potential value been realized in many of these applications. Realizing this value is dependent upon a variety of factors such as organizational analytics culture, executive support, expertise, and compatibility with existing technological infrastructure (Palmer, 2013). However, it is increasingly apparent that the benefits of analytics will continue to expand and span a variety of dimensions, including overall improvements in the quality and speed of decisions, better alignment of resources to strategies, increased revenues, and improvements in cost efficiencies (Computerworld, 2009). Not only do IT departments need to adopt the new tools of search and discovery, information classification, manipulation and management, information security, but business managers need to be trained and ready to deal with the syndication of outputs, that can now be pulled out of the digital universe.

Most IT departmental functions — from infrastructure to applications to governance — need to be part of a single integrated team and work closely with business users of big data in ways that are very distinct from traditional enterprise IT approaches (Lawler, 2016). The cloud providers will play a key enabling role in nearly every facet of the big data space. First, they will be among the most important collectors of data streams and content. Second, they will be among the most aggressive users of big data systems to run their own businesses. Third, they will also be in a position to enable big data use by technically savvy, but resource constrained, organizations. For example, cloud-based big data platforms will make it practical for smaller firms to access massive compute resources for short, semi predictable time periods without having to build their own big data farms. Therefore applications to create organizational value from the big data digital universe will have two components - organizational and technical.

The organizational components include:

1. Define a strategy among C-level executives to establish a process for migrating to shared resources — including virtualization and public and private cloud computing based on data requirements.
2. Begin laying the organizational groundwork with the specific analytical and managerial skill sets, mindsets, and processes necessary to make the company a data-driven organization.
3. Similar to any other IT innovation project, planning for a BI implementation project must be initiated by identifying key power users who are motivated to adopt the new technologies and put them to use.
4. Work with business partners such as suppliers and consumers thru mobile applications and devices to connect systems in real time.

The technical components include:

1. Adoption of the new cloud based tools for accessing, selecting, collecting and manipulating distributed data sets
2. Determine which big data projects will have the most business impact, along with the requisite data sets and applicable analytical tools.
3. Embrace new mobile personal tools from smartphones and iPads, which can make the syndication of analytics such as executive dashboards and real-time business intelligence easier.

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