Volume 15, No. 6
November 2017
ISSN: 1545-679X

Information Systems Education Journal

In this issue:

The **Information Systems Education Journal** (ISEDJ) is a double-blind peer-reviewed academic journal published by **EDSIG**, the Education Special Interest Group of AITP, the Association of Information Technology Professionals (Chicago, Illinois). Publishing frequency is six times per year. The first year of publication was 2003.

ISEDJ is published online (http://isedj.org). Our sister publication, the Proceedings of EDSIGCon (http://www.edsigcon.org) features all papers, panels, workshops, and presentations from the conference.

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Information Systems Education Journal is pleased to be listed in the 1st Edition of Cabell's Directory of Publishing Opportunities in Educational Technology and Library Science, in both the electronic and printed editions. Questions should be addressed to the editor at editor@isedj.org or the publisher at publisher@isedj.org. Special thanks to members of AITP-EDSIG who perform the editorial and review processes for ISEDJ.

Understanding Business Analytics Success and Impact: A Qualitative Study

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Abstract

Business analytics is believed to be a huge boon for organizations since it helps offer timely insights over the competition, helps optimize business processes, and helps generate growth and innovation opportunities. As organizations embark on their business analytics initiatives, many strategic questions, such as how to operationalize business analytics in order to drive the most value, arise. Recent Information Systems (IS) literature have focused on explaining the role of business analytics and the need for business analytics. However, very little attention has been paid to understanding the theoretical and practical success factors related to the operationalization of business analytics. The primary objective of this study is to fill that gap in the IS literature by empirically examining business analytics success factors and exploring the impact of business analytics on organizations. Through a qualitative study, we gained deep insights into the success factors and consequences of business analytics. Our research informs and helps shape possible theoretical and practical implementations of business analytics.

Keywords: Business analytics, Grounded Theory, Success factors, Qualitative.

1. INTRODUCTION

Business analytics refers to the generation and use of knowledge and intelligence to apply data-based decision making to support an organization's strategic and tactical business objectives (Goes, 2014; Stubbs, 2011). Business analytics includes "decision management, content analytics, planning and forecasting, discovery and exploration, business intelligence, predictive analytics, data and content management, stream computing, data warehousing, information integration and governance" (IBM, 2013, p. 4).

Business analytics has been the hot topic of interest for researchers and practitioners alike due to the rapid pace at which economic and social transactions are moving online, enhanced algorithms that help better understand the structure and content of human discourse, ready availability of large scale data sets, relatively inexpensive access to computational capacity, proliferation of user-friendly analytical software, and the ability to conduct large scale experiments on social phenomena (Agarwal & Dhar 2014).

IBM estimates that the market for data analytics is estimated to be $187 billion by the end of the year 2015 (IBM, 2013). Although business analytics promises enhanced organizational performance and profitability, improved decision-making processes, better alignment of resources and strategies, increased speed of decision-making, enhanced competitive advantage, and reduced risks (Computerworld, 2009; Goodnight, 2015; Harvard Business Review Analytics Report, 2012), implementation success is far from assured. A survey of 3,000 executives conducted by MIT Sloan Management Review along with IBM Institute of Business Value (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011) revealed that the leading obstacle to widespread analytics adoption is "lack of understanding of how to use analytics to improve the business". Gartner's 2014 annual big data survey shows that while investment in big data technologies continues to increase, "the hype is wearing thin as business intelligence and information management leaders face challenges when tackling diverse objectives with a variety of data sources and technologies" (Gartner, 2014a). Several studies (Ariyachandra & Watson, 2006; Eckerson, 2005; Imhoff, 2004; Popovič et al., 2012; Yeoh & Koronios, 2010) have focused on the critical success factors related to business analytics implementation, while several others (Computerworld, 2009; Goodnight, 2015; Harvard Business Review Analytics Report, 2012) have covered the consequences of business analytics. However, there is a lack of a unified model of business analytics success factors and business analytics impact.

The research questions for this study are as follows: What are the determinants of business analytics success? What impact does business analytics have on organizations that plan to implement it? How can these success factors and impact dimensions be integrated into a unified model of business analytics value? Our study addresses these research questions by applying a grounded theory approach to 17 qualitative interviews conducted with 18 senior executives from 15 business analytics organizations in 7 industries.

The structure of this paper is as follows: The next section briefly reviews the most important business analytics conceptualizations and studies that informed our research. We then outline our methodological approach for answering the research questions. Subsequently, we present our findings and synthesize them into a unified model of business analytics success and impact. We conclude the paper with a discussion of our contributions to theory development and practice, limitations of our study, and strategic implications of our findings.

2. LITERATURE REVIEW

Business Analytics

IS researchers are familiar with the data → information → knowledge continuum. Pearlson & Saunders (2013) define data as "a set of specific, objective facts or observations" (p. 14). They add that information is data that has been "endowed with relevance and purpose" (Pearlson & Saunders, 2013, p. 15). Knowledge is then defined as "information that is synthesized and contextualized to provide value" (Pearlson & Saunders, 2013, p. 16).

Business analytics refers to the application of relevant measurable knowledge to strategic and tactical business objectives through data-based decision making (Stubbs, 2011). Goes (2014) adds that analytics refers to the higher stages in the data–knowledge continuum and is directly related to decision support systems, a well-established area of IS research. Business analytics is "the generation of knowledge and intelligence to support decision making and strategic objectives" (Goes, 2014, p. vi). Business analytics represents the analytical component in business intelligence (Davenport, 2006).

Chen et al., (2012) traced the evolution of business analytics and categorized business intelligence and analytics (BI&A) into BI&A 1.0 (DBMS-based, structured content), BI&A 2.0 (web-based, unstructured content), and BI&A 3.0 (mobile and sensor based, unstructured content). Chen et al. (2012) add that in addition to being data-driven, business analytics is highly applied, with the potential to revolutionize areas such as e-commerce and market intelligence, e-government and politics, science and technology, smart health and well-being, and security and public safety.

Most of the research on business analytics till date have focused on its application in marketing (Chau & Xu, 2012; Lau et al., 2012; Park et al., 2012; Sahoo et al., 2012) and financial services (Abbasi et al., 2012; Hu et al., 2012). Chau & Xu (2012) proposed a framework for gathering business intelligence from user-generated blogs (BI&A 2.0) using content analysis on the blogs and social network analysis of the bloggers' interaction networks to help increase sales and customer satisfaction in a marketing context. Lau et al., (2012) developed a novel due diligence balanced scorecard model that uses collective web intelligence (BI&A 2.0) techniques such as domain-specific sentiment analysis, business relation mining, and statistical learning to enhance decision making related to global mergers and acquisitions. Park et al. (2012) proposed a social network-based (BI&A 2.0) relational inference model which incorporated techniques such as social network analysis, user profiling, and query processing to determine the validity of self-reported customer profiles which form the basis of many organizational external data acquisition efforts to boost their business analytics outcomes. Sahoo et al., (2012) proposed a hidden Markov model that uses techniques such as statistical modeling and collaborative filtering (BI&A 1.0) to make personalized recommendations under conditions of changing user preferences. Abbasi et al., (2012) developed a meta-learning model that utilizes techniques such as adaptive learning, and classification and generalization (BI&A 1.0) to generate a confidence score associated with each of its predictions to help detect fraud in the financial services industry. Hu et al., (2012) use a network approach to risk management (NARM) which includes predictive modeling, statistical analysis, and discrete event simulation techniques (BI&A 1.0) to identify systemic risk in banking systems.

Determinants of Business Analytics Success

Popovič et al. (2012) developed a model of business intelligence systems (BIS) success that included the business intelligence dimensions of BIS maturity, information content quality, information access quality, analytical decision-making culture, and use of information for decision-making. BIS maturity refers to the state of the development of BIS within the organization. Information content quality, in the BIS context, refers to information relevance or output quality. Information access quality refers to the bandwidth, customization capabilities, and interactivity offered by the BIS. Analytical decision-making culture refers to the attitude towards the use of information in decision-making processes. Use of information for decision-making refers to the application of acquired and transmitted information to organizational decision-making (Leonard-Barton & Deschamps, 1988).

Popovič et al. (2012) tested their model on data collected from 181 organizations and found that BIS maturity has a strong impact on information access quality. Their results also showed that information content quality, and not information access quality, was relevant for the use of information for decision-making, and that analytical decision-making culture improved the use of information for decision-making while suppressing the direct impact of information content quality.

Ariyachandra & Watson (2006) analyzed the critical success factors for BI implementation and found that information quality, system quality, individual impacts, and organizational impacts are the four factors which determine whether an organization's BI efforts are successful. Their information quality dimension included sub-factors such as information accuracy, completeness of information, and consistency of information (Ariyachandra & Watson, 2006). The system quality dimension included sub-factors such as BI system flexibility, scalability, and integration (Ariyachandra & Watson, 2006). Individual impacts included quick access to data, ease of data access, and improved decision-making capabilities while organizational impacts include BI use, accomplishment of strategic business objectives, business process improvements, improved ROI, and enhanced communication and collaboration across business units (Ariyachandra & Watson, 2006).

Yeoh & Koronios (2010) classified business analytics success determinants into three categories, namely organizational success factors, process related success factors, and technology-related success factors. Their organizational success factors included determinants such as a clear organizational vision, and a well-established business case (Yeoh & Koronios, 2010). Their process-related success factors included determinants such as balanced team composition, well-established project management methodologies, and user-oriented change management procedures (Yeoh & Koronios, 2010). Their technology-related success factors included determinants such as a scalable and flexible architecture, and sustainable data quality and data integrity (Yeoh & Koronios, 2010).

Eckerson (2005) identified critical success factors for enterprise business intelligence (BI). Those critical success factors included support for all users via integrated BI suites, conformity of BI tools to the way users work rather than the other way around, ability of the BI tools to integrate with desktop and operational applications, ability of the BI tools to deliver actionable information, ability of the analytics team to rapidly develop tools and reports to meet fast changing user requirement, and an underlying BI platform that is robust and extensible (Eckerson, 2005).

Imhoff (2004) identified five success factors that are critically important to any business wishing to develop a BI environment. Those success factors included a dependable architecture, strong partnership between the business community and IT, an agile/prototyping methodology, well-defined business problems, and a willingness to accept change (Imhoff, 2004).

Howson (2008) identified four critical success factors while exploring the characteristics of a killer BI app. Those BI success determinants included culture, people's views of the value of information, exploratory and predictive models, and fact-based management (Howson, 2008).

Consequences of Business Analytics Success

Jim Goodnight, CEO of SAS Institute Inc., states that business analytics has a tremendous impact on organizational performance and profitability adding that the "ability to predict future business trends with reasonable accuracy will be one of the crucial competitive advantages of this new decade. And you won't be able to do that without analytics." (Goodnight, 2015, p.3).

A Computerworld survey (Computerworld, 2009) of 215 business analytics organizations showed that the key benefits derived from business analytics initiatives include improved decision-making processes (75%), increased speed of decision-making (60%), better alignment of resources and strategies (56%), greater cost savings (55%), quicker response to users' business analytics needs (54%), enhanced organizational competitiveness (50%), and improved ability to provide a single, unified view of enterprise information (50%).

According to a Harvard Business Review global survey of 646 executives, managers, and professionals, some of the key benefits from using business analytics include increased productivity, reduced risks, reduced costs, faster decision-making, improved programs, and superior financial performance (Harvard Business Review Analytics Report, 2012).

3. RESEARCH METHOD

To achieve our research objectives, we followed a qualitative-empirical research design. We adopted a grounded theory methodology that accounts for, and uncovers, organizational activities and behaviors with regards to business analytics (Glaser & Strauss, 1967). The grounded theory approach is becoming increasingly common in IS research literature because of its usefulness in helping develop rich context-based descriptions and explanations of the phenomenon being studied (Orlikowski, 1993). This methodology also enables researchers to "produce theoretical accounts which are understandable to those in the area studied and which are useful in giving them a superior understanding of the nature of their own situation" (Turner 1983, p. 348).

Data Collection

We gathered data through semi-structured interviews with executives and experts in business analytics such as: Chief Data Officer (CDO), Chief Information Officer (CIO), Chief Privacy Officer (CPO), Chief Medical Information Officer (CMIO), Chief Executive Officer (CEO), and Managers (see Appendix A). We conducted 17 interviews with 18 informants from 15 organizations in the U.S. We used a "snowball" technique (Lincoln & Guba, 1985) to identify more informants. Our selection can be considered a convenience sample that allowed us to achieve a large number of executives. However, with regards to theoretical replication (Benbasat et al., 1987; Yin, 2009), we tried to achieve sufficient variation across the organizations with respect to industry (banking, healthcare, insurance, manufacturing, retail, technology services, etc.), organization size (10 to 115,000 employees), interviewees' roles (CDO, CIO, CPO, CMIO, CEO, VP, etc.), and interviewees' area(s) of expertise (BA, BI, Enterprise BI, IT, innovation, leadership, privacy, etc.) in order to avoid any bias. Therefore, we interviewed informants with different expertise across multiple industries (see Appendix A). The interviews addressed ten major question categories (see Appendix B) and lasted between 40 and 90 minutes. Interviews were conducted between Fall 2014 and Spring 2015. All interviews were audio-recorded and transcribed.

Grounded Theory Analysis Process

For the purpose of clarity, we provide a brief overview of the tasks undertaken during the grounded theory approach: (1) First, for data collection and transcription, all interviews were recorded and then transcribed into Microsoft Word documents. (2) Second, as a part of data analysis, each transcribed interview was imported into Dedoose. Dedoose is a "cross-platform app for analyzing qualitative and mixed methods research with text, photos, audio, videos, spreadsheet data and so much more" (Dedoose, 2015). Transcripts were then manually coded. This involved selecting pieces of raw data and creating codes to describe them using an inductive approach, meaning that we did not use a predefined set of codes, but rather let the codes arise from the data. For the first order analysis, we embraced an open coding approach in order to brainstorm and to open up the data to all potentials and possibilities. Our coding involved the identification and comparison of key concepts using Strauss & Corbin's (2008) constant comparative approach. Our first order analysis results indicated that certain categories emerged, but not all relationships were defined. Corbin & Strauss (2008) refer to this next step as axial coding, which is the act of relating concepts and categories to each other and constructing a second order model at a higher theoretical level of abstraction. This step involved an iterative process of collapsing our first order codes into theoretically distinct themes (Eisenhardt, 1989). (3) Third, we reviewed extant literature to identify potential contributions of our findings. Our review consisted of business analytics related work with a special focus on existing theories and frameworks at the organizational level. Upon our review of the strengths and the weaknesses of existing literature in this area, we decided to focus on the success factors of business analytics and the consequences of business analytics. (4) The fourth and final stage of our grounded theory approach involved determining how the various themes we identified could be linked into a coherent framework.

Ensuring Trustworthiness and Validity

To ensure that our analysis met the following criteria for trustworthiness: credibility, transferability, dependability, and confirmability (Lincoln & Guba, 1985), we employed the following steps: (1) we relied on the expertise of the primary researcher who has significant industry experience in business analytics, (2) we provided a detailed first order analysis of our findings, (3) both authors coded the same three interviews individually and compared their coding line by line and came to an agreement when certain excerpts from the interview transcripts were coded differently. The remaining interviews were split between the authors and the new codes that emerged were revisited and compared.

Member checking was achieved by sharing the preliminary findings of this study with interview participants and soliciting their feedback on the researchers' interpretation of the data. Consensus suggests a reasonable degree of validity of the constructs and relationships in our unified research model of business analytics success and impact.

4. FINDINGS

In this section, we aggregate what we learned from the executives by interweaving both first order codes and second order themes to provide our grounded theoretical model of business analytics success and impact (see Appendix C).

Dimension	2nd Order Themes	1st Order Concepts
Organization	Culture	Leadership buy-in Buy-in from other functions
	Skills	Technical skills Business skills Soft skills
	Resources	Cost of BA Cost of human resources
Process	Best Practices	Unified view of the data Integration of disparate systems Standardization
	Business-IT Alignment	Business focus
	Measurements	KPIs Metrics Dimensions BA maturity scale Scorecards
Technology	Data Management	Data quality Data integrity Data governance Data maturity
	BA Techniques	Predictive analytics Programming Data mining
	BA Infrastructure	Tools and technologies Cloud BA Outsourcing and in-house

Table 1 depicts the identified determinants of Illustrative quotes for BA success determinants

Table 1. Business Analytics Success Determinants

are provided in Appendix D. According to our data analysis results, successful business analytics is determined by three major categories: Organizational factors which encompass culture, BA skills and BA resources; process-related factors that include business-IT alignment, BA measurements, and BA best practices; and technology-related factors that contains data management, BA techniques, and BA infrastructure. The central concept Business Analytics Success, as indicated by various interviewees, refers to the extent to which a set of clearly defined and transparent organizational, process-related, and technical factors are coherently integrated.

Dimension	2nd Order Themes	1st Order Concepts
Business Impact	Actionable Business Analytics	Recommendations on which states have the highest potential for success Exceptions
	Performance Improvement	Identifying waste Reducing cost Improving profit Catching Fraud Time savings Transparency
	Competitive Advantage	Negotiation advantage
	Regulatory Compliance	Ethical use of data and information Privacy & Security compliance

Table 2. Consequences of Business Analytics Success

Table 2 introduces the identified consequences of business analytics success. These include actionable business analytics, performance improvement, competitive advantage, and regulatory compliance. Illustrative quotes for BA impact are provided in Appendix E.

5. DISCUSSION AND IMPLICATIONS

This study investigated the ways in which organizations operationalize their business analytics practices. A grounded theory based analysis of the data led to a better understanding of the different business analytics success factors as well as the business impact of BA. We developed a framework (see Appendix C) that not only captures major constructs that span across industries, but also links these constructs to what matters most to organizations: actionable business analytics that leads to increased performance, enhanced competitive advantage, and better ethical and legal use of the data. These findings are further supported by a recent Gartner report that states that "Gartner's 2015 predictions focus on the cultural and organizational elements impacting big data deployments used in organizations. With the focus shifting away from technology, enterprises will face tough questions on deployments, investment and transparency as they relate to big data analytics." (Gartner, 2014b).

This research makes essential contributions to the field of business analytics: First, it uses a grounded theory methodology to provide a rich lens to understand the business analytics success factors and business analytics impact. Second, this study was designed to gain an in-depth understanding of how organizations from different industries operationalize their business analytics practices thereby directly addressing the leading obstacle to wide spread BA adoption, which is a "lack of understanding of how to use analytics to improve the business" (LaValle et al., 2011). Third, this research confirms the recent industry predictions related to business analytics deployment challenges (Gartner, 2014b) by offering in-depth insights on organizational, process-related, and technical constructs.

Our research also makes vital contributions to the area of IS education: First, from an organizational success factors perspective, we strengthen IS education by facilitating a dialog between practitioners (BA experts from different industries) and academic professionals (us) to address skills development and human resource related needs in the area of business analytics. Our findings show that technical skills, business skills, and soft skills are critical organizational success factors related to BA implementation. We also found that there is a lack of appropriate talent in BA. The market growth for BA, which is estimated to be $185 billion by the end of year 2015 (IBM, 2013), is driving the demand for BA talent. By 2018, McKinsey estimates a shortage of around 200,000 people with BA talent and a shortage of around 1.5 million BA managers (McKinsey, 2011). Our findings highlight the urgent need for business schools to redesign the way BA skills development is built into their curriculum in order to address this shortage. Second, from a process related success factors perspective, our findings suggest that there is a need for business schools to teach BA best practices, including integration, standardization, and the ability to provide a single unified view of data across the entire organization. Third, from a technical success factors perspective, our findings show that business schools need to integrate a variety of BA techniques (predictive analytics, programming, data mining, etc.) to teach data management using several different tools (Microsoft Azure, IBM Watson Analytics, etc.).

6. LIMITATIONS AND FUTURE RESEARCH

This study is not without limitations. With regard to the validity of the emerging theory, it is important to address generalizability, which is "the validity of a theory in a setting different from the one where it was empirically tested and confirmed" (Lee & Baskerville, 2003, p. 221). Lee & Baskerville (2003) clarified that the appropriate type of generalizability (not just statistical) should be applied to this particular type of study. The purpose of this study was not to achieve statistical validation, but rather to discover patterns for the purpose of theory building and gaining a better understanding of the main issues in its context. It is reasonable to assume that the insights gained from our emerging framework will guide future researchers to develop a more formal theory in this area (Orlikowski, 1993). Large scale additional data collection will further sharpen the findings in this study. Therefore, we propose a large scale study that examines the relationships among BA success factors and BA impact factors especially with regards to the changes needed to the IS curriculum. Our findings show that BA skills are extremely important and that there is a lack of appropriate talent. Therefore, a second research opportunity is to further examine the correlations among the required talent by industries and deliverable skills by IS programs. Doing so could facilitate the hiring and training of appropriate talent to achieve better decision making. Finally, the findings are based on different industries. Therefore, a third research opportunity could be to conduct a research study with focus on a particular industry for more-in-depth findings on its impact on the curriculum offered (e.g., more statistic courses, technical emphasis etc.).

7. CONCLUSION

Motivated by the significant increase in investments in business analytics technologies and growing concerns over BA implementation success, the primary goal of our paper was to examine how organizations operationalized their business analytics practices. We report the results of our grounded theory study that was carried out to understand how business analytics helps organizations handle the growing complexity of data, information, and business decisions. We thereby set out to identify the factors that influence and result from successful business analytics. Our analysis resulted in the emergence of a theoretical framework of business analytics success and impact. Our research provides the foundation for exploring further the operationalization of business analytics. Business analytics indeed is playing increasingly important role in decision making, and as BA deployments become more successful, organizations will see more opportunity for exceptional business impact.

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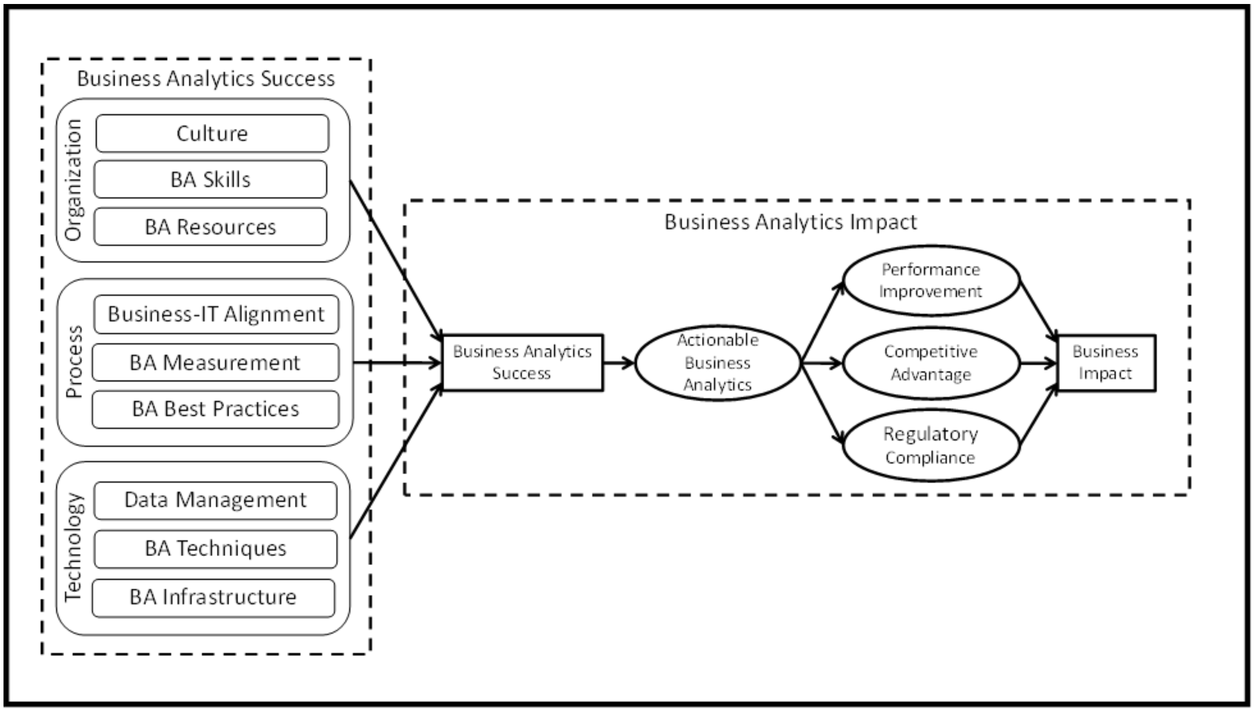
Appendix A: Data Collection with Business Analytics Experts

Interview /Interviewee	Industry	Emp-loyees	Interviewee Role	Interviewee Area(s) of Expertise	Length
1/1	Insurance	600	Vice President	Information Technology	60 min
2/2	Retail	38,900	Business Intelligence Manager	Business Intelligence	80 min
3/3	Technology and Services	6,200	Chief Privacy Officer	Information Privacy	52 min
4/4	Banking (Consulting)	10	Chief Executive Officer	Business Analytics and Leadership	81 min
5/5	Technology and Services	6,200	Vice President	Revenue and Sales Analytics	54 min
6/6	Government	68,100	Software Developer/Analyst	Information Technology	51 min
7/7	Healthcare	650	Chief Information Officer	Information Technology	55 min
8/8	Insurance	2,500	Vice President Manager	Enterprise Business Intelligence	68 min
8/9	Insurance	2,500	Manager	Enterprise Business Intelligence	68 min
9/10	Healthcare	13,000	Chief Information Officer	Information Technology	53 min
10/11	Healthcare	200	Chief Executive Officer	Leadership	92 min
11/12	Healthcare	4,750	President	Leadership	55 min
12/13	Technology and Services	128,076	Business Development Manager	Innovation	60 min
13/14	Manufacturing	115,000	Vice President	Information Technology	60 min
14/15	Healthcare	13,000	Chief Medical Information Officer	Medical Informatics	82 min
15/16	Insurance	1,878	Vice President	Business Analytics	64 min
16/17	Manufacturing (Consulting)	60	Senior System Architect	Manufacturing Intelligence	59 min
17/18	Insurance	5,500	Chief Data Officer	Business Analytics	40 min

Appendix B: Semi-Structured Interview Protocol

1. **General Information**
    a. About the informant (title, education, years in the profession)
    b. About the organization (size, location, industry, number of employees)
    c. Your definition of Big data/business analytics/business intelligence
2. **Design and Implementation Strategy BI**
    a. Current business analytics system implemented
    b. Implementation by department, function or at the organizational level
    c. Role of CIO with regards to business analytics
    d. Role of Chief Analytics Officer (CAO) if any
    e. How is it business analytics implemented? At divisions/at the corporate level.
3. **Techniques, Processes and Methods**
    a. For collection, management, storage, integration and exploitation of data
    b. Descriptive, predictive, and prescriptive analytics
    c. Outsourcing versus in house of business analytics?
    d. Visualization
4. **Data Management**
    a. Capturing data, cleaning data, aggregating/integrating data, and visualizing data
    b. Vertical or horizontal data location strategies
    c. The amount of data used in business analytics
5. **Culture**
    a. Support from executives/organizational culture
    b. Organizational openness to new ideas and approaches that challenge current practices
    c. Business analytics and a power shift in the organization
6. **Driving Value**
    a. The major drivers into embracing business analytics
    b. Pressure from senior management
    c. Best practices to analytics competency
7. **Challenges & Barriers**
    a. Most pressing issues you are dealing with in regards to BI
    b. Barriers to adoption/implementation
    c. Costs associated with BI implementation
    d. Buy-in from other functions/leadership
    e. Qualified critical thinkers, Ownership (IT, analytics staff)
8. **Privacy and Security Issues**
    a. Privacy practices with regards to business analytics
    b. Laws and regulations you have to comply with in your industry
    c. Ethical use of big data and analytics
9. **Business Analytics Talents and Skills**
    a. Skills (technical/business) needed to succeed as business analysts
    b. Balancing analytics and intuition
    c. Required skills to be taught in graduate/undergraduate programs
10. **Best Practices and Planned Growth**
    a. Most successful best practices within your organization
    b. Plans for more advanced BI techniques and processes
    c. Business area were you able to improve upon, create differentiation and drive growth
    d. Functional areas you are planning to make investments in analytics technology in the next 12 months, and/or have already made investments in the past 12 months
    e. Forward-looking analytics innovations you can apply to meet their mounting challenges

Appendix C: Model of Business Analytics Success and Impact



Appendix D: Illustrative Supporting Data for Business Analytics Success Determinants

2nd Order Themes	Illustrative 1st Order Data
Culture	"To be honest, it's because they don't have the enterprise buy-in or leadership buy-in to really focus on analytics capabilities. I look at our top 14 strategic initiatives sitting in front of me and number five is aggressively improve our BA capabilities. It has a board level focus and it has a senior leadership level focus."
Skills	"The reason I think these data scientists are rare it's kind of an unusual talent to find in the same person. Someone that actually understands the technology, not down to the very low levels, but utilize that while understanding the business problems … Somebody has got to bridge the gap. I don't know how to describe that set of skills but that's really the key individual." "Talent is a challenge … so short of going and hiring a Ph.D. data scientist I'm trying to look at the combined skill set that I would look for in that person so create a data science team rather than bring in these high dollar individuals."
Resources	"The biggest issue we have is resources. We just have lack of resources. When you factor in how much effort it takes … it's the day to day keeping the lights on activities that holds us back, that and the budget. It holds us back on how quickly we can implement improvements and new innovations."
Best Practices	"We still have disparate systems that do not talk to each another, we have billing and accounting receivable system, we have general ledger system for accounting, we have an HR system to manage our staff, and we have patient communication system. We have tried to drive the integration of technology, but then the ability to take that data and make that effective for us in terms of cost reduction."
Business-IT Alignment	"In a marketing campaign if I am measuring people that replied to my offer for a credit card, let's say I get a five percent response and that's profitable for me, and through business analytics I can drive it to a 7 percent response and everybody is wildly happy, but when I get to 7 percent my profit stays the same. The reason my profit stays the same is that the first response is not the ultimate answer to acquisition. Because the consumer replies to my offer, I now have to verify their credit is good enough to get that $2500 card or that $5000 card. If I did was simply measure their initial response and not my ability to ultimately give them the card based on their credit, but I am only getting a partial picture. Someone that doesn't understand the credit industry of business analyst may not even realize that what I need to be measuring is not just the initial response but also how many get through the credit approval step the backend step."
Measurements	"It's measuring business operation. If you go to somebody and say what are your business problems, they talk about logistics, or they talk about the economy or this that or the other. In a lot of cases they may not know what their business problems are. If you run a business mostly by intuition and by the books, a lot of the performance issues are hidden."
Data Management	"One thing I talked about is the integrity of the data and the standardization and it's not open to misinterpretation, so one of the challenges is to moving in the direction of more self-service BI, but then that complicates the data governance and the data stewardship side of things because as you open up more ad hoc capability then you are putting more on the users in terms of ownership in understanding on how to use the data. It kind of goes back to the whole governance and data integrity thing."
BA Techniques	"Applying more data mining techniques and doing this pattern detection."
BA Infrastructure	"The difference from Oracle or SQL Server you could learn the differences, but those reporting tools are all very different. You compare BusinessObjects to MicroStrategy to Tableau and those guys you have got to go to a training class to learn. You can't just pick it up."

Appendix E: Illustrative Supporting Data for Business Analytics Impact

2nd Order Themes	**Illustrative 1st Order Data**
Actionable Business Analytics	"I think the challenge in making this actionable is the key thing… my challenge is that we spend an enormous amount of time creating dashboards pushing information that I believe that is largely unused. If you ask for a dashboard with 20 metrics on it and you want it daily you can't decision 20 metrics daily."
Performance Improvement	"As an example, in one of our locations, we found out their product costs were too high. When we put the system in place it showed that someone was using cream instead of milk. Cream cost more than milk. It's a valid ingredient, they could put that in there, its' a valid alternative. What it showed was not only is that affecting your cost on this product, but it's also affecting your cost on this product. So if you will start using milk like you should in the first place, it's going to improve the profitability of your place." "We are helping the state get better use of the funds that they have to work with and the intelligence that we produce more often use to improve the processes, identify waste and fraud. An example of waste would be to make sure you don't have a supplier in a suspended status still receiving payment. That's a waste. We don't have someone who is technically on the unemployment role with the state, but working a job where they are getting paid."
Competitive Advantage	"My job is to develop a 3 to 5 year game plan, where we are today? Where we want to be? And how we want to use data and analytics to be competitive?" "We want our competitors all have to come to us to get the fuel to put into their cars. We don't want to be the hardware; we want to be the operating system that allows them to do all offline and online data." "You can negotiate with them because you could look at some of the different procedures they are performing there that would be just if you sent the patient to "City X", so you create the competition for that smaller hospital because if you can show this member will pay less just by going to "City X" they might take the trip to LR if it is less money out of pocket for them and that causes more competition for them."
Regulatory Compliance	"That's my big concern over [business analytics] from a privacy security perspective. Now, we do everything: intrusion prevention systems, firewalls all that kind of stuff. Ethical usage is huge. We constantly have to remind people what not to do. In some cases it's as simple as; don't market to somebody that's under 21. Or more recently, we were working on one; we probably shouldn't market to deceased people on this list. You definitely do not want to go out there having so much knowledge you scare your customer. For one bank, we had demographic data information that had age, income, home ownership, presence of children, occupation and a couple of other flags on there we put back on the CRM web page where they could look at that data before they called their customer and they had us turn it off. They had us turn it off because they were afraid that the end user would read this off to them, we've been looking in your window and we know the following about you. "