BUSINESS INTELLIGENCE SUCCESS: AN EMPIRICAL EVALUATION OF THE ROLE OF BI CAPABILITIES AND THE DECISION ENVIRONMENT

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Since the concept of business intelligence (BI) was introduced in the late 1980s, many organizations have implemented BI to improve performance but not all BI initiatives have been successful. Practitioners and academicians have discussed the reasons for success and failure, yet, a consistent picture about how to achieve BI success has not yet emerged.

The purpose of this dissertation is to help fill the gap in research and provide a better understanding of BI success by examining the impact of BI capabilities on BI success, in the presence of different decision environments. The decision environment is a composition of the decision types and the way the required information is processed to aid in decision making. BI capabilities are defined as critical functionalities that help an organization improve its performance, and they are examined in terms of organizational and technological capabilities.

An online survey is used to obtain the data and partial least squares path modeling (PLS) is used for analysis. The results of this dissertation suggest that all technological capabilities as well as one of the organizational capabilities, flexibility, significantly impact BI success. Results also indicate that the moderating effect of decision environment is significant for quantitative data quality. These findings provide richer insight in the role of the decision environment in BI success and a framework with which future research on the relationship between BI capabilities and BI success can be conducted. Findings may also contribute to practice by presenting information for managers and users of BI to consider about their decision environment in assessing BI success.

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CHAPTER 1

INTRODUCTION

Since the concept of business intelligence (BI) was introduced in the late 1980s by Howard Dresner, a Gartner Research Group analyst (Power, 2003; Buchanan and O'Connell, 2006), the information systems (IS[1]) field has witnessed the rapid development of systems and software applications providing support for business decision making. Organizations started migrating to complete BI environments so that they could have a "single version of the truth" through the use of cross-organizational data, provided by an integrated architecture (Eckerson, 2003; Negash, 2004). The total investment of organizations in BI tools is estimated to be $50 billion a year and is steadily growing with the introduction of new desktop data analysis tools, data warehousing technologies, data extraction middleware and many other tools and techniques into the market by BI vendors (Weier, 2007).

Organizations need these new tools and techniques to improve performance and profits (Watson et al., 2002; Eckerson, 2003; Williams and Williams, 2007). Organizations need to meet or exceed the expectations of their customers in order to stay competitive in today's highly aggressive business world, and managers are increasingly relying on BI to do so (Clark et al., 2007). Although many organizations have implemented BI, not all BI initiatives have been successful. Practitioners and academicians have discussed the reasons for success and failure extensively (Wixom and Watson, 2001; Watson et al., 2002; Solomon, 2005; Watson et al., 2006). Unfortunately, a consistent picture about how to achieve success with BI has not yet

[1] Research has used IS and IT interchangeably. While IT represents computer hardware, software and telecommunication technologies, IS implies a broader context that is composed of processes, people and information. This dissertation uses IS rather than IT.

emerged. This suggests that there are gaps in the research to be filled, and that research has perhaps overlooked one or more key constructs for a BI success model.

Various approaches to examining BI capabilities may be one of the reasons behind the gaps in the research about BI success. A lack of fit between the organization and its BI capabilities is one of the reasons for lack of success (Watson et al., 2002; Watson et al., 2006). Although research has defined the concept of fit differently in several areas of research (Venkatraman, 1989), for the purposes of this dissertation it is defined as the relationship between different BI capabilities and BI success, in the presence of different decision environments. The decision environment is defined as the combination of different types of decisions made and the information processing needs of the decision maker to make those decisions (Munro and Davis, 1977).

Although BI capabilities have been studied from organizational (Eckerson, 2003; Watson and Wixom, 2007) and technological (Manglik and Mehra, 2005; Watson and Wixom, 2007) perspectives, some organizations still fail to achieve BI success (Jourdan et al., 2008). This may be because the influence of the decision environment on BI capabilities has remained largely unexamined. Examining this relationship is, however, appropriate because the primary purpose of BI is to support decision-making in organizations (Eckerson, 2003; Buchanan and O'Connell, 2006). The purpose of this dissertation is to help fill this gap in research and provide a better understanding of BI success by examining the impact of BI capabilities on BI success, in the presence of different decision environments.

There is an extensive amount of research on the success of information technology in organizations that draws on organizational design theory. Some researchers examine this from an individual perspective (Lovelace and Rosen, 1996; Ryan and Schmit, 1996), while others investigate the organization as the level of analysis (Premkumar et al., 2005; Setia et al., 2008). Because the main interest of this dissertation is to examine BI success in light of different decision environments and BI capabilities, the organization is used as the unit of analysis.

The suitability of BI capabilities and the decision environment includes the match between organizational structure and the technology (Galbraith, 1977; Alexander and Randolph, 1985), and the match between information processing needs and information processing capabilities (Tushman and Nadler, 1978; Premkumar et al., 2005). Organizational structure and information processing needs are part of the decision environment (Munro and Davis, 1977; Zack, 2007). Capabilities provided by the BI include both the technology used by the BI and the information processing capabilities of the BI. Although existing research improves knowledge about BI, little or no research examines how BI capabilities influence BI success in light of the decision environment of an organization. Little research examines the decisions made in the organization as well as the information processing needs of the decision maker. This dissertation examines this by using a theoretical lens grounded in decision making and information processing. Specifically, Galbraith's (1977) organizational information processing theory and Gorry and Scott Morton's (1971) decision support framework are used to examine the decision environment of an organization.

The decision environment of an organization is defined as a composition of the decision types and the way the required information is accessed and processed to aid in decision making in that organization (Galbraith, 1977; Beach and Mitchell, 1978; Eisenhardt, 1989). Decisions are largely distinguished by the type of problem that needs to be solved and who needs to make the decision (Power, 2002). The problem addressed by a decision impacts the decision making approach. Problems can be classified as programmed or nonprogrammed (Simon, 1960). A decision is programmed if it is repetitive and routine, and it is nonprogrammed when there is no fixed method of handling it and the decision is consequential (Simon, 1960). In general, programmed and nonprogrammed decisions are referred to as “structured” and “unstructured” respectively, because these terms “imply less dependence on the computer and relate more directly to the basic nature of the problem-solving activity in question” (Keen and Scott Morton, 1978, p. 86). An example of a structured decision is a sales order or an airline reservation, whereas choosing a location for a new plant is an example of an unstructured decision.

In addition to Simon’s (1960) two decision types, Gorry and Scott Morton’s (1971) framework for information systems includes a third type of decision: semistructured. Semistructured decisions are decisions that cannot be solved by only autonomous decision making or only human judgment (Gorry and Scott Morton, 1971). Semistructured decisions require both. Gorry and Scott Morton’s (1971) framework includes nine categories of decisions based on the decision type and management activity. Although this model has been applied to various IS scenarios (Kirs et al., 1989; Ashill and Jobber, 2001; Millet and Gogan, 2005), it has not been applied to the BI context. It is appropriate to do so, however, because BI is developed to support decision making (Eckerson, 2003; Buchanan and O’Connell, 2006).

Different decisions need different types of information, depending on the managerial activities with which they are associated (Gorry and Scott Morton, 1971). Thus, the way information is processed for decision making purposes is also a part of the decision environment of an organization (Tushman and Nadler, 1978). Galbraith's (1977) organizational information processing theory spawned much work on the role of information processing in organizations. Subsequently, research indicates that the information processing capabilities of an organization directly impact organizational effectiveness (Tushman and Nadler, 1978; Keller, 1994; Premkumar et al., 2005). Research has also examined the relationship between technology and information processing capabilities and showed that organizational performance increases when the technology that suits the organization's information processing capabilities is used (Keller, 1994; Premkumar et al., 2005).

BI helps organizations meet their information processing needs by facilitating organizational information processing capacity (Gallegos, 1999; Nelson et al., 2005). BI does so by combining data collection, data storage and knowledge management with analytical tools so that decision makers can convert complex information into effective decisions (Negash, 2004). BI capabilities within an organization can be divided into two groups; *technological* (e.g.,, data sources used and data reliability) and *organizational* (Feeney and Willcocks, 1998; Bharadwaj et al., 1999). Organizational capabilities are those that impact the way the BI is used within an organization (e.g., flexibility and risk-taking level of the organization).

Technology is critical to BI success, although it is not the only driving force (Cooper et al., 2000; Wixom and Watson, 2001; Clark et al., 2007). Research has extensively examined how technology impacts BI success (Rouibah and Ould-ali, 2002; Watson et al., 2006). Findings suggest that having the right technology for supporting decision making can help an organization increase its decision-making capabilities (Arnott and Pervan, 2005). For example, the appropriateness of the technology employed affects the efficiency and effectiveness of the data warehouse implementation and usage (Wixom and Watson, 2001).

BI organizational capabilities also impact BI success and include BI flexibility, level of acceptable risk for the organization, and the level of intuition the decision maker can involve in the decision making process with BI (Hostmann et al., 2007; Bell, 2007; Loftis, 2008). One of the reasons why organizations employ BI is the support it provides for decision making (Eckerson, 2003). The strictness of business process rules and regulations in an organization as well as the level of risk tolerated impacts the way BI supports decision making in an organization (Hostmann et al., 2007). Research suggests that organizations where employees use hard data rather than intuition to make decisions are more likely to succeed in BI (Eckerson, 2003). Using the collected data, BI can provide notifications to users and run predictive analytics to help users make well informed decisions. Although making decisions based on facts as opposed to gut feelings has become an approach preferred by many (Watson and Wixom, 2007), decision makers still use their intuition while making decisions, especially for decisions that are not straightforward to make (Harding, 2003).

To better support emerging BI user needs and best practices, a coordinated effort across users, technology, business processes and data is required (Bonde and Kuckuk, 2004). This endeavor, if successful, can improve the fit between BI and the organization within which it is implemented. The primary research question that this dissertation addresses is how BI capabilities influence BI success for different decision environments. BI capabilities include both technological and organizational capabilities. The decision environment is defined as the organizational decision types and information processing needs of the organization. The goal of this study is to examine the extent to which these two constructs moderate the impact of BI capabilities on BI success.

This study is relevant to both researchers and practitioners. This dissertation proposes to extend current research in BI and provide a parsimonious and intuitive model for explaining the relationship between BI success and BI capabilities in the presence of different decision environments, based on theories from decision making and organizational information processing. This dissertation contributes to academic research by providing richer insight in the role of the decision environment in BI success and providing a framework with which future research on the relationship between BI capabilities and BI success can be conducted. The practitioner oriented contribution of this study is that it helps users and developers of BI understand how to better align their BI capabilities with their decision environments and presents information for managers and users of BI to consider about their decision environment in assessing BI success.

The results of this dissertation suggest that all technological capabilities as well as one of the organizational capabilities (flexibility) studied in this dissertation significantly impact BI success. This may indicate that technology drives the BI initiative, rather than the organizational capabilities. Results also indicate that the moderating effect of decision environment is significant for quantitative data quality. This means that the quality of quantitative data impact BI success stronger for operational control activities.

The remainder of the dissertation is organized as follows. Chapter 2 includes a review of prior research about BI, BI success measures, BI capabilities and the role of the decision environment. This chapter also presents a conceptual model and the proposed hypotheses.

Chapter 3 contains a detailed description of the methodology employed. The chapter also discusses the sampling frame, the operationalization of constructs, and how validity and reliability issues are addressed. Chapter 4 presents the detailed analysis process and the results of the analysis. This dissertation concludes with Chapter 5, which provides a discussion of the findings, presents the limitations of the study as well as its implications for both managers and academics, and concludes by providing future research directions.

CHAPTER 2

LITERATURE REVIEW

Business intelligence (BI) is the top priority for many organizations and the promises of BI are rapidly attracting many others (Evelson et al., 2007). Gartner Group's BI user survey reports suggest that BI is also a top priority for many chief information officers (CIOs) (Sommer, 2008). More than one-quarter of CIOs surveyed estimated that they will spend at least $1 million on BI and information infrastructure in 2008 (Sommer, 2008). Organizations today collect enormous amounts of data from numerous sources, and using BI to collect, organize, and analyze this data can add great value to a business (Gile et al., 2006). BI can also provide executives with real time data and allow them to make informed decisions to put them ahead of their competitors (Gile et al., 2006). Although BI matters so much to so many organizations, there are still inconsistencies in research findings about BI and BI success.

Various definitions of BI have emerged in the academic and practitioner literature. While some broadly define BI as a holistic and sophisticated approach to cross-organizational decision support (Moss and Atre, 2003; Alter, 2004), others approach BI from a more technical point of view (White, 2004; Burton and Hostmann, 2005). Table 1 provides some of the more prevalent definitions of BI.

Table 1

Selected BI Definitions

BI Definition	Author(s)	Definition Focus
An umbrella term to describe the set of concepts and methods used to improve business decision-making by using fact-based support systems	Dresner (1989)	Technological
A system that takes data and transforms into various information products	Eckerson (2003)	Technological
An architecture and a collection of integrated operational as well as decision support applications and databases that provide the business community easy access to business data	Moss and Atre (2003)	Technological
Organized and systemic processes which are used to acquire, analyze and disseminate information to support the operative and strategic decision making	Hannula and Pirttimaki (2003)	Technological
A set of concepts, methods and processes that aim at not only improving business decisions but also at supporting realization of an enterprise's strategy	Olszak and Ziemba (2003)	Organizational
An umbrella term for decision support	Alter (2004)	Organizational
Results obtained from collecting, analyzing, evaluating and utilizing information in the business domain.	Chung et al. (2004)	Organizational
A system that combines data collection, data storage and knowledge management with analytical tools so that decision makers can convert complex information into competitive advantage	Negash (2004)	Technological
A system designed to help individual users manage vast quantities of data and help them make decisions about organizational processes	Watson et al. (2004)	Organizational

(table continues)

Table 1 *(continued)*.

BI Definition	Author(s)	Definition Focus
An umbrella term that encompasses data warehousing (DW), reporting, analytical processing, performance management and predictive analytics	White (2004)	Technological
The use and analysis of information that enable organizations to achieve efficiency and profit through better decisions, management, measurement and optimization	Burton and Hostmann (2005)	Organizational
A managerial philosophy and tool that helps organizations manage and refine information with the objective of making more effective decisions	Lonnqvist and Pirttimaki (2006)	Organizational
Extraction of insights from structured data	Seeley and Davenport (2006)	Technological
A combination of products, technology and methods to organize key information that management needs to improve profit and performance	Williams and Williams (2007)	Organizational
Both a process and a product, that is used to develop useful information to help organizations survive in the global economy and predict the behavior of the general business environment	Jourdan et al. (2008)	Organizational

These definitions largely reflect either a technologically or organizationally driven perspective. BI, however, is comprised of both technical and organizational elements (Watson et al., 2006). In the most general sense, BI presents historical information to its users for analysis to enable effective decision making and for management support (Eckerson, 2003). For the purpose of this dissertation, BI is defined as a system comprised of both technical and organizational elements that presents historical information to its users for analysis, to enable effective decision making and management support, for the overall purpose of increasing organizational performance.

One of the goals of BI is to support management activities. Computer based systems that support management activities and provide functionality to summarize and analyze business information are called management support systems (MSS) (Scott Morton, 1984; Gelderman, 2002; Clark et al., 2007; Hartono et al., 2007). Decision support systems (DSS), knowledge management systems (KMS), and executive information systems (EIS) are examples of MSS (Forgionne and Kohli, 2000; Clark et al., 2007; Hartono et al., 2007). These systems have commonalities that make them all MSS (Clark et al., 2007). These common properties include providing decision support for managerial activities, (Forgionne and Kohli, 2000; Gelderman, 2002; Clark et al., 2007), using and supporting a data repository for decision-making needs (Cody et al., 2002; Arnott and Pervan, 2005; Clark et al., 2007), and improving individual user performance (Gelderman, 2002; Hartono et al., 2005; Clark et al., 2007).

BI can also be included in the MSS set (Clark et al., 2007). First, BI supports decision making for managerial activities (Eckerson, 2003; Hannula and Pirttimaki, 2003; Burton and Hostmann, 2005). Second, BI uses a data repository (usually a data warehouse) to store past and present data and to run data analyses (Eckerson, 2003; Moss and Atre, 2003; Anderson-Lehman et al., 2004; Clark et al., 2007). BI is also aimed at improving individual user performance through helping individual users manage enormous amounts of data while making decisions (Watson et al., 2004; Burton et al., 2006; Clark et al., 2007). Thus, BI can be classified as an MSS (Clark et al., 2007; Baars and Kemper, 2008). Examining BI in the light of research based on other types of MSS may lead to better decision support and a higher quality of BI systems (Clark et al., 2007). Findings of this dissertation may also be applied to other types of MSS that exist now and that may emerge in the future.

The MSS classification of BI may also help research address gaps that result from examining MSS separately, without considering their common properties. Research examines success antecedents of many MSS extensively (Hartono et al., 2006), but consistent factors that help organizations achieve a successful BI have not yet emerged. Research suggests that fit between an MSS and the decision environment in which it is used is an MSS success antecedent (Hartono et al., 2006; Clark et al., 2007). For example, using appropriate information technology for knowledge management systems provides more successful decision support (Baloh, 2007). The complexity level of the technology also impacts MSS effectiveness and success (Srinivasan, 1985). However, research has not looked specifically at the role of the decision environment in BI success. It is important to do so because although it is an MSS, BI has requirements that are significantly different from those of other MSS (Wixom and Watson, 2001).

The purpose of this dissertation is to help fill this gap in BI research by examining how BI capabilities impact BI success and how the decision environment influences this relationship. The decision environment is composed of the types of decisions made in the organization and the information processing needs of the decision maker (Galbraith, 1977; Beach and Mitchell, 1978; Eisenhardt, 1989). BI capabilities include both organizational and technological capabilities (Feeney and Willcocks, 1998; Bharadwaj et al., 1999). Figure 1 provides a high level overview to help orient the reader to the model this dissertation addresses.

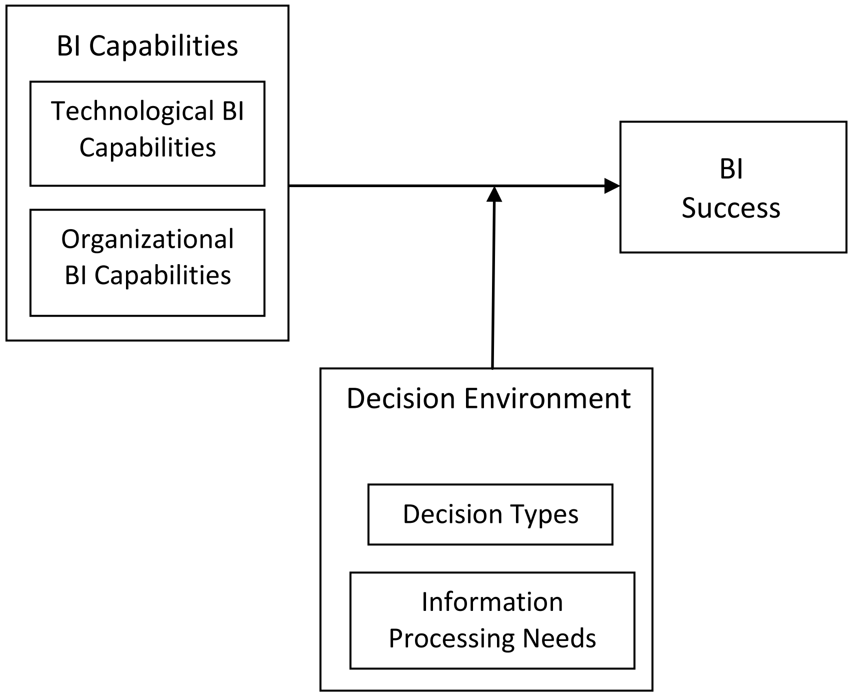

Figure 1. High level overview of the model.

The following sections review the literature for each construct of the model provided above. After BI success, discussions on the decision environment and BI capabilities follow.

BI Success

BI success is the positive value an organization obtains from its BI investment (Wells, 2003). The organizations that have BI also have a competitive advantage, but how an organization defines BI success depends on what benefits that organization needs from its BI initiative (Miller, 2007). BI success may represent attainment of benefits such as improved profitability (Eckerson, 2003), reduced costs (Pirttimaki et al., 2006), and improved efficiency (Wells, 2003). For the purpose of this dissertation, BI success is defined as the positive benefits organizations achieve through use of their BI.

Most organizations struggle to measure BI success. Some of them want to see tangible benefits, so they use explicit measures such as return on investment (ROI) (Howson, 2006). BI success can also be measured with the improvement in the operational efficiency or profitability of the organization (Vitt et al., 2002; Eckerson, 2003). If the "costs are reasonable in relation to the benefits accruing" (Pirttimaki et al., 2006, p. 83), then organizations may conclude that their BI is successful. Other companies are interested in measuring intangible benefits; these include whether users perceive the BI as mission critical, how much stakeholders support BI and the percentage of active users (Howson, 2006). Specific BI success measures differ across organizations and even across BI instances within an organization. For example, one firm may implement to achieve better management of its supply chain, while another may implement to achieve better customer service.

Research, however, does consistently point to at least one high level commonality among successful BI implementations. Organizations that have achieved success with their BI implementations have created a strategic approach to BI to help ensure that their BI is consistent with corporate business objectives (Eckerson, 2003; Watson et al., 2002; McMurchy, 2008). How Continental Airlines improved its processes and profitability through successful implementation and use of BI is a good example of aligning BI with business needs (Watson et al., 2006). Cardinal Health Care is also a good example of the importance of BI and business alignment because this organization has shaped its BI according to its business requirements (Malone, 2005).

Research provides valuable insight into how to align BI with business objectives and offers explanations for failures to do so (Eckerson, 2003; McMurchy, 2008). However, much of this research is derived from a small number of cases and/or it is not strongly grounded in theory (e.g., Cody et al., 2002; Watson, 2005). Other research provides a solid theoretical foundation for examining BI success, yet provides limited empirical evidence (e.g., Gessner and Volonino, 2005; Clark et al., 2007). Research that provides a sound theoretical background as well as empirical evidence focuses on specific technologies of BI, such as data warehousing (e.g., Cooper et al., 2000; Nelson et al., 2005) or web BI (e.g., Srivastava and Cooley, 2003; Chung et al., 2004), rather than a more holistic model.

Finally, although research suggests several success models for MSS (Forgionne and Kohli, 1995; Gelderman, 2002; Clark et al., 2007; Hartono et al., 2007), there is little theory-based research solely focusing on understanding BI success from the perspective of BI capabilities and the influence of the decision environment in which the BI is used. DSS and its success factors, for example, have been studied comprehensively in the literature (e.g., Sanders and Courtney, 1985; Guimaraes et al., 1992; Finlay and Forghani, 1998; Alter, 2003; Hung et al., 2007). KMS success factors have also been widely examined using various theories from IS (e.g., Wu and Wang, 2006; Kulkarni et al., 2007; Tsai and Chen, 2007) as well as the management literature (e.g., Al-Busaidi and Olfman, 2005; Oltra, 2005). Common features among these MSS success studies is that they all suggest research models on how to increase organizational and financial benefits obtained from these systems by testing the impact of various factors such as user satisfaction (e.g., Wu and Wang, 2006), system quality (e.g., Tsai and Chen, 2007), or management support (e.g., Al-Busaidi and Olfman, 2005).

Research has identified some of the factors that influence BI success as well (Negash, 2004; Solomon, 2005; Clark et al., 2007). For example, BI usability is an important determinant of system performance and user satisfaction (Bonde and Kuckuk, 2004; Chung et al., 2005). Other important performance indicators include technology and infrastructure (Negash, 2004; Gessner and Volonino, 2005) and management support (Cooper et al., 2000; Anderson-Lehman et al., 2004). Table 2 summarizes research on factors that affect BI success.

Table 2

Concepts Examined in Research About BI Success

Success Factors	Author(s)	Key Findings
Organizational strategy	Cooper et al. (2000)	This article presents how a data warehousing technology can transform an organization by improving its performance and increasing its competitive advantage. The authors have observed the First American Cooperation changing its corporate strategy and provide lessons for managers who plan to use BI to increase competitive advantage.
	Raymond (2003)	This article provides a conceptual framework for business intelligence activities in small and medium enterprises. Authors suggest that the framework they propose can guide the design and specification of BI projects. Based on their framework, authors divide the BI project into 5 phases; including searching for strategic information that provide competitive advantage.
	Watson et al. (2004)	This article discusses how companies justify and assess data warehousing investments. They examine the approval process and post-implementation review for data warehouses. They discuss that benefits gained can be tangible or intangible; operational, informational or strategic; revenue enhancing or cost saving; and time savings or improved decision making.
Technology & Infrastructure	Wixom and Watson (2001)	This article investigates data warehousing success factors. The authors argue that a data warehouse is different from a regular IS project and various implementation factors affect data warehousing success. Findings indicate that project, organizational and technical implementation successes are positively related to data quality and system quality.
	Nelson et al. (2005)	In this article, the authors' main goal is to find out the determinants of the quality in data warehouses. Findings indicate that reliability, flexibility, accessibility and integration are significant determinants of system quality for BI tools. Also, they present that information and system quality are success factors for data warehouses.

(table continues)

Table 2 *(continued)*.

Success Factors	Author(s)	Key Findings
Technology & infrastructure	Solomon (2005)	This article gives a guideline for successful data warehouse implementation and suggestions to managers on how to avoid pitfalls and overcome challenges in enterprise-level projects. These guidelines are mostly technical-oriented, such as; ETL tool selection, data transport and data conversion methods.
Presentation & usability	Alter (2003)	Defining BI as a new umbrella term for decision support, Alter suggests that structure of business processes, participants, technology, information quality, availability and presentation, product and services, infrastructure, environment and business strategy are success factors for better decision support.
	Lönnqvist and Pirttimaki (2006)	This article is a literature review that discusses various methods used for measuring business intelligence. Among the reasons to measure BI is to show that it is worth the investment. It also helps manage the BI process by ensuring that BI products satisfy the users' needs and the process is efficient. They use total cost of ownership and subjective measurements of effectiveness as examples of BI measures.
Management support	Eckerson (2003)	Based on a TDWI survey, this article provides an overview of BI concepts and components and also examines the key success factors of BI. One of these factors emphasizes the top management commitment and mentions that it is the commitment and support from the business sponsors and managers that drives an organization's BI initiative and furthers its strategic objectives.
	McMurchy (2008)	This article identifies several factors for success in developing BI business cases. His key findings indicate that organizations need to tie BI strategy to overall strategy, sustain top management support and user enthusiasm to maximizing the ROI on their BI.
Performance measures	Watson et al. (2001)	This article assesses the benefits of the data warehousing and provided a taxonomy. They group benefits as easy and hard to measure as one dimension, and their impact being local and global as the other dimension. An interesting result of this study shows that there is an inverse relationship between the expected and received benefits, and the potential impact of the benefits.

(table continues)

Table 2 *(continued)*.

Success Factors	Author(s)	Key Findings
Performance measures	Gessner and Volonino (2005)	This article discusses how right timing can improve ROI on BI, specifically for marketing applications. They argue that, if BI process does not increase the customer value, it would only increase the expenses. They measure BI success through ROI, and examine the change in ROI by maximizing Customer Lifetime Value (CLV), where the change in CLV is the link between technology infrastructure investments and profits.
	Pirttimaki et al. (2006)	This article discusses available measurement methods for BI. Since there is not enough measure available for the BI process; business performance measurement literature can be used as a reference for this purpose. They suggest a measurement system that can be used as a tool to develop and improve BI activities.
Information & decision quality	Dennis et al. (2001)	This article develops a model for interpreting Group Support Systems effects on performance, and they test the fit between the task and the GSS structures selected for use. The findings indicate the importance of information and decision quality on performance.
	Clark et al. (2007)	This article proposes a conceptual model for MSS. Mainly from the IS success literature, 20 variables are selected and formed the basis of the model. Some of them that are; perceived MSS benefits, management decision quality, usability of MSS, MSS costs, MSS functionality, MSS training, and MSS quality.
Structure of business processes	Yoon et al. (1995)	The goal of this article is to identify and empirically test the determinants of Expert Systems success. The authors have come up with 8 major success determinants, and measured the relationship between them and user satisfaction; problem characteristics, developer skill, end-user characteristics, impact on job, expert characteristics, shell characteristics, user involvement and manager support.
	Watson et al. (2002)	This article investigates why some organizations receive more benefits from data warehousing. It presents a framework that shows how data warehouses can transform an organization through time savings for both data suppliers and users, more and better information, better decisions, improvement of business processes and support for the accomplishment of strategic business objectives.

Common characteristics of successful BI solutions are business sponsors who are highly committed and actively involved; business users and the BI technical team working together; BI being viewed as an enterprise resource and given enough funding to ensure long-term growth; static and interactive online views of data being provided to the users; an experienced BI team assisted by vendor and independent consultants; and, organizational culture reinforcing the BI solution (Eckerson, 2003; Howson, 2006). Fit between BI strategy and business objectives, commitment from top management with long-term funding, and a realistic BI strategy with expected benefits and key metrics are also important characteristics of a successful BI (McMurchy, 2008). In addition, sound infrastructure and appropriate technology are characteristics of a successful BI (Solomon, 2005; Lönnqvist and Pirttimaki, 2006).

To succeed, organizations must develop their own measures for BI success (Howson, 2006) because BI success can have more than one meaning depending on the context in which it is being used. The following section reviews measures of BI success.

Measuring BI Success

BI success can be measured by an increase in an organization's profits (Williams and Williams, 2007) or enhancement to competitive advantage (Herring, 1996). Return on investment (ROI), however, is the most frequently used measure of BI success (McKnight, 2004). For example, Gessner and Volonino (2005) use ROI to measure BI success for marketing applications. They argue that if BI does not increase customer value, it only increases expenses and therefore does not produce an adequate ROI. ROI is also used in approving and assessing data warehouses (Watson et al., 2001; Watson et al., 2004). ROI, however, is often difficult to measure (Watson et al., 2004). Thus, revenue enhancement, time savings, cost savings, cost avoidance and value contribution are variables that are also used to measure BI effectiveness in addition to ROI (Herring, 1996, Sawka, 2000).

The Competitive Intelligence Measurement Model (CIMM) has been suggested as an alternative approach to ROI to measure BI success (Davison, 2001). This model calculates the return on BI investment by considering completion of objectives, satisfaction of decision makers, and the costs associated with the project (Lonnqvist and Pirttimaki, 2006).The suitability of the technology, whether business users like the BI, and how satisfied business sponsors are with BI are other measures used to assess BI success (Moss and Atre, 2003; Lonnqvist and Pirttimaki, 2006).

Another approach to measure BI success is subjective measurement (Lonnqvist and Pirttimaki, 2006). This involves measuring the satisfaction of the decision maker with BI by asking questions regarding the effectiveness of the BI (Davison, 2001). This way, it is possible to learn what users think of various aspects of the system, such as ease of use, timeliness, and usefulness. With this method, it is also possible to understand the perceptions of the extent to which the users realized their expected benefits with BI.

This dissertation employs the subjective measurement method to measure BI success. Many of the commonly used success measures mentioned above require that quantitative data, such as ROI, be collected from various operations of the organization. In many cases it is difficult, if not impossible, to measure the necessary constructs (Kemppila and Lonnqvist, 2003). For example, many benefits provided by BI are intangible and non-financial, such as improved quality and timeliness of information (Hannula and Pirttimaki, 2003). Although it may transfer into financial benefits in the form of cost savings or profit increase, the time lag between the actual production of intelligence and financial gain makes it difficult to measure the benefits (Lonnqvist and Pirttimaki, 2006). Also, using subjective measurement based on the satisfaction of the decision makers and their perception of the extent to which they realized their expected benefits with BI shows how effective the BI is considered by its users (Davison, 2001; Lonnqvist and Pirttimaki, 2006). As suggested by the CIMM model, measuring user satisfaction regarding timeliness, relevancy and quality of the information provided by the BI also gives insight regarding how successful the BI is (Lonnqvist and Pirttimaki, 2006).

Relationship between BI Capabilities and the Decision Environment

This dissertation posits that a key antecedent of BI success is having the right BI capabilities, and right BI capabilities depend on the decision environment in which the BI is used. The match between the decision environment and what an MSS provides has been studied as an indicator of success, and is widely recognized as an organizational requirement (Arnott, 2004; Clark et al., 2007).

This has also been examined as the match between MSS and the problem space within which it is implemented (Clark et al., 2007). This match is defined as "how closely the designed MSS reflects the goals of the organization in decision outcomes" (Clark et al., 2007, p. 586). Complexity of the decisions that organizations face every day impacts the level of this match (Clark et al., 2007). MSS are developed to address a variety of decisions and MSS effectiveness is a direct outcome of how well these decisions are supported (Gessner and Volonino, 2005). For example, various BI applications are developed to help organizations decide on the best time to present offers to customers, and the effectiveness of BI is judged according to the effectiveness of these decisions (Gessner and Volonino, 2005). Thus, understanding how the decision environment affects the impact of BI capabilities is useful and important.

Organizational structure and strategy are two significant components of the decision environment of an organization (Duncan, 1974). The appropriateness of an MSS to an organization's structure and strategy is a significant factor that impacts MSS success (Cooper and Zmud, 1990; Hong and Kim, 2002; Setia et al., 2008). For example, Setia et al.'s (2008) findings indicate that supply chain systems provide enhanced agility if there is a strategy and task fit between supply chain systems and the organizational elements. As the match between MSS and organizational structure increases, the performance of the organization improves (Weil and Olson, 1989). The strategic alignment model developed by Henderson and Venkatraman (1993) suggests that the fit among business strategy, organizational structure and technology infrastructure increases the ability to obtain value from IS investments.

As can be seen from the examples above, research examines how MSS capabilities moderated by the decision environment impacts MSS success. However, this concept has not been used specifically to examine BI success. Focusing on the decision environment and BI capabilities, this dissertation examines the effect of the BI capabilities on BI success, moderated by the decision environment.

Decision Environment

The decision environment can be defined as "the totality of physical and social factors that are taken directly into consideration in the decision-making behavior of individuals in the organization" (Duncan, 1974, p. 314). This definition considers both internal and external factors. Internal factors include people, functional units and organization factors (Duncan, 1974). External factors include customers, suppliers, competitors, sociopolitical issues and technological issues (Duncan, 1974; Power, 2002).

Decision types are a part of the decision environment because the extent to which decisions within the decision environment are structured or unstructured influences the performance of the analytical methods used for decision making (Munro and Davis, 1977). The types of decisions supported by the decision environment should be considered in selecting techniques for determining information requirements for that decision (Munro and Davis, 1977).

The information processing needs of the decision maker are also a part of the decision environment, provided that decision making involves processing and applying information gathered (Zack, 2007). Because appropriate information depends on the characteristics of the decision making context (Zack, 2007), it is hard to separate the information processing needs from decision making. This indicates that information processing needs are also a part of the decision environment.

Information processing and decision making are the central functions of organizations. They are topics of interest in research and have been discussed from both technical and managerial perspectives (Soelberg, 1967; Galbraith, 1977; Tushman and Nadler, 1978; Saaty and Kearns, 1985). According to the behavioral theory of the firm, decision making in organizations is a reflection of people's limited ability to process information (Galbraith, 1977). Contradictory to this, the operations research/management science perspective argues that decision making can be improved by rationalizing the process, formulating the decision problem as a mathematical problem, and testing alternatives on the model before actually applying one to a real world problem (Galbraith, 1977). This approach opened the way for computer applications and information technology that support decision making processes. With the great information processing power of computers, information systems such as MSS were developed.

IS research has used various information processing theories to explain the impact of information processing on organizational performance, but organizational information processing theory is one of the most frequently used theories (Premkumar et al., 2005; Fairbank et al., 2006). The following section provides an overview of organizational information processing theory including definition, constructs and its use in IS research.

Organizational Information Processing Theory

Organizational Information Processing (OIP) theory emerged as a result of an increasing understanding among organizational researchers that information is possibly the most important element of today's organizations (Fairbank et al., 2006). The first researcher that proposed this theory was Galbraith (1973). He suggested that specific structural characteristics and behaviors can be associated with information requirements, and various empirical studies have found support for his propositions (Tushman and Nadler, 1978; Daft and Lengel, 1986; Karimi et al., 2004).

In OIP theory, organizations are structured around information. The relationship between information and how it is used is a direct antecedent of organizational performance. OIP focuses on information processing needs, information processing capability, and the fit between them to obtain the best possible performance in an organization (Premkumar et al., 2005). In this context, information processing is defined as the "gathering, interpreting, and synthesis of information in the context of organizational decision making” (Tushman and Nadler, 1978, p. 614), and information processing needs are the means to reduce uncertainty and equivocality (Daft and Lengel, 1986).

OIP theory assumes that organizations are open social systems that deal with work-related uncertainty (Tushman and Nadler, 1978) and equivocality (Daft and Macintosh, 1981). Uncertainty is the difference between information acquired and information needed to complete a task (Galbraith, 1973; Tushman and Nadler, 1978; Premkumar et al., 2005). Task characteristics, task environment and task interdependence are among the sources of uncertainty (Tushman and Nadler, 1978). Equivocality can be defined as multiple and conflicting interpretations about an organizational situation (Daft and Macintosh, 1981; Daft and Lengel, 1986). It refers to an unclear situation where new and/or more data may not be enough to clarify (Daft and Lengel, 1986).

One reason why organizations process information is to reduce uncertainty and equivocality (Daft and Lengel, 1986). Organizations that face uncertainty must acquire more information to learn more about their environment (Daft and Lengel, 1986). When tasks are non-routine or highly complex, uncertainty is high; hence, information processing requirements are greater for effective performance (Daft and Macintosh, 1981). Equivocality is very similar to uncertainty. However, rather than lack of information, it is associated with lack of understanding (Daft and Lengel, 1986). In other words, a decision maker may process the required data, but not clearly understand what it means or how to use it. For example, a problem may be perceived differently by managers from different functional departments in an organization; an accounting manager may interpret some specific information different than a system analyst. Both uncertainty and equivocality impact information processing in an organization and should be minimized to achieve performance (Daft and Lengel, 1986; Keller, 1994).

OIP theory has important implications for organizational design because different organizational structures are more effective in different situations (Tushman and Nadler, 1978; Daft and Lengel, 1986). Specifically, the degree of uncertainty and equivocality may imply how organizational structure should be designed (Daft and Lengel, 1986; Lewis, 2004). Here, organizational structure is defined as the “allocation of tasks and responsibilities to individuals and groups within the organization, and the design of systems to ensure effective communication and integration of effort” (Daft and Lengel, 1986, p. 559). Thus, it is important for organizations to have a structure that fits their uncertainty and equivocality levels, so that they can perform well.

Organizations must develop information processing systems capable of dealing with uncertainty (Zaltman et al., 1973). IS provides a way of managing uncertainty and equivocality in organizations (Daft and Lengel, 1986; Keller, 1994; Premkumar et al., 2005). Various researchers have studied how IS impacts uncertainty and equivocality (Tushman and Nadler, 1978; Jarvenpaa and Ives, 1993; Premkumar et al., 2005), and also how this affects organizational effectiveness (Tuggle and Gerwin, 1980; Wang, 2003).

Several IS studies use OIP as the central theory in their models to explain how to obtain effectiveness in organizations through the use of information technologies (Galbraith, 1977; Tushman and Nadler, 1978; Daft and Lengel, 1986). For example, Premkumar et al. (2005) suggest that the fit between information processing needs and information processing capabilities has a significant impact on organizational performance. The fit between organizational structure and information technology is an important contributor to organizational effectiveness as well (Sauer and Willcocks, 2003). Table 3 provides examples from IS research that have used OIP theory.

Table 3

Examples of Organizational Information Processing Theory in Information Systems

Concept	Author(s)	Key Findings
IS Fit	Jarvenpaa and Ives (1993)	This study examines various organizational designs for IS in globally competing organizations. Findings show that there are inconsistencies among how the organizations are structured and how they manage their IS capabilities, revealing that there is a lack of fit between organizational environment and IT.
	Premkumar et al. (2005)	This study examines the fit between information processing needs and information processing capability in a supply chain context and examines its effect on performance. Findings indicate that the fit of information needs and IS capability has a significant impact on performance.
	Stock and Tatikonda (2008)	This study suggests a conceptual model on the fit of IS adopted from an external source. Authors base their arguments on organizational information processing theory and their findings show that the fit between IS and information processing requirements affect IS effectiveness.
IS Design & Development	Tatikonda and Rosenthal (2000)	Using information processing theory, this paper examines the relationship between product development project characteristics and project outcomes. Results show that technology novelty and project complexity characteristics contribute to project task uncertainty, which impacts project execution outcomes.
	Jain et al. (2003)	This study suggests that when compared to the traditional approach, component-based software development (CBSD) improves the requirements identification process. They use the information processing theory to show how CBSD could facilitate the identification of user requirements.

(table continues)

Table 3 *(continued)*.

Concept	Author(s)	Key Findings
IS Architecture & Management	Anandarajan and Arinze (1998)	This study uses information processing theory to examine the match between an organization's information processing requirements and its client/server architectures, and its impact on effectiveness. The results indicate that a fit between task characteristics and architectures directly affects system effectiveness.
	Douglas (1998)	This study examines the fit between organizational structures and information processing needs, specifically in the health care industry. Findings suggest that vertical and horizontal information systems offer the best opportunity for information processing capability.
	Cooper and Wolfe (2005)	This study uses information processing theory to examine the IS adaptation process in organizations. Authors suggest that the fit between information processing volume and, uncertainty and equivocality reduction contributes to successful IS adaptation.
Organizational Performance	Tuggle and Gerwin (1980)	This study suggests a simulation model that integrates the processes of key environmental factors, strategy formulation by the organization, routine operating decision executions and standard operating procedures. Findings suggest that uncertainty and sensitivity to changes impacts organizational effectiveness negatively.
	Fairbank et al. (2006)	This study examines the relationship between IS and organizational performance in the health insurance industry. Authors examine how IS is deployed in organizations through information processing design choices. Results show that information processing design choices are generally related to organizational performance.
IS Costs & Benefits	Tatikonda and Montoya Weiss (2001)	This study examines relationships among organizational process factors, product development capabilities, critical uncertainties, and operational/market performance in product development projects. The findings show that the organizational process factors are associated with achievement of operational outcome targets for product quality, unit-cost and time-to-market.
	Gattiker and Goodhue (2004)	Using organizational information processing theory, this study suggests factors that influence enterprise resource planning (ERP) costs and benefits. The organizational characteristics they focus on are interdependence and differentiation. While high interdependence among organizational units is found to be contributing to the positive ERP effects, high differentiation seems to increase costs.

Although there is IS research using OIP theory to explain various phenomena, there is very little research focusing on BI through the lens of OIP theory. BI is an information processing mechanism that allows each user to process, analyze, and share information and to turn it into useful knowledge (Hannula and Pirttimaki, 2003), thus it seems important to study BI from OIP perspective.

In the BI context, the extent of information processing is a direct result of BI capabilities (both technological and organizational). Employing the right capabilities for information processing is an important issue for effective decision making and organizational performance (Daft and Lengel, 1986; Fairbank et al., 2006), hence it is important to understand the dynamics of information processing for BI.

Processing information allows organizations to develop a more effective decision making process and an acceptable level of performance. Decision making is a key part of managers' jobs because it involves taking actions on behalf of their organization, and the managers are evaluated based on the effectiveness of their decisions (Simon, 1960; Power, 2002). Thus, it is important to understand the underlying decision making mechanism, and how decisions differ based on their characteristics. The next section provides a literature review of the second component of the decision environment; decision types made in the organization.

Decision Types

Decisions types are different problems that are distinguished based on who needs to make the decision and the steps the decision maker needs to follow to solve the problem (Power, 2002). A problem is a structured decision if it is repetitive and routine, and it is unstructured if there is no fixed method of handling it and the decision is consequential (Simon, 1960). Any other type of problem that falls between these two types is a semi-structured decision (Keen and Scott Morton, 1978).

Simon’s framework distinguishes between different types of decisions based on different techniques that are required to handle them (Simon, 1965; Gorry and Scott Morton, 1971; Adam et al., 1998). For example, while structured decisions are mostly made with standard operating procedures using well-defined organizational channels, unstructured decisions require judgment, creativity and training of executives (Simon, 1965; Kirs et al., 1989). Semistructured decisions fall in between these two and require managerial judgment as well as the support system (Keen and Scott Morton, 1978; Teng and Calhoun, 1996). Structured decisions can largely be automated therefore do not involve a decision maker. Unstructured decisions require judgment; hence the involvement of a decision maker at all times (Gorry and Scott Morton, 1971; Teng and Calhoun, 1996).

Another categorization of decision making activities was suggested by Anthony (1965). To categorize managerial activities according to their decision-making requirements, Anthony (1965) developed a framework of decision types, associating decisions with organizational levels. This framework includes three categories; strategic planning, management control, and operational control. The *strategic planning* category involves decisions related to long term plans, strategic plans and policies that may change direction of the organization (Anthony, 1965; Shim et al., 2002). This typically involves senior managers and analysts because the problems are highly complex, nonroutine, and require creativity (Gorry and Scott Morton, 1971). Anthony defines strategic planning as “the process of deciding on objectives of the organization, on changes in these objectives, on the resources used to attain these objectives, and on the policies that are to govern the acquisition, use, and disposition of these resources" (p. 24). Introducing a new product line can be given as an example of a decision in this category.

In Anthony's (1965) framework, the *management control* category includes both planning and control, involves making decisions about what to do in the future based on the guidelines established in the strategic planning (Otley et al., 1995; Shim et al., 2002). Anthony defines management control as "the process by which managers assure that resources are obtained and used effectively and efficiently in the accomplishment of the organization's objectives" (p. 27). For instance, planning upon next year's budget is an example of a management control activity. The *operational control* category involves decisions related to operational control, which is "the process of assuring that specific tasks are carried out effectively and efficiently" (Anthony, 1965, p. 69). Here, individual tasks and transactions are considered, such as a sales order or inventory procurement.

The boundaries between Anthony's three categories are not always clear. There can be overlaps between them, forming a continuum between highly complex activities and routine activities (Anthony, 1965; Gorry and Scott Morton, 1971; Shim et al., 2002). When information requirements of Anthony's (1965) three managerial activities are considered, it can be seen that they are very different from one another. This difference is attributable to the fundamental characteristics of the information needs at different managerial levels (Gorry and Scott Morton, 1971). Thus, Anthony's (1965) framework also represents different information processing needs of the decision makers at different management levels (Gorry and Scott Morton, 1971).

Similar to Anthony's (1965) classification, Simon's (1965) classification of business decisions as structured and unstructured also form a continuum between these two types of decisions. Simon (1960) classifies decisions based on the ways used to handle them, and Anthony's (1965) categorization is based on the purpose and requirements of the managerial activity that involves the decision (Shim et al., 2002). Gorry and Scott Morton (1971) combine these two views and suggest a broader framework for decision support for managerial activities. A table representation of this framework as adapted from Gorry and Scott Morton (1971) is shown in Table 4.

The framework that results from the combination of Anthony's (1965) and Simon's (1960) frameworks includes nine categories. Cell (1), the *structured operational control*, involves decisions like inventory reordering which can be done through a computer-based system without requiring any judgment. Decisions in cells (2) and (3) differ from cell (1) on the level of system support they require. For example, while bond trading is an example of semistructured operational control, cash management is an unstructured operational control decision (Gorry and Scott Morton, 1971). In a similar fashion, while the degree of automatization reduces from cell (4) to cell (6), the decisions involved in management control are at the tactical level rather than the operational level. Examples of cells (4), (5) and (6) are budget analysis, variance analysis, and hiring new managers, respectively. In strategic planning (cells 7, 8, 9), the decisions are made at the executive level. Warehouse location, mergers, and R&D planning are examples of cells (7), (8), (9) respectively.

Table 4

A Framework for Information Systems, Adapted From Gorry and Scott Morton (1971)

	Management Activity		
Decision Type	Operational Control	Management Control	Strategic Planning
Structured	(1)	(4)	(7)
Semistructured	(2)	(5)	(8)
Unstructured	(3)	(6)	(9)

Gorry and Scott Morton's (1971) framework has implications for both system design and organizational structure (Shim et al., 2002). Because information requirements differ among different types of decisions, the data collection and maintenance techniques for decision types are also different. Information differences among the three decision areas imply related differences in hardware and software requirements (Gorry and Scott Morton, 1971; Parikh et al., 2001). For example, techniques used for operational control are rarely useful for strategic planning, and the records in the operational control database may be too detailed to be used for strategic decision making (Gorry and Scott Morton, 1971).

Organizational structure related implications of this framework are that managerial and analytical skills for each type of decision are different. For example, decision makers involved in the operational control area usually have different backgrounds and training than the ones in management control. Thus, the skills and the decision making styles of managers in strategic, operational and managerial areas differ significantly (Gorry and Scott Morton, 1971; Parikh et al., 2001).

In summary, for the purposes of this dissertation, Gorry and Scott Morton's (1971; 1989) framework represents the decision environment because it categorizes both internal and external factors related to the decision-making activities in an organization (Duncan, 1974), such as the different technological requirements of different decisions and different information needs of managerial activities. This framework groups decisions according to the managerial activities with which they are associated and the methods used to handle them. Different decision types require different methods, techniques and skills to be handled. These differences lead to variations in technology infrastructure as well as organizational characteristics that best handle specific types of decisions. This dissertation argues that BI should be employed in accordance with these differences.

BI Capabilities

Adapting to today's rapidly changing business environment requires agility from organizations and BI has an important role in providing this agility with the capabilities it provides (Watson and Wixom, 2007). BI capabilities are critical functionalities of BI that help an organization improve its adaptation to change as well as improve its performance (Watson and Wixom, 2007). With the right capabilities, BI can help an organization predict changes in product demand or detect an increase in a competitor's new product market share and respond quickly by introducing a competing product (Watson and Wixom, 2007).

BI capabilities have been examined by practitioner-oriented research, especially from the BI maturity model perspective (Eckerson, 2004; Watson and Wixom, 2007). Yet, BI capabilities have remained largely unexamined in academic IS research. IS research has examined IS capabilities extensively to explain the role of IS in organizational performance and competitive advantage (Bharadwaj, 2000; Bhatt and Grover, 2005; Ray et al., 2005; Zhang and Tansuhaj, 2007). IS capabilities are the functionalities that organize and deploy IS-based resources in combination with other resources and capabilities (Bharadwaj, 2000). While some research conceptualizes IS capabilities in managerial terms (Sambamurthy and Zmud, 1992; Ross et al., 1996), other research focuses on technological capabilities (Sabherwal and Kirs, 1994; Teo and King, 1997). More recent models incorporate both managerial and technical aspects of IS (Bharadwaj, 2000; Ray et al., 2005).

Similarly, BI capabilities can be examined from both organizational and technological perspectives (Howson, 2004; Watson and Wixom, 2007). Technological BI capabilities are sharable technical platforms and databases that ideally include a well-defined technology architecture and data standards (Ross et al., 1996). Organizational BI capabilities are assets for the effective application of IS in the organization, such as the shared risks and responsibilities as well as flexibility (Ross et al., 1996; Howson, 2004). For example, while the data sources and data types used by BI are technological BI capabilities, BI flexibility and level of risk supported by BI are organizational BI capabilities (Hostmann et al., 2007).

Gartner Group's research report about the evolution of BI groups organizations into four categories based on their BI capabilities (Hostmann et al., 2007). Figure 2 shows the categories as adopted from Hostmann et al. (2007).

Based on the exponential increase of accessible information and the increasing need for skilled business users, different types of BI applications and their evolution can be characterized with two dimensions, (1) information access and analysis, and (2) decision making style (Hostmann et al., 2007). The first dimension of information access and analysis includes methods and technologies used to collect and analyze the information. The second dimension, decision style, includes the decision structure, i.e. unstructured or structured. Based on the information access and analysis methods and the types of decisions made, an organization can be characterized as the decision factory, the information buffet, the brave new world or the hypothesis explored. Which quadrant an organization belongs to in this model depends on capabilities such as the sources the data is obtained from, data types that can be analyzed, data reliability, user access in terms of authorization and/or authentication, flexibility of the system, interaction with other systems, acceptable risk level by the system, and how much intuition can be involved in the analysis process.

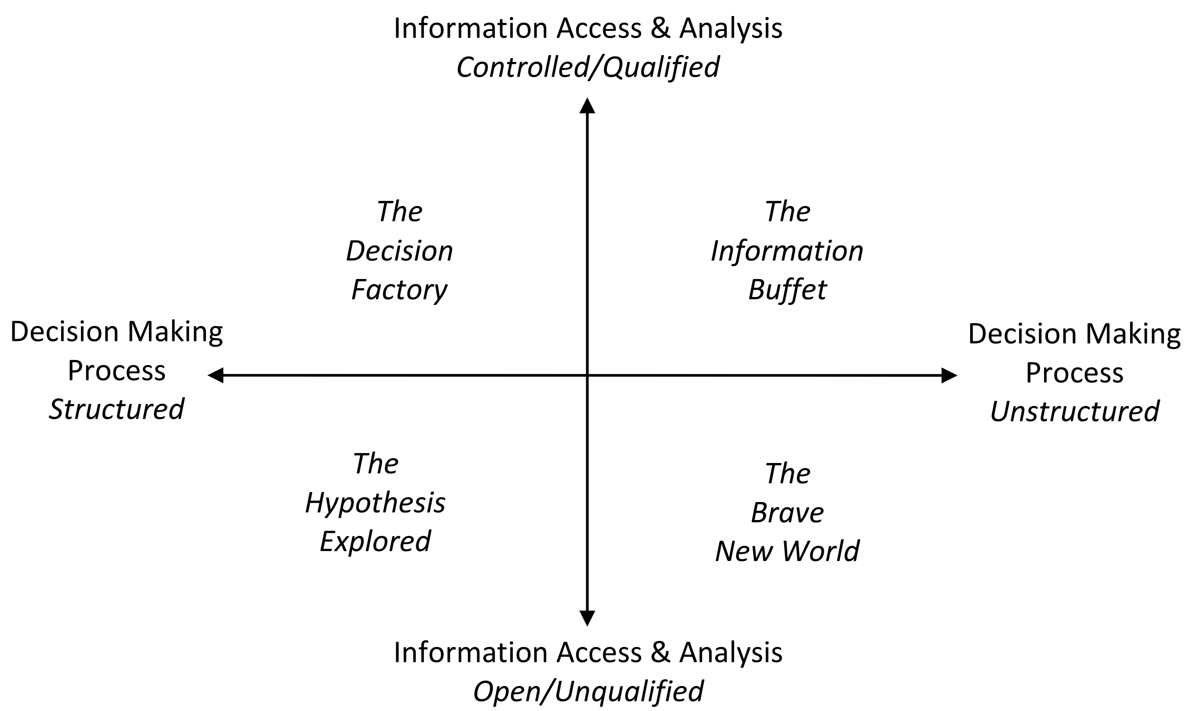

Figure 2. The four worlds of BI adopted from Hostmann et al. (2007).

As organizations take advantage of these capabilities, their BI use increases, and so does the maturity level of BI (Watson and Wixom, 2007). Mature BI increases organizational responsiveness, which positively affects organizational performance. Thus, it is important to recognize BI capabilities to better apply it to strategic needs (Ross et al., 1996).

Data Sources

A data source can be defined as the place where the data that is used for analysis resides and is retrieved (Hostmann et al., 2007). BI requires the collection of data from both internal and external sources (Harding, 2003; Kanzier, 2002). Internal data is generally integrated and managed within a traditional BI application information management infrastructure, such as a data warehouse, a data mart, or an online analytical processing (OLAP) cube (Hostmann et al., 2007). External data includes the data that organizations exchange with customers, suppliers and vendors (Kanzier, 2002). This is rarely inserted into a data warehouse. Often, external data is retrieved from web sites, spreadsheets, audio files, and video files (Kanzier, 2002).

Organizations may use internal, external, or both types of data for BI analysis purposes. For example, Unicredit built a sophisticated BI environment and created an OLAP architecture composed of data warehouse and data marts, to aggregate all the information used for analysis (Schlegel, 2007). Although they were using external data sources, the data collected from these sources were internalized first. In the case of Richmond Police Department, the BI collected crime data from untraditional data sources and used text mining to analyze that data (Hostmann et al., 2007). Other examples are pharmaceutical and medical researchers who analyze experimental data or legal information related to suspicious activities or individuals (Hostmann et al., 2007). Because of its direct connection to BI infrastructure and software characteristics, the data source is a technological capability for BI.

Data Types

Data type refers to the nature of the data; numerical or non-numerical and dimensional or non-dimensional. Numerical data is data that can be measured or identified on a numerical scale, and analyzed with statistical methods, such as measurements, percentages, and monetary values (Sukumaran and Sureka, 2006). If data is non-numerical, then it cannot be used for mathematical calculations. Non-numerical refers to data in text, image or sound format that needs to be interpreted for analysis purposes. For example, financial data is categorized as numerical data, whereas data collected from online news agencies is categorized as non-numerical data.

Dimensional data refers to data that is organized and kept within relational data structure and is a core concept for data warehouse implementations (Ferguson, 2007). Dimensional data is subject oriented (Hostmann et al., 2007). Examples are customer-centric dimensions such as product category, service area, sales channel or time period (Ferguson, 2007). Non-dimensional data refers to unorganized and unstructured data (Hostmann et al., 2007). Non-dimensional data might be obtained from a website, for example. Because BI infrastructure directly impacts the data types supported by the system, it is a technological BI capability. In this dissertation, numerical and dimensional data is referred to as quantitative data and non-numerical and non-dimensional data as qualitative data.

Interaction with Other Systems

Many organizations prefer having IS applications interacting at multiple levels so that enterprise business integration can occur (White, 2005). This integration can be at the data level, application level, business process level, or user level, yet these four levels are not isolated from each other (White, 2005). Although data integration provides a unified view of business data, application integration unifies business applications by managing the flow of events (White, 2005). User interaction integration provides a single personalized interface to the user and business process integration provides a unified view of organization's business processes (White, 2005). There are different technologies available for these integration types. For example, enterprise information integration (EII) enables applications to see dispersed data as though it resided in a single database and enterprise application integration (EAI) enables applications to communicate with each other using standard interfaces (Swaminatha, 2006).

Data integration is very important especially for organizations that collect data from multiple data sources; techniques such as EAI makes it possible to quickly and efficiently integrate heterogeneous sources (Swaminatha, 2006). These technologies also provide benefits for end users. For example, Constellation Energy Company integrated their BI system with Microsoft Excel because it was a popular application frequently used throughout the company. Since employees were using excel for data entry, they could continue using it even after the roll-out of BI. As a result of this integration, change management issues and time spent on training was reduced significantly (Briggs, 2006). Interaction with other systems is a technological BI capability because of its reliance on BI infrastructure.

User Access

Because one size does not fit all with BI, there are different BI tools with different capabilities, serving different purposes (Eckerson, 2003). Organizations may need to employ these different BI tools from different vendors because different groups of users have different reporting and analysis needs as well as different information needs (Howson, 2004). In contrast, some organizations may choose to deploy a BI that provides unlimited access to data analysis and reporting tools to all users (Havenstein, 2006). Because user access depends on BI infrastructure and application characteristics, it is a technological BI capability.

Whether the organization prefers to use best-of-breed applications or a single BI suite, matching the tool capabilities with user types is always a good strategy (Howson, 2006). While some organizations limit user access through practicing authorization/authentication and access control, others prefer to allow full access to all types of users through a web-centric approach (Hostmann et al., 2007). For example, BI tools provided by Lyzasoft Inc. is an all-in-one tool that includes integrated reporting, ad hoc query and analysis, dashboards, and connectivity to data sources as a client-side desktop application (Swoyer, 2008). On the other hand, QlikTech International developed QlikView, a web-centric BI application that provides analytical and reporting capabilities for all types of users, especially easier to use for nontechnical users (Havenstein, 2006). While web-centric systems are generally shared by large numbers of users, desktop applications are mostly dedicated to specific users (Hostmann et al., 2007).

Data Reliability

Organizations make critical decisions based on the data they collect every day, so it is vital for them to have accurate and reliable data. Yet, there is evidence that organizations of all sizes are all negatively impacted by imperfection, duplication and inaccuracy of the data they use (Damianakis, 2008). Gartner Group estimates that more than 50% of BI projects through 2007 would fail because of data quality issues and TDWI estimates that customer data quality issues alone cost U.S. businesses over $600 billion dollars a year (Graham, 2008).

Data that organizations collect from sources that are unqualified or uncontrolled also give rise to errors. For example, the data from a Web site or from spreadsheets throughout the organization contains errors that may not be caught prior to use in the BI (Hostmann et al., 2007). Data reliability may be a problem for externally sourced data because there is no control mechanism validating and integrating it; for example, getting the data from web blogs or RSS feeds. Internal data is also prone to error. Poor data handling processes, poor data maintenance procedures, and errors in the migration process from one system to another can cause poor data reliability (Fisher, 2008). If the information analyzed is not accurate or consistent, organizations cannot satisfy their customers' expectations and cannot keep up with new information-centric regulations (Parikh and Haddad, 2008). The technological capability of BI delivering accurate, consistent and timely information across its users can enable the organization improve its business agility (Parikh and Haddad, 2008).

Risk Level

Risk can be defined as making decisions when all the facts are not known (Harding, 2003). Risk and uncertainty exist in every business decision; some organizations use BI to minimize uncertainty and make better decisions. Thus this is an organizational BI capability. For risk-taking organizations, the decisions supported by the BI are entrepreneurial and motivated by exploration and discovery of new opportunities as well as new risks (Hostmann et al., 2007). Typically, innovative organizations tolerate high levels of risk but organizations that have specific and well-defined problems to solve have a low tolerance for risk (Hostmann et al., 2007).

People, processes, technology and even external events can cause risks for an organization (Imhoff, 2005). The capabilities of the BI impact how successfully the organization manages risk. BI can help the organization manage risk by monitoring the financial and operational health of the organization and by regulating the operations of the organization through key performance indicators (KPIs), alerts and dashboards (Imhoff, 2005). For example, the Richmond Police Department deployed a number of analytical and predictive tools to determine likely areas of criminal activity in Virginia, so that officers could take action early to prevent crimes, rather than respond to criminal activity after it happened. Other than analytical and predictive tools, modeling and simulation techniques also enable companies make decisions that balance risk and obtain higher value (Business Wire, 2007).

Flexibility

An IS needs to be flexible in order to be effective (Applegate et al., 1999). Flexibility can be defined as the capability of an IS to “accommodate a certain amount of variation regarding the requirements of the supported business process” (Gebauer and Schober, 2006, p. 123). The amount of flexibility directly impacts the success of an IS; while insufficient flexibility may prevent the IS use for certain situations, too much flexibility may increase complexity and reduce usability (Silver, 1991; Gebauer and Schober, 2006).

To achieve competitive advantages provided by BI, organizations need to select the underlying technology to support the BI operations carefully (Dreyer, 2006), and flexibility is one of the important factors to consider. Ideally, the system must be compatible with existing tools and applications to minimize cost and complexity to the organization (Dreyer, 2006). The strictness of business process rules and regulations supported by the BI directly impacts the flexibility of BI. If there are strict sets of policies and rules embedded in the applications, then BI has relatively low flexibility, because as the regulations get stricter, dealing with exceptions and urgencies gets harder. Technology does not always support exceptional situations although organizations need the flexibility and robust functionality to obtain the optimum potential from BI (Antebi, 2007). Because flexibility is a direct result of organizational rules and regulations, it is an organizational BI capability (Martinich, 2002).

For example, Richmond Police Department in Virginia, United States, deployed a BI system to help them organize their fight against crime, and find out areas that criminal activity is likely to occur (Hostmann et al., 2007). They used a wide variety of non-traditional data sources rather than a single and traditional one such as a data warehouse, and analyzed that collected data with different types of analytical tools. Through the flexibility of data sources and data analysis methods, they were able to reduce the crime rate significantly and became proactive in deterring crime (Hostmann et al., 2007).

Intuition Involved in Analysis

Intuition, in the context of analysis, can be described as rapid decision making with a low level of cognitive control and high confidence in the recommendation (Gonzales, 2005). Although BI has improved significantly with the developing technology, its core processes have rarely changed. People use their intuition to manage their businesses whether they have a technology accompanying it or not (Harding, 2003). Thus, intuition is an organizational BI capability. Research, however, suggests that intuition by itself is not enough to competitively run a business in today’s business world (Gonzales, 2005). Making decisions based on facts and numbers as opposed to decision making based on gut feelings has become a suggested approach for more successful BI applications and improved enterprise agility (Watson and Wixom, 2007). On the opposite side to intuition is using the analytic process for decision making; it is slower, requires a high level of cognitive control, and the recommended solution is often chosen with a low level of confidence (Gonzales, 2005).

Although most of the applications using BI do not involve intuition at all in their analysis (Hostmann et al., 2007), using intuition has not been totally drawn out of the BI scene. Technology can monitor events, provide notifications and run predictive analysis, even automate a response in straightforward cases, but for the decisions requiring human thought intuition is still required (Bell, 2007). For example, the City of Richmond Police Department's use of BI to predict crimes is a good example how BI can also help officers and other field personnel compare their expectations and intuitions against actual demographic trends (Swoyer, 2008). With the help of BI, the police department covers areas that are likely to have high crime while empowering the officers to include their instincts to figure out what actually in happening at the location (Swoyer, 2008). There are other organizations that do not involve intuition in the decision making process as much as in the case of Richmond Police Department, but rather use it only for executive level decision making.

In summary, BI provides both technological and organizational capabilities to organizations. These capabilities impact the way organization processes information and the performance of the organization (Bharadwaj, 2000; Ray et al., 2005; Zhang and Tansuhaj, 2007). Thus, it is imperative that these capabilities should match the decision environment. Table 5 summarizes the above mentioned BI capabilities and their levels associated with the four quadrants of BI worlds.

Table 5

BI Capabilities and Their Levels Associated with the Four BI Worlds, Adapted From Hostmann et al. (2007)

	The Decision Factory	*The Information Buffet*	*The Brave New World*	*The Hypothesis Explored*
Data Source	Internal	Internal	Mostly external	Mostly external
Data Type	quantitative	Both	qualitative	Both
Data Reliability	System	System and Individual	Individual	System
Flexibility	Low	High	High	Low
Intuition Involved in Analysis	None	Sometimes	Always	Always
Interaction with Other Systems	Low	High	High	High
Risk Level	Low	Low	High	High
User Access	Web-centric	Specific	Web-centric	Specific

Research Model and Hypotheses

Although BI success is widely addressed, there are still many inconsistencies in findings about achieving success with BI. This is partly because one size does not fit all. Therefore, this dissertation suggests that examining BI from a capabilities perspective, considering the presence of different decision environments may provide better guidance on achieving BI success. This study suggests that organizations should be aware of their needs based on their decision environments and tailor BI solutions accordingly. Specifically, this dissertation argues that as long as BI capabilities that fit the decision environment are in place, the BI initiative will be successful. Below Figure 3 provides the conceptual model.

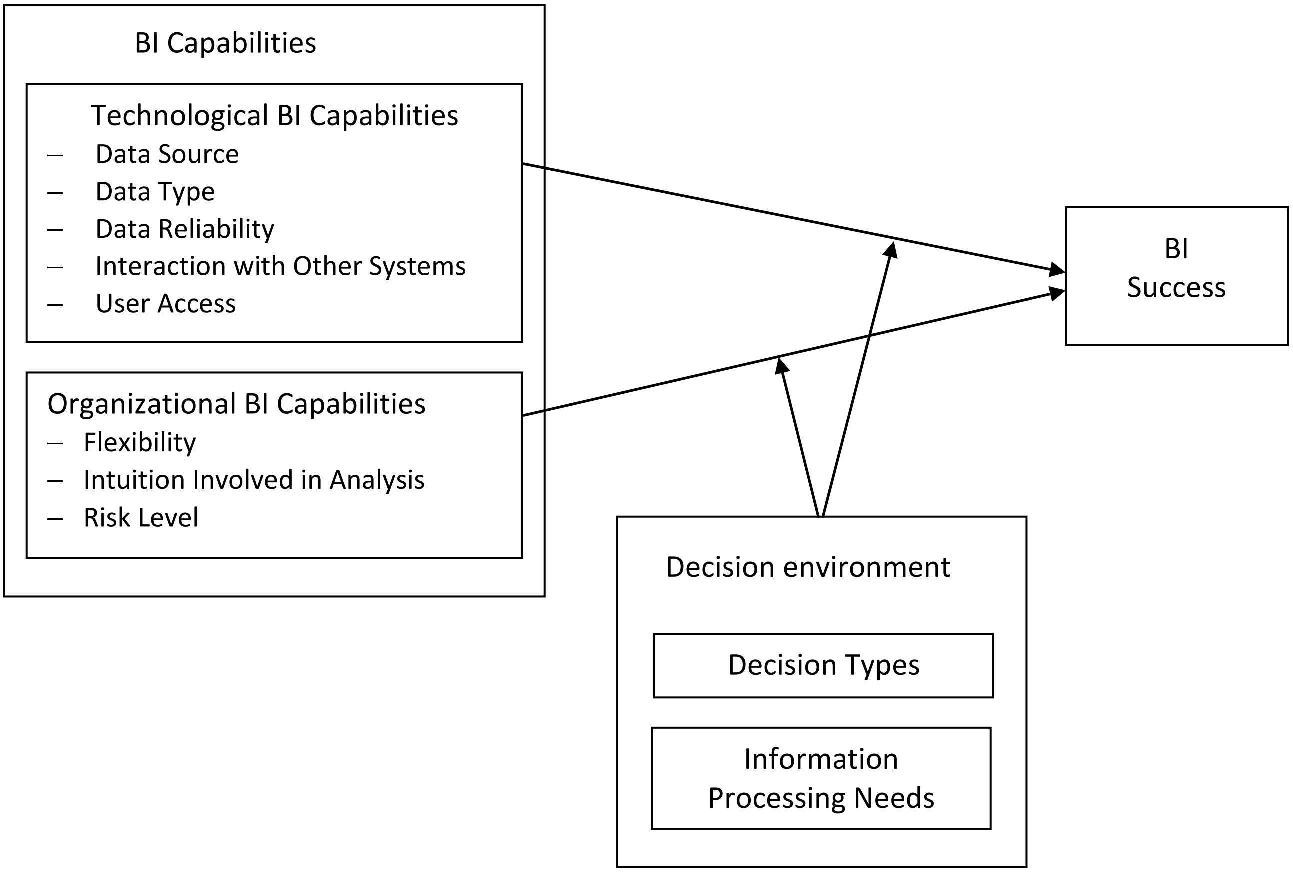

Figure 3. Conceptual model.

The amount of information available to users increases exponentially and it is not possible to examine every piece of information to sort out what is useful or not (Clark et al., 2007). Thus, identifying the appropriate information for the decision environment in a timely manner is critical (Chung et al., 2005; Clark et al., 2007). Information system is a key concept in identifying useful information (Eckerson, 2003; Clark et al., 2007). But, if IS is employed in the organization just for the sake of using technology, and its capabilities do not match the decision environment, then success may be limited (Clark et al., 2007).

Research suggests that a lack of fit between an organization and its BI is one of the reasons for lack of success (Watson et al., 2002; Watson et al., 2006; Eckerson, 2006). It is not only appropriate but necessary to examine the relationship between BI capabilities and BI success, and how this relationship is affected by different decision environments. BI capabilities include technological capabilities as well as organizational capabilities (Feeney and Willcocks, 1998; Bharadwaj et al., 1999). Technological capabilities are important success factors for any IS (Watson and Wixom, 2007). Research shows that having a well-defined technology architecture and data standards positively affect IS success (Ross et al., 1996). This is also true for BI; having an effective infrastructure, reliable and high quality data, as well as pervasiveness are important factors that influence BI maturity and success (Watson and Wixom, 2007). The quality of technological BI capabilities in an organization has a positive influence on its BI success.

Technological BI capabilities studied in this dissertation are data sources used to obtain data for BI, data types used with BI, reliability of the data, interaction of BI with other systems used in the organization, and BI user access methods supported by the organization. Although these capabilities are present in every BI, their quality differs from organization to organization (Hostmann et al., 2007). The difference in the quality of these capabilities is one of the factors that may explain why some organizations are successful with their BI initiative while some are not. For example, clean and relevant data is one of the most important BI success factors (Eckerson, 2003; Howson, 2006). Organizations that have earned awards due to successful BI initiatives, such as Allstate insurance company and 1-800-Contacts retailer, pay critical attention to the sources from which they obtain their data, the type of data they use, and the reliability of their data by acting early during their BI initiative and dedicating a working group to data related issues (Howson, 2006).

The quality of interaction of BI with other systems in the organization is another critical factor for BI success (White, 2005). For organizations that use data from multiple sources and feed the data to multiple information systems, the quality of communication between these systems directly affects the overall performance (Swaminatha, 2006). Likewise, BI user access methods are critical for BI success. Because organizations have multiple purposes and user groups with BI, they may employ different BI applications with different access methods (Howson, 2004). While most of the web-centric applications are relatively easier to use, especially for non-technical users, desktop applications are mostly dedicated to specific users and provide specialized functionalities for more effective analysis (Hostmann et al., 2007). Thus, the former may increase BI success with faster analysis, while the latter may increase it with more effective decision making. Based on the above discussions, the following are hypothesized:

H1a: The better the quality of data sources in an organization, the greater its BI success.

H1b: The better the quality of different types of data in an organization, the greater its BI success.

H1c: The higher the data reliability in an organization, the greater its BI success.

H1d: The higher the interaction of BI with other systems in an organization, the greater its BI success.

H1e: The higher the quality of user access methods to BI in an organization, the greater its BI success.

Organizational BI capabilities include the level of intuition involved in analysis by the decision maker, flexibility of the system, the level of risk that can be tolerated by the system

(Hostmann et al., 2007). The levels of these capabilities change from organization to organization, depending on different business requirements and organizational structures (Watson and Wixom, 2007). Regardless of their levels, these organizational capabilities significantly impact BI success (Hostmann et al., 2007; Watson and Wixom, 2007). For example, risk exists in every type of business, but there is evidence that entrepreneurial organizations are motivated by it and can handle it better (Busenitz, 1999). Thus, an entrepreneurial organization has a more successful BI if it can tolerate high levels of risk as one of their organizational BI capabilities, compared to having a risk-averse system (Hostmann et al., 2007). On the other hand, organizations that have specific and well-defined problems to solve may have a low tolerance for risk and may have a more successful BI with a risk-averse system (Hostmann et al., 2007). Flexibility is similar to the risk level in the sense that innovative and dynamic organizations have a more successful BI if the system provides high flexibility (Dreyer, 2006; Antebi, 2007). For organizations that shape their business with strict rules and regulations, high flexibility may even become problematic by complicating business. Thus, a system with low flexibility provides a more successful BI for these type of organizations (Hostmann et al., 2007).

The level of intuition involved in analysis by the decision maker depends on the type of decision being made (Simon, 1965; Hostmann et al., 2007). For decisions that do not have a cut-and-dried solution, the decision maker involves his intuition, which involves his experience, gut feeling and judgment as well as creativity. Thus, BI that enables the decision maker to incorporate his intuition in the decision making process is beneficial in these type of situations and results in greater success (Harding, 2003). In opposition, organizations develop specific processes for handling routine and repetitive decisions, so that the decision maker does not need to use his intuition while making the decision, but only the information that is available (Watson and Wixom, 2007). Based on the above discussion, the following hypotheses are proposed;

H2a: The level of BI flexibility positively influences BI success.

H2b: The level of intuition allowed in analysis by BI positively influences BI success.

H2c: The level of risk supported by BI positively influences BI success.

The primary purpose of BI is to support decision-making in organizations (Eckerson, 2003; Buchanan and O'Connell, 2006), and different decision types have different technology requirements (Gorry and Scott Morton, 1971). Hence, employing the right technological capabilities to provide support for the right type of decisions is critical for organizational performance. For example, for structured decisions the decision making process can mostly be automated, which is generally handled by computer-based systems, like transaction processing systems (TPS) (Kirs et al., 1989). At the same time, DSS are better suited for semi-structured decisions (Kirs et al., 1989) while BI is suitable for all types of decision structures (Blumberg and Atre, 2003; Negash, 2004).

IS should be centered on the important decisions of the organization (Gorry and Scott Morton, 1971). Thus, the types of decisions to be made should be taken into consideration while using an MSS. For example, strategic planning decisions may require a database which requires a complex interface although it is not frequently used (Gorry and Scott Morton, 1971). On the other hand, operational control decisions may need a larger database which is frequently used and requires continuous updating (Gorry and Scott Morton, 1971). Thus, the relationship between technological BI capabilities and BI success is influenced by the decision environment.

The data source used to retrieve information is one of the technological capabilities of BI and it can be either internal or external (Harding, 2003; Kanzier, 2002). Internal data is generated within the organization and it is managed through organizational structures (Hostmann et al., 2007). Because internal data is ideally validated and integrated, it significantly impacts the outcome of structured decisions and operational control activities (Keen and Scott Morton, 1978). Because structured decisions are best handled with routine procedures and operational control activities involve individual tasks or transactions, they all require accurate, detailed and current information; and this need is best addressed with internal data (Keen and Scott Morton, 1978). On the other hand, unstructured decisions have no set procedure for handling because they are complex, and strategic planning activities involve mostly unstructured decisions and require creativity. So, just internal data is almost never enough to handle them. They need a wide scope of information, and external data sources are used to retrieve what is needed from web sites, spreadsheets, audio and video files (Hostmann et al., 2007). Whether the data is internal or external, its quality is a key to success with BI (Friedman et al., 2006). Thus, the following is hypothesized:

> *H3a: The influence of high quality internal data sources on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.*

H3b: The influence of high quality external data sources on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.

Besides the data sources, data types are also among technological BI capabilities and their quality may impact BI success differently for different decisions and different management activities. Because operational control activities are about assuring that core business tasks are carried out effectively and efficiently, and that they are carried out rather frequently, they require data that is easily analyzable (Anthony, 1965). Similarly, structured decisions require detailed and accurate information (Keen and Scott Morton, 1978). Both for structured decisions and operational management activities, quantitative data is used (Keen and Scott Morton, 1978; Hostmann et al., 2007). Because non-numerical or qualitative data is generally not detailed and its accuracy open to discussion, it is not appropriate for structured decisions and operational activities. Rather, qualitative data is best used for unstructured decisions because they are complex, they include non-routine problems and quantitative data is not enough for solving those (Hostmann et al., 2007). Furthermore because strategic planning activities need a wide scope of information with an aggregate level of detail, data used better be qualitative so that it can be interpreted and used for subjective judgment (Keen and Scott Morton, 1978). As mentioned in the data sources discussion, the quality of data is a key to success with BI (Friedman et al., 2006). Thus, the following is hypothesized:

H3c: The positive influence of high quality quantitative data on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.

H3d: The positive influence of high quality quantitative data on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.

Data reliability is another factor that influences BI success, whether at the system level or at the individual level. Operational control activities are related to basic operations that are critical for an organization's survival, so the data being used should be consistent and accurate throughout the organization, requiring system-level reliability. Structured decisions also require system-level reliability because they require consistent and current information for routine processes (Keen and Scott Morton, 1978). On the other hand, strategic planning activities and unstructured decisions are complex, non-routine and mostly solved by individuals or a small group of people who use their subjective judgment and intuition (Keen and Scott Morton, 1978). This kind of information must be reliable at the individual level. The required information for these activities is generally obtained from external and multiple sources in addition to internal sources. This makes it harder to obtain system-level reliability. Low data reliability leads to confusion and lack of understanding in analysis (Drummord, 2007). It is important to use highly reliable data in BI, whether it is system-level or individual-level reliability. Thus, the following is hypothesized:

H3e: The positive influence of high data reliability at the system level on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.

H3f: The positive influence of high data reliability at the individual level on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.

Many organizations implement multiple information systems or multiple applications for different purposes. These applications often need to interact at multiple levels for the enterprise business integration and data integration to occur (White, 2005). This interaction of BI with other systems is especially critical to unstructured decision making and strategic planning activities, because they collect data from multiple data sources (Swaminatha, 2006). Thus, the following is hypothesized;

H3g: The positive influence of high quality interaction of BI with other systems in the organization on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.

How users access and use BI is another factor that influences BI success. User access can be either shared, where large numbers of users access the same system through a web-based application, or individual, where the tools are used with desktop computers and dedicated to a specific user (Hostmann et al., 2007). For structured decisions and operational activities, shared user access methods provide greater BI success. This is because decision makers need access to real-time and transaction-level details to support their day-to-day work activities at these levels, and a single integrated user interface to access the data eliminates the burden of accessing multiple BI applications and saves time for the decision maker, which is vital for operational activities (Manglik, 2006). The situation is different for unstructured decisions and strategic planning activities. They require cross-functional business views that span heterogeneous data sources and a more aggregated view (Fryman, 2007). Because these types of activities are not as frequently handled as operational activities, the performance is not as vital and due to the fact that users are executives, complexity is rarely an issue. That is why a user-specific desktop application applies better. Thus, the following is hypothesized:

H3h: The positive influence of high quality shared user access methods to BI on BI success is moderated by the decision environment, such that the effect is stronger for structured decision types and operational control activities.

H3i: The positive influence of high quality individual user access methods to BI on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.

Different types of decisions and management activities also require different organizational BI capabilities, such as using intuition while making decisions and the level of risk the organization tolerates. The decision maker involved in structured decisions and operational activities needs to be different in terms of skills and attitudes from the decision maker involved in unstructured decisions and strategic planning activities (Keen and Scott Morton, 1978). For example, a system analyst who is involved in the development of a new transaction processing system as a decision maker (structured operational control decision) may not be as successful as a decision maker in an R&D portfolio development (unstructured strategic decision). While structured decisions do not require intuition, decision makers need involve their intuition while making unstructured decisions (Khatri and Ng, 2000). The decision environment influences the impact of organizational BI capabilities on BI success.

The required level of BI flexibility, one of the organizational BI capabilities, is different for different decision types and managerial activities. For example, if there is a need for information that requires little processing (e.g., structured operational decisions) then rules and regulations within the organization's structure can provide a well-established response to problems. For situations that require rich information and equivocality reduction (e.g., unstructured strategic decisions), then group meetings (which is a more flexible communication method) where decision makers can exchange opinions and judgments face-to-face can help them define a solution (Daft and Lengel, 1986). Therefore, the information processing and decision making capabilities of an organization are directly related to the flexibility of the IS the organization is using (Burns and Stalker, 1967). As the organization becomes more flexible, its information processing capacity increases (Tushman and Nadler, 1978). This is useful for strategic and unstructured decisions because they need a lot of information that is not always easy to process. On the other hand, too much flexibility may result in complexity and reduced usability (Silver, 1991; Gebauer and Schober, 2006). Thus, it is important to use the right level of flexibility for the right decision types and activities. Therefore, the following is hypothesized:

H4a: The influence of BI flexibility on BI success is moderated by decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.

Most of the decision makers use their intuition to manage their businesses whether they have a technology accompanying it or not (Harding, 2003). This is especially necessary for unstructured decisions and strategic planning activities because they need the decision maker use his experiences, creativity and gut feeling due to their nature (Kirs et al., 1989). These problems need more than the available data, so BI would be more successful if the decision maker uses intuition for decision making. Yet, this is not the case for structured decisions and operational control activities; the decision maker solely relies on data, logic and quantitative analysis for these problems. When subjective judgment is involved, it is very difficult to apply rational reasoning and doing so may even jeopardize the quality of the outcome (Hostmann et al., 2007). Accuracy and consistency required for operational decision making may not be provided. Thus, the following is hypothesized:

H4b: The influence of the intuition allowed in analysis on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.

In addition to the decision making process, the level of risk taken by the decision maker may also differ for different decision types and different managerial activities. For example, as organizations become more innovative, they also become more risk-tolerant and the decisions they make become more and more unstructured (Hostmann et al., 2007). On the other hand, organizations that generally make structured decisions tend to have routine and well-defined problems to solve, and, they are more risk-averse (Hostmann et al., 2007). It is important to tolerate the appropriate level of risk depending on the existing types of decisions and managerial activities within an organization. Thus, the following is hypothesized:

H4c: The influence of tolerating risk on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.

The research model is provided in Figure 4.

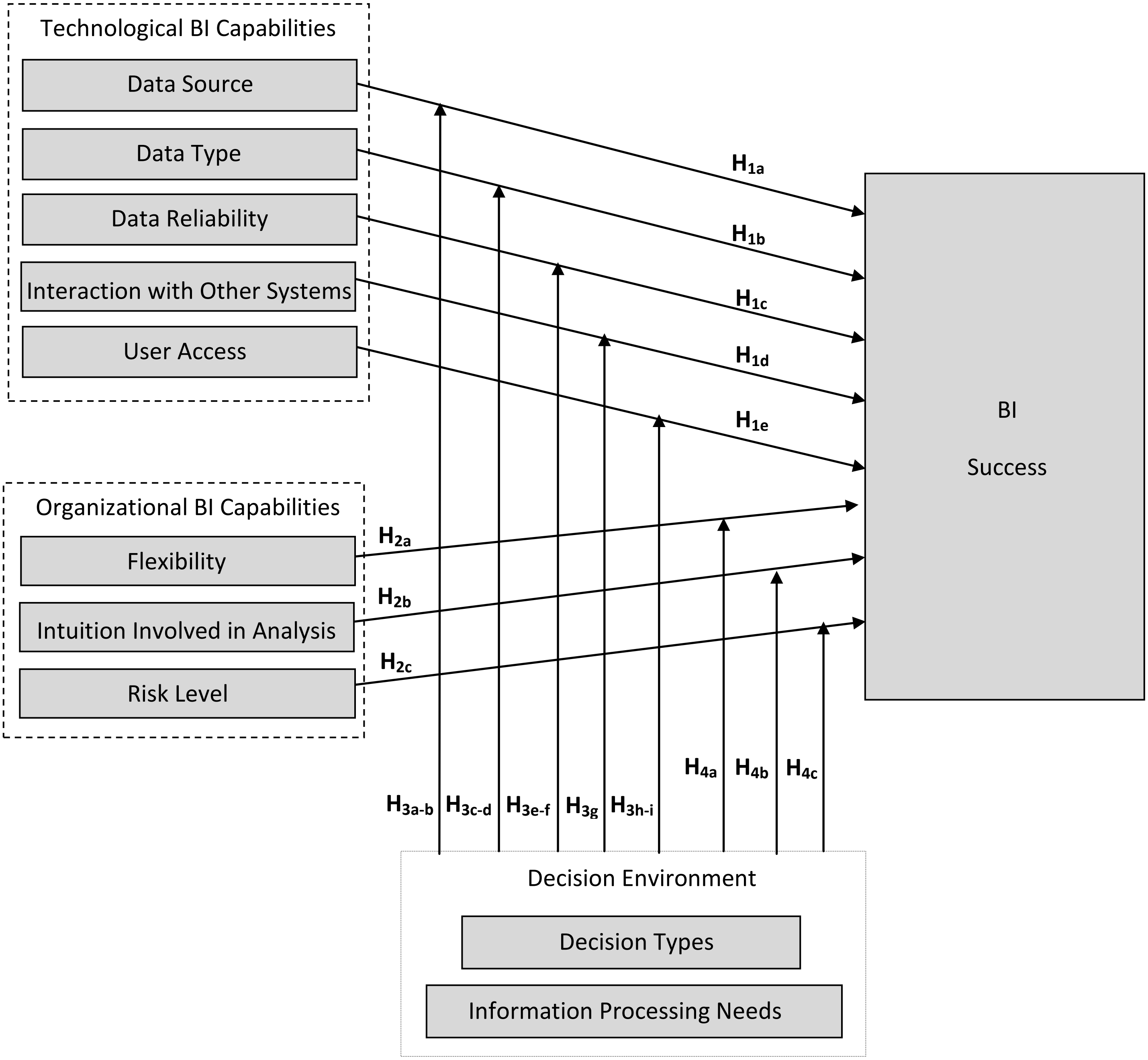

Figure 4. Research model.

CHAPTER 3

METHODOLOGY

This chapter describes the research methodology used to test the dissertation's hypotheses. How the data were collected and analyzed is explained, as are the research methods employed and the development of the research instrument. Reliability and validity issues are discussed and the data analysis procedures employed are described. The chapter is composed of the following sections: description of the research population and sample, description of the research design, discussion of instrument design and development, survey administration, reliability and validity issues, and data analysis procedures.

Research Population and Sample

Business Intelligence (BI) success research largely draws from the population of business managers, including IS professionals and business sponsors (Eckerson, 2003). This study draws from a similar population because the goal is to measure BI success by examining BI capabilities and decision environment. The research population for this dissertation consists of business managers who use BI for strategic, tactical and operational decision making across a range of organizations and industries. Data are collected from business firms located in the United States. The firms are randomly selected, and the names and contact information of decision makers are obtained from a publicly available mailing list of a market research company, L.I.S.T. Inc., which maintains the Business Intelligence Network e-mail list from B-EYE-Network.com web community, which is a collection of over 60,000 corporate and IS buyers of BI.

Research Design

The research design used in this dissertation is a field study. The research method used is a formal survey. Using a survey helps the researcher gather information from a representative sample and generalize those findings back to a population, within the limits of random error (Bartlett et al., 2001). Advantages of survey research include flexibility in reaching respondents from a broad scope (Kerlinger and Lee, 2000). In this dissertation, the data is collected through a web-based survey. Advantages of using web-based surveys are the elimination of paper, postage, mail out, and data entry costs, and reduction in time required for implementation (Dillman, 2000). Web-based surveys also make it easier to send reminders, follow-ups and importing collected data into data analysis programs (Dillman, 2000).

Two consistent flaws in business research are the lack of attention to sampling error when determining sample size and the lack of attention to response and nonresponse bias (Wunsch, 1986). Determining sample size and dealing with nonresponse bias is essential for research based on survey methodology (Bartlett et al., 2001). This dissertation investigates nonresponse bias by comparing the average values for dependent, independent and demographic variables between early and late respondents, depending on the time of the completed surveys are received, with *t*-tests (Armstrong and Overton, 1977; Kearns and Lederer, 2003). In addition, *t*-tests are also performed between the pilot study respondents and main data collection respondents.

Depending on the research design of the study, various strategies can be used to determine an adequate sample size. A priori power analysis is recommended to find out the appropriate sample size (Cohen, 1988). The power of a statistical test of a null hypothesis is the probability that it will be rejected, meaning that the phenomenon of interest exists (Cohen, 1988). Power is related to Type I error (α), Type II error (β), sample size (N) and effect size (ES). With a priori power analysis, the required sample size is calculated by holding the other three elements of power analysis constant.

The first step in a priori power analysis is to specify the amount of power desired. The recommended level of power to achieve is .80 (Chin, 1998). The second step is to specify the criterion for statistical significance, α level, which typically is .05 (Chin, 1998). The third step is to estimate the effect size. In new areas of research inquiry, effect sizes are likely to be small and it is common practice to estimate a small effect size, which corresponds to .2 (Cohen, 1988). Using these statistics, sample size is calculated using a free, general power analysis software application, G*Power 3 (Erdfelder et al., 1996). Assuming an effect size of .2, an α level of .05, and a power of .8, a minimum sample size of 132 is needed.

Instrument Design and Development

The content and the wording of the questions in a survey are among the factors that impact the effectiveness of surveys. Research suggests various methods to improve a survey questionnaire. Brief and concise questions (Armstrong and Overton, 1971), careful ordering of questions (Schuman and Pressor, 1981), and use of terminology that is clearly understood by the respondents (Mangione, 1995) are methods suggested for survey improvement.

The survey used in this dissertation was refined in several steps. First, several IS academic experts reviewed the survey. Based on their suggestions, I addressed ambiguity, sequencing and flow of the questions. Second, a pilot study was conducted with 24 BI professionals who have experience with BI implementation and use. The appropriateness of the questions was assessed based on the results of the pilot study. The survey instrument was finalized after making the necessary changes based on the feedback from pilot study participants.

The survey instrument used in this dissertation consists of four parts. The first part contains items used to collect demographic information from the respondents. The second part measures the dependent variable, BI success. The third part includes items measuring the independent variable, BI capabilities, and the fourth part includes items used to measure the moderator variable, the decision environment. Decision environment is operationalized as the types of decisions made (decision types) and the information processing needs of the decision maker. BI capabilities are operationalized as organizational and technological BI capabilities. Refer to Appendix A for a copy of the instrument.

BI Success

In this study, user satisfaction is used as a surrogate measure for BI success. User satisfaction has been frequently used as a surrogate for IS success (Rai et al., 2002; Hartono et al., 2006). The reason behind measuring user satisfaction as the surrogate measure is the direct relationship among IS user satisfaction, IS use and decisional or organizational effectiveness that IS research shows to exist (DeLone and McLean, 1992; Rai et al., 2002). Items measuring user satisfaction are selected from Hartono et al.'s (2006) Management Support System (MSS) success dimensions and Doll and Torkzadeh's (1988) end-user satisfaction measure. Hartono et al. (2006) identify and collect empirical studies that examine only MSS success measures from peer-reviewed IS journals, which are then synthesized using DeLone and McLean's (1992; 2003) taxonomy of IS success measures. The items that measure satisfaction are developed based on construct definitions stated in quantitative studies on MSS, published in peer-reviewed information systems (IS) journals. Doll and Torkzadeh's (1988) instrument merges ease of use and information product items, focusing on end users interacting with a specific application for decision making (Doll and Torkzadeh, 1988). From both studies, survey items measuring user's satisfaction regarding decision making, information obtained, and user friendliness are adapted for this study.

BI Capabilities

BI capabilities of an organization directly impact BI effectiveness and success (Clark et al., 2007; Watson and Wixom, 2007). BI capabilities were first identified in eight dimensions extracted from the Gartner Group report on the evolution of BI (Hostmann et al., 2007). Three of these dimensions were identified as organizational BI capabilities; level of risk tolerated, BI flexibility, and level of intuition decision makers use during analysis. Five of the dimensions were identified as technological BI capabilities; data sources used, data types analyzed, data reliability, interaction with other systems and user access methods. Both technological and organizational BI capabilities were operationalized with questions developed based on the same Gartner Group report as well as other practitioner oriented publications from the Data Warehousing Institute (TDWI) related to the eight BI capabilities (Harding, 2003; Gonzales, 2005; Sukumaran and Sureka, 2006; Ferguson, 2007; Damianakis, 2008).

The quality of technological BI capabilities, specifically quality of data sources and data types, are measured with questions adapted from Wixom and Watson's (2001) model that measures data warehousing implementation success. Responses to each item are recorded on a 5-point Likert scale.

Decision Environment

Decision environment was operationalized based on the two dimensional decision support framework suggested by Gorry and Scott Morton (1971), which was later validated by Kirs et al. (1989) and Klein et al. (1997).The first dimension addresses decision types and the second dimension addresses the level of the management with which the decision is associated and the information processing needs. To measure the first dimension, I ask respondents questions pertaining to the nature of the decisions they make, such as the repetitiveness of the decision or the managerial involvement in the decision making process. The objective of these questions is to understand whether the decisions they make are structured, semistructured or unstructured. For the second dimension, respondents indicate the organizational level with which their decisions are associated; operational, tactical or strategic. Based on the respondents' answers, each decision is categorized as one of nine decision possibilities in Gorry and Scott Morton's (1971) framework. The questions measuring these were developed based on Gorry and Scott Morton (1971), Kirs et al. (1989), Klein et al. (1997) and Shim et al. (2002). Responses to each item are recorded on a 5-point Likert scale. Table 6 lists the operationalization and measurement properties of the constructs measured in the survey.

Survey Administration

The response rate is a reflection of the cooperation of all potential respondents included in the sample (Kviz, 1977). A low response rate may affect the quality of the results by impacting the reliability or generalizability of findings. In order to increase the response rate, some recommended methods are used in this study, including oofering an executive report on the findings of the survey and providing anonymity to the respondents (Dillman, 2000). Survey instructions also clearly stated that participation is voluntary and that no identifying information is gathered by the administrator of the survey. To encourage participation, a final analysis and executive summary of findings was provided upon the completion of the dissertation to those who request them.

Table 6

Research Variables Used in Prior Research

Construct Names	*Sources*	*Number of items*	*Reliability (Cronbach's α)*	*Validity Assessed?*	*Directly incorporated /adapted / developed*
Decision Environment	Gorry and Scott Morton (1971), Kirs et al. (1989), Klein et al. (1997), Shim et al. (2002)	10	No	No	Developed*
BI success	Hartono et al. (2006)	2	No	No	Adapted
	Doll and Torkzadeh (1988)	3	>.80	Yes	Adapted
Organizational BI capabilities	Hostmann et al. (2007) Imhoff (2005) Gonzales (2005)	9	No	No	Developed*
Technological BI capabilities	Hostmann et al. (2007) White (2005) Eckerson (2003)	15	No	No	Developed*
Quality of data types and data sources	Watson and Wixom (2001)	5	> .70	Yes	Adapted

* The research cited did not use survey items to measure decision environment and BI capabilities. The items used in this dissertation are developed based on their writings.

The sample data was obtained through a web-based survey. The procedure was completed in two steps. First, the hyperlink to the instrument was e-mailed along with a personalized cover letter explaining the purpose of the study. See Appendix B for a copy of the cover letter. I did not have the chance to send a reminder to the same group of recipients.

Thus, to increase the number of respondents, the hyperlink to the instrument was e-mailed to a different but smaller group of recipients two weeks after the first e-mail.

Reliability and Validity Issues

An instrument has adequate reliability if (1) it yields the same results when applied to the same set of objects, (2) it reflects the true measures of the property measured, and (3) there is a relative absence of measurement error in the instrument (Kerlinger and Lee, 2000). Internal consistency is one of the most frequently used indicators of reliability (Cronbach, 1951). Internal consistency assesses how consistently individuals respond to items within a scale. Cronbach's coefficient alpha is widely used as the criterion to assess the reliability of a multi-item measurement. A set of items with a coefficient alpha greater than or equal to 0.80 is considered to be internally consistent (Nunnally and Bernstein, 1994). This dissertation uses Cronbach's coefficient to assess the reliability of multi-item measurement scales.

Validity refers to the accuracy of the instrument. Content validity concerns the degree to which various items collectively cover the material that the instrument is supposed to cover (Huck, 2004). Content validity is judgmental (Kerlinger and Lee, 2000) and is generally determined by having experts compare the content of the measure to the instrument's domain (Churchill, 1979; Huck, 2004). One step taken to ensure content validity in this dissertation is that some of the items are adapted from prior research. Content validity is also addressed by asking BI experts both in academia and industry to review the instrument and provide feedback on whether the items adequately cover the relevant dimensions of the topic being examined. Experts evaluate the content of the questions, their wording, and their ordering as well as the instrument's format. The instrument is modified based on their feedback.

Construct validity refers to the correspondence between the results obtained from an instrument and the meaning attributed to those results (Schwab, 1980). Construct validity links psychometric notions to theoretical notions; it shows that inferences can be made from operationalizations to theoretical constructs (Kerlinger and Lee, 2000). Dimensionality is one psychometric property used to assess construct validity. It relates to whether the items thought to measure a given construct measure only that construct (Hair et al., 1998). Exploratory factor analysis is a frequently used method to assess construct validity when the measurement properties of the items are unknown. Because many of the items in this study are developed by the researcher, exploratory factor analysis is used to assess the dimensionality of the items used to measure a given construct.

In this dissertation, principle axis factor analysis with an orthogonal rotation was used to assess all the dependent variables and the moderators. Dimensionality of each factor is assessed by examining the factor loading. According to Hair et al. (1998), factor loadings over 0.3 meet the minimal level, over 0.4 are considered more important, and 0.5 and greater practically significant. It is also suggested that the loadings over 0.71 are excellent, over 0.55 good, and over 0.45 are fair (Tabachnick and Fidell, 2000; Komiak and Benbasat, 2006). The factor analyses conducted in this study are assessed according to these criteria. Then confirmatory factor analysis was applied to the resulting factor structure to further assess dimensionality and confirm that the items result in the number of factors specified.

Convergence and discriminability are also aspects of construct validity (Hair et al., 1998). Convergent validity indicates that there is a significant relationship between constructs that are thought to have a relationship, and that items purporting to measure the same thing are highly correlated (Kerlinger and Lee, 2000). Discriminant validity indicates that there is no significant relationship between constructs that are not thought to have a relationship, and that items measuring different variables have a low correlation (Kerlinger and Lee, 2000). Correlations among constructs were used to assess these two types of validities.

External validity refers to the validity with which a casual relationship can be generalized to various populations of persons, settings and times (Kerlinger and Lee, 2000). It refers to the degree to which the findings of a single study from a sample can be generalized to the population. Sample of this study are BI users who reasonably represent the population of business managers who use BI for strategic, tactical and operational decision making across a range of organizations and industries. Thus, results from this dissertation can be generalized to the population of BI users.

Data Analysis Procedures

A moderator variable affects the strength of the relationship between an independent variable and a dependent variable (Baron and Kenny, 1986). Two methods of testing a model that includes a moderator variable are suggested (Baron and Kenny, 1986). One method involves multiple regression analysis and regressing the dependent variable on both the independent variable and the interaction of the independent variable with the moderator (Baron and Kenny, 1986). Research shows, however, that measuring multiplicative interactions results in low power when measurement error exists (Busemeyer and Jones, 1983). Thus, Baron and Kenny (1986) recommend an alternate approach, Structural Equation Modeling (SEM), if measurement error is expected in the moderating variable, which is often the case in psychological and behavioral variables. SEM is a covariance-based modeling technique is capable of dealing with the measurement error, in contrast to regression analysis (Hair et al., 1998).

The characteristics that distinguish SEM from other multivariate techniques are the estimation of multiple and interrelated dependence relationships and its ability to represent unobserved concepts in these relationships (Hair et al., 1998). SEM estimates a series of multiple regression equations simultaneously by specifying the structural model. The advantages of SEM include flexibility in modeling relationships with multiple predictor and criterion variables, use of confirmatory factor analysis to reduce measurement error, and the ability to test models overall rather than coefficients individually (Chin, 1998; Hair et al., 1998).

This dissertation employs SEM to test the research hypotheses. The research model suggests that there is a relationship between BI capabilities and BI success, and that this relationship is moderated by the decision environment. Table 7 shows the statistical tests associated with each hypothesis.

Table 7

Hypotheses and Statistical Tests

Hypotheses	*Statistical Tests*
H1a: The better the quality of data sources in an organization, the greater its BI success.	$Ysucc = \beta_0+\beta_1 ds+\varepsilon$
H1b: The better the quality of different types of data in an organization, the greater its BI success.	$Ysucc = \beta_0+\beta_1 dt+\varepsilon$
H1c: The higher the data reliability in an organization, the greater its BI success.	$Ysucc = \beta_0+\beta_1 dr+\varepsilon$
H1d: The higher the quality of interaction of BI with other systems in an organization, the greater its BI success.	$Ysucc = \beta_0+\beta_1 inr+\varepsilon$
H1e: The higher the quality of user access methods to BI in an organization, the greater its BI success.	$Ysucc = \beta_0+\beta_1 ua+\varepsilon$
H2a: The level of BI flexibility positively influences BI success.	$Ysucc = \beta_0+\beta_1 fx+\varepsilon$
H2b: The level of intuition allowed in analysis by BI positively influences BI success.	$Ysucc = \beta_0+\beta_1 intu+\varepsilon$

(table continues)

Table 7 *(continued)*.

H2c: The level of risk supported by BI positively influences BI success.	Ysucc = $\beta_0+\beta_1 rsk+\varepsilon$
H3a: The influence of high quality internal data sources on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.	Ysucc = $\beta_0+\beta_1 ds+\beta_2(ds*dty)+\beta_3(ds*inf)+\varepsilon$
H3b: The influence of high quality external data sources on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.	Ysucc = $\beta_0+\beta_1 ds+\beta_2(ds*dty)+\beta_3(ds*inf)+\varepsilon$
H3c: The positive influence of high quality quantitative data on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.	Ysucc = $\beta_0+\beta_1 dt+\beta_2(dt*dty)+\beta_3(dt*inf)+\varepsilon$
H3d: The positive influence of high quality qualitative data on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.	Ysucc = $\beta_0+\beta_1 dt+\beta_2(dt*dty)+\beta_3(dt*inf)+\varepsilon$
H3e: The positive influence of high data reliability at the system level on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.	Ysucc = $\beta_0+\beta_1 dr+\beta_2(dr*dty)+\beta_3(dr*inf)+\varepsilon$
H3f: The positive influence of high data reliability at the individual level on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.	Ysucc = $\beta_0+\beta_1 dr+\beta_2(dr*dty)+\beta_3(dr*inf)+\varepsilon$
H3g: The positive influence of high quality interaction of BI with other systems in the organization on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	Ysucc = $\beta_0+\beta_1 inr+\beta_2(inr*dty)+\beta_3(inr*inf)+\varepsilon$
H3h: The positive influence of high quality shared user access methods to BI on BI success is moderated by the decision environment, such that the effect is stronger for structured decision types and operational control activities.	Ysucc = $\beta_0+\beta_1 ua+\beta_2(ua*dty)+\beta_3(ua*inf)+\varepsilon$
H3i: The positive influence of high quality individual user access methods to BI on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	Ysucc = $\beta_0+\beta_1 ua+\beta_2(ua*dty)+\beta_3(ua*inf)+\varepsilon$

(table continues)

Table 7 *(continued)*.

H4a: The influence of BI flexibility on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	$Ysucc = \beta_0 + \beta_1 fx + \beta_2(fx*dty) + \beta_3(fx*inf) + \varepsilon$
H4b: The influence of the intuition allowed in analysis on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	$Ysucc = \beta_0 + \beta_1 int + \beta_2(int*dty) + \beta_3(int*inf) + \varepsilon$
H4c: The influence of tolerating risk on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	$Ysucc = \beta_0 + \beta_1 rsk + \beta_2(rsk*dty) + \beta_3(rsk*inf) + \varepsilon$

*** Notations

suc – BI Success
ds – data sources
dt – data types
dr- data reliability
inr- interaction with other systems
ua – user access
dty- decision types
inf – information processing needs
fx- flexibility
intu – intuition involved in analysis
rsk- risk level

CHAPTER 4

DATA ANALYSIS AND RESULTS

This chapter describes the data analysis and results of the dissertation. The first section discusses response rate and analysis of non-response bias. The next section reports the sample characteristics, followed by a discussion on the validity and reliability of the data and the survey instrument. Finally, the statistical tests that are performed to test the research framework and hypotheses are discussed and results of these tests are presented.

Response Rate and Non-Response Bias

The research population for this dissertation consisted of business managers who use BI for strategic, tactical and operational decision making across a range of organizations and industries. Data are collected from business firms located in the United States. The firms are randomly selected, and contact information of decision makers are obtained from a publicly available mailing list of a market research company, L.I.S.T. Inc., which maintains the Business Intelligence Network e-mail list from B-EYE-Network.com web community, which is a collection of over 60,000 corporate and IS buyers of business intelligence (BI).

As the first step of the data collection process, a pilot study was conducted. For this pilot study, the survey was sent out to mailing list, which consists of operational managers using SAS software for data analysis purposes. A total of 24 responses were received, all were complete and usable.

After purchasing the right to use the e-mail addresses from L-I-S-T Inc., the survey was administered to 8,843 BI users through two e-mails. Although the content of the e-mails was the same, the second e-mail was sent three weeks after the first e-mail was sent. In the case of the first e-mail, twenty-nine %of the mailing was undeliverable, and hence, 6281 were delivered to potential respondents. Out of 6281 professionals, 1.7% clicked the survey link, but only 29 respondents actually completed the survey. The second e-mail was sent out to compensate for the high undeliverable rate of the first e-mail, and it was delivered to another 2,500 recipients.

Overall, a total of 97 responses were collected during the data collection process. This corresponds to a response rate lower than 1%. This result is not necessarily surprising for web-based surveys (Basi, 1999). Among the reasons for not completing the survey could be time constraints, dislike of surveys and lack of incentives (Basi, 1999). Of the 97 responses, 5 were incomplete and hence were dropped from subsequent analyses, yielding 92 usable responses.

To assess the non-response bias early respondents were compared to late respondents, with respect to dependent, independent, moderator variables and demographics. With this approach, it is assumed that subjects who respond less readily are more like those who do not respond at all compared to subjects who respond readily (Kanuk and Berenson, 1975). This method has been shown to be a useful way to assess non-response bias and has been adopted by IS researchers frequently (Karahanna, Straub and Chervany 1999; Ryan, Harrison and Schkade 2002). The differences between the responses to the first e-mail (n = 53) and the responses to the second e-mail (n = 39) were examined with t-tests. There were no significant differences between groups for dependent, independent or moderating variables at the .05 significance level. Table 8a shows the results of the t-tests. For the variables where the Levene's Test was significant (BI success, decision type and data sources), the t-values reflect the assumption of unequal variances between groups.

I also performed *t*-tests to see if there were any significant differences in terms of demographics. Table 8b shows the results of these *t*-tests. For the variables where the Levene's Test was significant (highest education level and number of employees), the t-values reflect the assumption of unequal variances between groups. No significant differences were observed among the variables.

Table 8a

Independent Samples t-*Tests for Non-response Bias*

		Levene's Test for Equality of Variances		*t*-Test for Equality of Means				
		F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Dependent Variable	BI Success	7.015	.010	-1.938	85.977	.056	-.34168	.17629
Moderator	Decision Type	4.487	.037	1.406	56.052	.165	.14256	.10138
	Information Processing Needs	.059	.808	-.365	86	.716	-.04594	.12589
Independent Variables	Data Sources	8.677	.004	-1.693	56.028	.096	-.26078	.15401
	Data Types	.682	.411	-.104	86	.918	-.01388	.13402
	Reliability	1.668	.2	-.785	83	.435	-.09237	.11772
	Interaction with Other Systems	.061	.805	-1.321	85	.190	-.25234	.19100
	User Access	3.704	.058	.586	83	.559	.06923	.11805
	Flexibility	.155	.695	-1.291	82	.200	-.23882	.18502
	Intuition Involved in Analysis	.166	.685	-.412	86	.681	-.04011	.09735
	Risk Level	.001	.980	-1.620	79	.109	-.27990	.17281

Table 8b

Independent Samples t-*Tests for Non-response Bias - Demographics*

	Levene's Test for Equality of Variances		*t*-Test for Equality of Means				
	F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean Difference	Std. Error Difference
HighestEdLevel	5.890	.017	.664	65.273	.509	.167	.252
Gender	.339	.562	.290	90	.773	.017	.060
TimeInOrg	2.200	.141	.503	90	.616	.731	1.453
ManagerialPosition	.321	.573	.458	90	.648	.055	.119
FunctArea	.613	.436	.280	90	.780	.181	.646
LevelInOrg	.421	.518	-.089	90	.929	-.016	.184
NumEmployees	4.438	.038	-.604	73.305	.548	-.250	.414
TotalRevenue	.000	.995	.422	90	.674	.129	.305
Industry	.126	.724	.324	90	.747	.767	2.365
BIclass	1.495	.225	-1.237	90	.219	-.173	.140

The data collected from the pilot group was analyzed to check if there are any anomalies or unexpected factor loadings were present and nothing unexpected was found. Then, this data set was compared with the data collected from the e-mail recipients. The *t*-tests were used to examine the differences between pilot group of users, who responded between May 6, 2009 and May 27, 2009, and the rest of the respondents. There were no significant differences between groups for dependent or independent variables but there were significant differences in terms of the moderator(Table 9a). In terms of demographics, some significant differences were observed (Table 9b). In both tables, for the variables where the Levene's Test was significant, the t-value reflects the assumption of unequal variances between groups.

The reason for significant difference between the pilot group respondents versus other respondents for the moderator and for the differences in functional area and level in organization can be explained by the differences in the respondent outlets. The first set of respondents belongs to North Texas SAS Users Group, while the second set was recruited from a BI professionals mailing list. The SAS Users Group is composed of operational managers that are responsible for generating and using advanced BI applications, while the mailing list was comprised of a broader segment of BI users and managers. This may explain the significant difference in terms of the types of decisions made and the information characteristics required to make those decisions. Furthermore, total revenue and number of employees was greater for the mailing list group. This group was comprised of a broader segment of industries and companies, and thus may have tapped more of the larger firms than the pilot group from North Texas.

Table 9a

Independent Samples t-*Tests for Response Bias: Pilot Data Set vs. Main Data Set*

	Levene's Test for Equality of Variances		*t*-Test for Equality of Means				
	F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean Difference	Std. Error Difference
BI Success	.232	.631	-.732	110	.466	-.14545	.19881
Decision Type	1.413	.237	-3.825	111	**.000**	-.36788	.09619
Information Processing Needs	4.092	.046	-4.892	53.771	**.000**	-.47159	.09641
Data Sources	.203	.653	.245	111	.807	.03710	.15137
Data Types	.990	.322	1.035	110	.303	.14015	.13535
Reliability	.195	.660	-.846	106	.400	-.10377	.12269
Interaction with Other Systems	.286	.594	.638	108	.525	.12806	.20077
User Access	.803	.372	-.775	107	.440	-.09931	.12807
Flexibility	.134	.715	-1.012	105	.314	-.20018	.19784
Intuition Involved in Analysis	3.336	.070	1.444	110	.152	.16061	.11124
Risk Level	.023	.879	-.359	101	.720	-.06411	.17836

Table 9b

Independent Samples t-*Tests for Response Bias on Demographics: Pilot Data Set vs. Main Data Set*

	Levene's Test for Equality of Variances		*t*-Test for Equality of Means				
	F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean Difference	Std. Error Difference
HighestEdLevel	1.140	.288	1.086	114	.280	.266	.245
Gender	1.207	.274	-.562	114	.575	-.038	.068
TimeInOrg	.910	.342	1.087	114	.279	1.636	1.504
ManagerialPosition	1.145	.287	-.916	114	.361	-.116	.127
FunctArea	.133	.716	-2.737	114	.007	-1.902	.695
LevelInOrg	1.458	.230	-4.773	114	.000	-.971	.203
NumEmployees	1.577	.212	-2.175	114	.032	-.929	.427
TotalRevenue	1.128	.291	-2.652	114	.009	-.871	.329
Industry	1.434	.234	1.252	114	.213	2.926	2.337
BIclass	2.527	.115	.761	114	.448	.121	.160

Further analysis was conducted to see if there were significant differences between the pilot group and the operational managers who were members of the mailing list. There were no significant differences in any of the independent, dependent or moderator constructs (Table 10a). There were also no significant differences found in demographic variables (Table 10b). For the variables where the Levene’s Test was significant, the t-value reflects the assumption of unequal variances between groups.

Table 10a

Independent Samples t-*Test: Pilot Data Set vs. Operational Managers in the Main Data Set*

	Levene's Test for Equality of Variances		*t*-Test for Equality of Means				
	F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean Difference	Std. Error Difference
BI Success	.425	.520	-.444	27	.661	-.217	.488
Decision Type	.006	.939	-.479	27	.636	-.117	.244
Information Processing Needs	4.557	.042	-1.107	7.240	.304	-.258	.233
Data Sources	.120	.731	1.047	27	.305	.425	.406
Data Types	2.800	.106	.443	27	.661	.133	.301
Reliability	3.511	.072	.573	27	.571	.175	.305
Interaction with Other Systems	.203	.656	.572	27	.572	.258	.451
User Access	.934	.342	-1.262	27	.218	-.317	.251
Flexibility	1.746	.197	-.058	27	.954	-.025	.432
Intuition Involved in Analysis	.004	.950	-.401	27	.692	-.108	.270
Risk Level	1.022	.321	.074	27	.942	.025	.339

Next, the operational manager respondents were removed from the main data set, and the remaining group was compared to the pilot data set to see if there were still significant differences found between the pilot group respondents and other respondents who were non-operational managers. There were significant differences in the two dimensions for the moderator (decision type and information needs). There was also a significant difference for the intuition construct although it was not significant for any of the other *t*-tests performed. See Table 11a for the results of this *t*-test. Table 11b shows the results of the *t*-test for demographics. For the variables where the Levene's Test was significant (Decision type and information processing needs), the t-values reflect the assumption of unequal variances between groups.

Table 10b

Independent Samples t-*Test on Demographics: Pilot Data Set vs. Operational Managers in the Main Data Set*

	Levene's Test for Equality of Variances		*t*-Test for Equality of Means				
	F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean Difference	Std. Error Difference
HighestEdLevel	.195	.662	.471	27	.641	.342	.725
Gender	2.048	.164	.651	27	.521	.083	.128
TimeInOrg	4.915	.035	-.044	4.330	.967	-.183	4.201
ManagerialPosition	.220	.642	1.103	27	.280	.267	.242
FunctArea	.584	.451	-1.850	27	.075	-2.825	1.527
LevelInOrg	.785	.383	-.367	27	.716	-.325	.885
NumEmployees	.003	.960	-.747	27	.462	-.508	.681
TotalRevenue	.507	.482	.479	27	.636	4.158	8.685
Industry	1.022	.321	-.074	27	.942	-.025	.339
BIclass	.195	.662	.471	27	.641	.342	.725

There were significant differences between groups for the highest education level, level in organization, number of employees in the organization and total revenue of the organization. Because I am comparing operational managers to non-operational managers, the significant difference in the level in the organization is expected. The difference in the highest education level can also be explained by the groups being operational managers versus non-operational managers. One possible explanation for the difference between the number of employees and the total revenue may be because the pilot group consisted of operational managers from companies in the North Texas group, and is not as diverse as the mail data set.

Table 11a

Independent Samples t-*Tests for Response Bias: Pilot Data Set vs. Non-Operational Managers in the Main Data Set*

	Levene's Test for Equality of Variances		*t*-Test for Equality of Means				
	F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean Difference	Std. Error Difference
BI Success	.384	.537	-.711	90	.479	-.142	.200
Decision Type	6.053	.016	-3.058	39.744	*.004*	-.348	.114
Information Processing Needs	36.360	.000	-4.911	76.272	*.000*	-.542	.110
Data Sources	.041	.840	.509	90	.612	.083	.164
Data Types	1.076	.302	1.409	90	.162	.216	.153
Reliability	.197	.658	-.399	90	.691	-.059	.148
Interaction with Other Systems	.512	.476	.841	90	.403	.181	.216
User Access	1.431	.235	-.103	90	.918	-.015	.143
Flexibility	.116	.734	-.679	90	.499	-.147	.216
Intuition Involved in Analysis	1.895	.172	2.095	90	*.039*	.292	.139
Risk Level	.117	.733	-.815	90	.417	-.162	.199

These *t*-tests provide support for the idea that the significant differences found between the pilot group data set versus the main data set is because all of the respondents in the pilot group are operational managers whereas the main data set includes a diverse group of respondents with only 5 operational managers. The difference in the level of intuition involved in analysis also is not surprising considering that I hypothesize that non-operational managers use their intuition while making decisions more than operational managers would. The mean for the intuition for non-operational managers is higher than the mean for the intuition for operational managers. Considering that there were only five operational managers in the main data set, to be able to represent the operational managers equally, the pilot data set was added to main data set. Because I am interested in responses that represent all these groups, and because I made no changes to the survey from the pilot group, the responses from both sets were combined for subsequent data analysis without any discrepancies. This provided 116 usable responses.

Table 11b

Independent Samples t*-Test on Demographics: Pilot Data Set vs. Non-Operational Managers in the Main Data Set*

	Levene's Test for Equality of Variances		*t*-Test for Equality of Means				
	F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean Difference	Std. Error Difference
HighestEdLevel	4.323	.040	-5.665	36.171	*.000*	-1.255	.222
Gender	.025	.876	1.803	90	.075	.390	.216
TimeInOrg	1.030	.313	-.516	90	.607	-.037	.071
ManagerialPosition	1.893	.172	1.317	90	.191	2.199	1.669
FunctArea	.274	.602	-1.404	90	.164	-.186	.133
LevelInOrg	.463	.498	-2.936	90	*.004*	-2.088	.711
NumEmployees	2.173	.144	-2.446	90	*.016*	-1.081	.442
TotalRevenue	.461	.499	-3.362	90	*.001*	-1.120	.333
Industry	6.436	.013	1.640	54.285	.107	2.047	1.248
BIclass	2.830	.096	.816	90	.417	.135	.165

Treatment of Missing Data and Outliers

The data was examined for missing values. There were five cases that did not answer any of the questions, thus they were dropped. The rest of the cases that include missing values were not dropped due to the sample size concerns. Instead, missing values were imputed using SAS Enterprise Miner Decision Tree imputation algorithm. Decision tree algorithms are useful for missing data completion due to their high accuracy for single value prediction (Lakshminarayan et al., 1996).

The data was examined for normality and tests were run for all independent and dependent variables. Results show that the data is skewed to the right. To learn more about the distribution of the data, skewness and kurtosis values were examined. Skewness values for the dependent, independent and moderator variables were all between -1 and +1, within the acceptable range (Huck, 2004). All kurtosis values were between -1 and +2, again all in the acceptable range (Huck, 2004), thus the data were not judged to be significantly skewed or kurtotic (Kline, 1997).

Demographics

The respondent pool for the survey has made up of 90.4% male and 9.6% female professionals. While 47.8% of the respondents had a graduate degree, the highest education level was post graduate (25.2 %). The respondents represent a broad sample with respect to organizational size, annual total revenue, and the organizational industry. The descriptive statistics for the size, annual revenue and the industry of the organization is summarized below in Tables 12, 13 and 14 respectively.

Table 12

Descriptive Statistics on Organizational Size

	Number of responses	*Percentage*
Less than 100	27	23.3
100-499	11	9.5
500-999	10	8.6
1,000-4,999	27	23.3
5,000-9,999	11	9.5
10,000 or more	30	25.9
Total	116	100.0

Table 13

Descriptive Statistics on Annual Organizational Revenue

	Number of responses	*Percentage*
Less than $100 million	38	32.8
$100 million to $499 million	15	12.9
$500 million to $1 billion	11	9.5
More than $1 billion	40	34.5
Don't know/not sure	12	10.3
Total	*116*	*100.0*

Almost 50% of the respondents indicated information technology as their functional area in the organization, while the rest of the respondents belong to various other functional areas. Forty %of the respondents are middle managers and 18% are executive level managers. The descriptive statistics for the functional area and the organizational level of the respondents is summarized below in Table 15 and Table 16 respectively.

Table 14

Descriptive Statistics on Organizational Industry

	Number of the responses	*Percentage*
Aerospace	1	.9
Manufacturing	12	10.3
Banking	6	5.2
Finance / Accounting	3	2.6
Insurance / Real Estate / Legal	11	9.5
Federal Government (Including Military)	2	1.7
State / Local Government	2	1.7
Medical / Dental / Health	10	8.6
Internet Access Providers / ISP	1	.9
Transportation / Utilities	9	7.8
Data Processing Services	5	4.3
Wholesale / Resale / Distribution	9	7.8
Education	13	11.2
Marketing / Advertising / Entertainment	3	2.6
Research / Development Lab	3	2.6
Business Service / Consultant	17	14.7
Computer Manufacturer	3	2.6
Computer / Network Consultant	2	1.7
Computer Related Retailer / Wholesaler / Distributor	2	1.7
VAR/VAD/Systems or Network Integrators	1	.9
Missing	*1*	*.9*
Total	*116*	*100.0*

58% of the respondents had worked at their respective organizations for five or fewer years, and 5.3% had twenty or more years of experience. The average organizational experience of all respondents is approximately seven years. 54% of the respondents held a managerial position. 51% of the respondents identify themselves as advanced BI users, and 12% see themselves as new to BI. Therefore, the respondents represent a range of users and experience. Thus, they are appropriate for answering questions in this study. Table 17 below shows the descriptive statistics on BI user experience levels.

Table 15

Descriptive Statistics on Functional Area

	Number of responses	*Percentage*
Management	11	9.5
Finance / Accounting / Planning	9	7.8
Information technology	54	46.6
Manufacturing / Operations	1	.9
Marketing	9	7.8
Sales	6	5.2
Supply chain	3	2.6
Other	23	19.8
Total	*116*	*100.0*

Table 16

Descriptive Statistics on Level in the Organization

	Number of responses	*Percentage*
Executive	21	18.1
Middle	47	40.5
Operational	29	25.0
Other	19	16.4
Total	*116*	*100.0*

Table 17

Descriptive Statistics on BI User Levels

	Number of responses	*Percentage*
New BI user	14	12.1
Intermediate BI user	43	37.1
Advanced BI user	59	50.9
Total	*116*	*100.0*

Exploratory Factor Analysis and Internal Consistency

In this dissertation, the number of factors extracted with exploratory factor analysis was based on the criteria that the Eigenvalue should be greater than one. To extract the factors, principal component analysis with a Varimax rotation was used. According to Hair et al. (1998), factor loadings over 0.3 meet the minimal level, over 0.4 are considered more important, and 0.5 and greater practically significant. It is also suggested that the loadings over 0.71 are excellent, over 0.55 good, and over 0.45 are fair (Tabachnick and Fidell, 2000; Komiak and Benbasat, 2006). The factor analyses conducted in this study are assessed according to these criteria.

A separate factor analysis was conducted for independent variables, dependent variables and moderator variables, instead of one factor analysis where all indicators on multiple factors are analyzed. Factor analyzing all 68 indicators together would result in a correlation matrix of over 2000 relationships, thus, would not produce meaningful outcomes (Jones and Beatty, 2001; Gefen and Straub, 2005).

For the dependent variable, BI success, five items were hypothesized to load on a single factor, and all items loaded on one factor with 0.783 or higher. Following the factor analysis, internal consistency of the BI success factor was examined. Cronbach's alpha is the most widely used measure to assess the internal consistency of a scale (Huck, 2004). A Cronbach's alpha of 0.7 is generally considered acceptable (Hair et al, 1998). Yet, literature suggests that 0.6 may be accepted for newly created measurement scales (Nunnally, 1978; Robinson, Shaver, and Wrightsman, 1994). Cronbach's alpha for the BI success factor was .914 and this is good, considered to be an internally consistent measure. Table 18 below shows the factor loadings for BI success along with the Cronbach's alpha value.

Table 18

Factor Analysis for the Independent Variable

Items	*Components*
BIsat5	0.927
BIsat2	0.889
BIsat3	0.869
BIsat1	0.863
BIsat4	0.783
Mean	3.716
Variance Explained	75.254%
Cronbach's Alpha	0.914

Factor analysis of independent variables was carried out in two steps. First each construct was factor analyzed individually, to see if the items loaded as posited for each construct, because items were largely developed by the researcher and there is no prior validation. In the second step, the constructs were factor analyzed together. This dissertation examines five technological BI capabilities (data quality, data sources quality, user access methods, data reliability and interaction with other systems), three organizational BI capabilities (flexibility, intuition involved in analysis and the level of risk supported by BI). First, technological BI capabilities were factor analyzed individually.

Data quality has two dimensions, quantitative and qualitative data quality. All items measuring both qualitative and quantitative data quality were retained (Table 19). Qualitative data quality had an internal consistency of 0.970 and quantitative data quality had an internal consistency of 0.926.

Table 19

Factor Analysis for the Data Quality

Items	*Components*	
	Qualitative Data Quality	*Quantitative Data Quality*
QualDataQuality4	.943	.225
QualDataQuality2	.934	.222
QualDataQuality3	.929	.201
QualDataQuality1	.929	.222
QuantDataQuality3	.189	.908
QuantDataQuality1	.182	.896
QuantDataQuality4	.204	.881
QuantDataQuality2	.251	.843
Mean	3.291	3.830
Variance Explained	62.885%	24.174%
Cronbach's Alpha	.970	.926

Data sources have two dimensions, internal and external data sources. All four items measuring internal data source quality and all three items measuring external data source quality were retained, with internal consistencies of 0.828 and 0.916, respectively (Table 20).

Table 20

Factor Analysis for the Data Source Quality

Items	*Components*	
	External Data Source Quality	*Internal Data Source Quality*
ExtDataSrcQ3	.930	.084
ExtDataSrcQ2	.915	.131
ExtDataSrcQ1	.872	.154
IntDataSrcQ2	.085	.894
IntDataSrcQ1	-.083	.881
IntDataSrcQ3	.316	.727
IntDataSrcQ4	.466	.641
Mean	2.888	3.532
Variance Explained	50.703%	25.822%
Cronbach's Alpha	.916	.828

User access quality was measured with three items. Factor analyzing these items resulted in a single factor as expected, with an internal consistency of 0.768. Table 21 shows the results.

Table 21

Factor Analysis for the User Access Quality

Items	*Components*
UserAccess_qual3	.898
UserAccess_qual1	.879
UserAccess_qual2	.716
Mean	3.739
Variance Explained	69.989%
Cronbach's Alpha	.768

Data reliability has two dimensions, internal and external data reliability. Each of these dimensions is measured by four items. Factor analysis of these eight items yielded two separate factors as expected (Table 22). One of the items measuring external data reliability had a negative low loading of -0.372, thus was dropped from the scale. The remaining three items (ExtDataReliability1, 3 & 4) had an internal consistency of 0.829. All items measuring internal data reliability were retained with an internal consistency of 0.815.

Interaction with other systems was measured with four items. All items were retained with loadings above .702 and have an internal consistency of 0.803. Table 23 shows the results.

Table 22

Factor Analysis for the Data Reliability

Items	*Components*	
	Internal Data Reliability	*External Data Reliability*
IntDataReliability1	.892	.074
IntDataReliability3	.883	.145
IntDataReliability4	.752	.094
IntDataReliability2_Coded	.705	-.196
ExtDataReliability3	-.019	.896
ExtDataReliability4	-.060	.870
ExtDataReliability1	.181	.816
Mean	3.599	3.230
Variance Explained	39.513%	31.547%
Cronbach's Alpha	.815	.829

Table 23

Factor Analysis for the Interaction with Other Systems

Items	*Components*
interaction3	.875
interaction1	.820
interaction4	.769
interaction2	.702
Mean	3.353
Variance Explained	63.119%
Cronbach's Alpha	.803

Next, organizational BI capabilities are factor analyzed individually. Eight items were used to measure flexibility. They loaded on two factors, yet the items were designed to measure one dimension (Table 24a). Careful examination of questions indicated that one of the factors measures scalability. Scalability relates to the flexibility of BI to operate in a larger environment. Because the purpose is to measure flexibility in a given environment, questions measuring scalability were dropped. The remaining four items (flex1, 2, 3 & 8) had loadings greater than 0.60, with an internal consistency of 0.837. Table 24b shows the results.

Table 24a

Factor Analysis for Flexibility - I

Items	*Components*	
flex6_sca3	.903	.141
flex7_sca4	.873	.194
flex5_sca2	.800	.439
flex4_sca1	.788	.426
flex8	.079	.864
flex2	.313	.848
flex3	.349	.789
flex1	.409	.532
Mean	3.442	3.619
Variance Explained	60.491%	14.921%

Table 24b

Factor Analysis for Flexibility - II

Items	*Components*
flex2	.910
flex3	.866
flex8	.801
flex1	.696
Mean	3.442
Variance Explained	67.612%
Cronbach's Alpha	.837

Intuition involved in analysis was measured by five items. They loaded on two factors, yet the items were designed to measure one dimension (Table 25a). Items 5, 2, and 3 loaded together and items 1 and 4 loaded together. I first examine item 1 (Intuition1-coded). Careful consideration of this question (Using my BI, I make decisions based on facts and numbers) reveals that it may not actually tap the level of intuition involved in analysis. The extent to which the decision maker is using facts and numbers to make decisions may not be an indicator of the extent to which he/she uses intuition while making decisions. Consideration of Item 4 (The decisions I make require a high level of thought) indicates that it is appropriate. Before re-running the factor analysis, however, I re-considered each of the other items to ascertain whether they indeed seemed to be appropriate indicators of the use of intuition in decision making. The third item, Intuition3, (With my BI, it is easier to use my intuition to make better informed decisions) seems to tap how much BI supports intuitive decision making, rather than the extent to which intuition is used. Thus, items 1 and 3 were removed and the factor analysis was rerun (Table 25b). Only one factor emerges in this assessment. The loadings are acceptable, although the reliability is borderline. I examined whether adding item 3 back would result in a substantively stronger Cronbach's alpha, but it did not. Therefore, I chose to use the three items for the Intuition construct.

Table 25a

Factor Analysis for Intuition - I

Items	*Components*	
intuition5	.782	.165
intuition2	.781	.038
intuition3	.702	.024
intuition1_coded	.112	-.870
intuition4	.353	.659
Mean Variance Explained	3.739 39.620%	2.892 21.868%

Table 25b

Factor Analysis for Intuition - II

Items	*Components*
intuition5	.791
intuition2	.778
intuition4	.671
Mean	3.807
Variance Explained	56.079%
Cronbach's Alpha	.605

The Cronbach's alpha for intuition is .605. Although this is lower than the suggested level, reliability values as low as 0.5 are acceptable for new instruments (O'Leary-Kelly and Vokurka, 1998). Therefore, because the items measuring intuition was newly developed based on the literature, this new instrument was concluded as reliable for this study.

Level of risk was measured with four items. All items were retained with loadings above .76 and have an internal consistency of 0.802. Table 26 shows the results.

Table 26

Factor Analysis for the Risk Level

Items	*Components*
risk3	.821
risk4	.812
risk2	.774
risk1	.766
Mean	3.560
Variance Explained	62.992%
Cronbach's Alpha	.802

These individual analyses lend support for the strength of the measurement properties of these items and factors. To further assess measurement properties of these, exploratory factor analysis was conducted, assessing these items in the presence of others. Factor analyzing all 68 indicators at the same time would result in a correlation matrix of over 2000 relationships, thus, would not produce meaningful outcomes (Jones and Beatty, 2001; Gefen and Straub, 2005). After careful examination of the dimensions that resulted in the prior factor analyses, it was determined to divide this assessment into two groups. One set of factors all relate to data oriented issues; data quality, data reliability and data source quality. Thus, these are more closely related to technological BI capabilities. The other factors all relate to organizational or user behavior/perceptions of the system, and thus are more closely related to organizational BI capabilities. I first discuss the organizational BI capability factors; Table 27a shows the initial results.

One of the items measuring interaction with other systems (interaction2) was dropped from the analysis due to its cross-loading with user access quality. The remaining items were factor analyzed again and Table 27b shows the results.

Table 27a

Factor Analysis for the Organizational BI Capability Variables - I

Items	*Components*				
	Flexibility	*Interaction*	*Risk*	*Intuition*	*User Access Quality*
flex2	.769	.121	.277	.305	.012
flex3	.760	.145	.111	.388	.000
flex1	.703	.061	.217	-.013	.146
flex8	.655	.288	.195	.313	-.058
risk1	.603	.488	.128	-.102	-.155
risk2	.541	.529	.146	-.049	-.071
risk4	.189	.720	.331	.159	-.096
intuition4	.032	.629	-.265	.055	.527
risk3	.239	.609	.318	.285	.045
UserAccess_qual3	.291	.550	.259	.476	-.122
UserAccess_qual1	.220	.515	.336	.452	-.084
interaction3	.263	.159	.827	.045	.110
interaction4	.232	.103	.752	.087	-.018
interaction1	.123	.423	.707	.129	-.101
UserAccess_qual2	.132	.160	.007	.847	.012
interaction2	.221	.038	.504	.540	.129
intuition2	-.071	-.071	.042	.059	.822
intuition5	.082	-.030	.043	-.054	.808

Table 27b

Factor Analysis for the Organizational BI Capability Variables - II

Items	*Components*				
	Flexibility	*Risk*	*Interaction*	*User Access Quality*	*Intuition*
flex2	.777	.103	.277	.308	.017
flex3	.773	.162	.087	.344	-.004
flex1	.698	.101	.222	-.018	.145
flex8	.650	.258	.190	.353	-.054
risk4	.149	.696	.341	.277	-.084
risk3	.224	.646	.282	.290	.040
risk2	.500	.593	.132	.009	-.080
intuition4	-.012	.578	-.249	.190	.538
risk1	.559	.564	.117	-.046	-.164
interaction3	.269	.157	.822	.056	.112
interaction4	.236	.033	.788	.157	.003
interaction1	.113	.429	.693	.161	-.099
UserAccess_qual2	.172	.037	.002	.824	.036
UserAccess_qual3	.272	.398	.301	.639	-.088
UserAccess_qual1	.202	.337	.390	.635	-.043
intuition2	-.046	-.046	.026	-.027	.819
intuition5	.088	-.064	.055	-.039	.813
Mean	3.442	3.560	3.230	3.739	3.807
Variance Explained	38.380%	10.177%	7.750%	7.166%	6.148%
Cronbach's Alpha	.837	.802	.804	.768	.605

Flexibility, interaction and user access quality factors loaded clearly as expected. One of the items measuring intuition (intuition4) cross-loaded with the items measuring risk. This item is "The decisions I make require a high level of thought." Decisions that involve high level of uncertainty also involve a high level of risk associated with them, and they require high level thinking by the decision maker. To further understand the relationship among these items, another factor analysis was conducted including only intuition and risk items, and the analysis was forced to produce two factors. Results, as presented in Table 28, show clear loadings for two factors, with both eigenvalues greater than 1. The level of risk and intuition had 0.802 and 0.605 internal consistency values, respectively. Therefore, in subsequent analyses the four items measuring risk were used together to measure risk and three items measuring intuition were used together to measure intuition.

Table 28

Factor Analysis for Risk and Intuition

Items	Components	
	Risk	Intuition
risk4	.810	.005
risk3	.807	.123
risk2	.776	-.004
risk1	.760	-.102
intuition5	-.099	.795
intuition2	-.112	.787
intuition4	.334	.648
Mean	3.560	3.807
Variance Explained	37.512%	24.168%
Cronbach's Alpha	.802	.605
Eigenvalues	2.626	1.692

Next, the technological BI capability items, (data quality, data source quality and data reliability) were factor analyzed. This resulted in five rather than the expected six factors. Items measuring external data reliability and external data source quality loaded together. All other items loaded as expected. Table 29 shows the factor loadings as well as the reliability statistics.

Table 29

Factor Analysis for the Technological BI Capability Variables

Items	Components				
	External Data Source Quality & External Data Reliability	Qualitative Data Quality	Quantitative Data Quality	Internal Data Source Quality	Internal Data Reliability
ExtDataSrcQ2	.856	.199	.021	.053	.163
ExtDataSrcQ3	.820	.135	-.123	-.077	.245
ExtDataSrcQ1	.817	.110	.020	-.045	.234
ExtDataReliability1	.804	.013	.243	.171	-.062
ExtDataReliability3	.792	-.100	.095	.011	.002
ExtDataReliability4	.723	-.119	.262	-.116	.000
QualDataQuality4	.056	.927	.216	.102	.113
QualDataQuality1	.041	.919	.203	.053	.141
QualDataQuality3	.071	.915	.189	.099	.108
QualDataQuality2	-.003	.902	.216	.160	.151
QuantDataQuality3	.093	.180	.860	.180	.130
QuantDataQuality1	.111	.191	.850	.189	.065
QuantDataQuality4	.144	.196	.830	.135	.167
QuantDataQuality2	.149	.265	.811	.059	.074
IntDataReliability1	.048	.137	.273	.815	.145
IntDataReliability3	.082	.173	.323	.792	.149
IntDataReliability2_Coded	-.082	.039	-.052	.769	.187
IntDataReliability4	-.062	.141	.531	.536	.168
IntDataSrcQ3	.188	.247	.056	.055	.803
IntDataSrcQ2	.074	.106	.297	.295	.738
IntDataSrcQ4	.363	.215	-.008	.154	.702
IntDataSrcQ1	-.054	-.035	.341	.421	.677
Mean	3.059	3.291	3.830	3.256	3.532
Variance Explained	34.518%	17.175%	11.217%	8.990%	5.059%
Cronbach's Alpha	.900	.970	.926	.836	.828

One possible explanation for double loading in the first factor may be due to the nature of the constructs. The items measuring the other four factors may have been perceived by respondents as relating to internal issues. The items measuring internal data source quality and internal data reliability are clearly focused on internal issues. However, the items measuring qualitative and quantitative data quality do not specify internal or external. Given that majority of data in most organizations originates internally, it is reasonable that respondents answer with internal data in mind. Another possible explanation is that external data source quality and external data reliability were comingled in the respondents' perceptions as they answered.

To further understand the relationship for this external factor, another factor analysis was conducted including only external data reliability and external data source quality items, forcing the analysis to produce two factors. Results including the eigenvalues are presented in Table 30. They show clear loadings for two factors as expected, with 0.916 and 0.829 internal consistency values for external data reliability and external data source quality, respectively. Thus, the items were separated in survey analysis.

Table 30

Factor Analysis for the Dependent Variables - External Data reliability and External Data Source Quality

Items	*Components*	
	External Data Source Quality	*External Data Reliability*
ExtDataSrcQ2	.905	.298
ExtDataSrcQ3	.880	.244
ExtDataSrcQ1	.837	.338
ExtDataReliability4	.215	.874
ExtDataReliability3	.299	.856
ExtDataReliability1	.530	.633
Mean	2.888	3.230
Variance Explained	66.779%	14.398%
Cronbach's Alpha	.916	.829
Eigen values	4.007	.864

Next, exploratory factor analysis was conducted for the moderator variable. It is posited to have two dimensions; information processing needs and decision types. Six items measured information needs (InfoChar1-6), and five items were used to measure decision types (DecType1-5). Initial factor analysis resulted in five factors rather than the expected two factors. Table 31a shows the results of this initial factor analysis.

Table 31a

Factor Analysis for the Moderator Variable - I

Items	*Components*				
	Information Needs 1	*Decision Types 1*	*Decision Types 2*	*Information Needs 2*	*Decision Types 3*
InfoChar5	.780	.067	.151	.114	.077
InfoChar2	.733	.015	-.049	-.033	-.058
InfoChar6	.639	.030	-.205	.009	.180
InfoChar1	.460	-.187	.036	.198	.259
DecType2_coded	-.027	.832	-.169	.227	.161
DecType4_coded	-.066	-.785	-.225	.119	.336
DecType1	.051	-.141	.824	.097	-.223
DecType3	-.162	.237	.757	.009	.393
InfoChar3	-.055	.009	.085	.852	-.049
InfoChar4	.199	.084	.005	.728	.082
DecType5	.248	-.072	-.009	.008	.887

Careful examination of the items loading for the Information Needs 2 factor (InfoChar3 and InfoChar4) indicated that this factor refers to the general type of information collected, whereas the Information Needs 1 factor (InfoChar1, 2, 5 & 6) represents the different characteristics of the information used. Because the intention of this dissertation is to examine different characteristics of information collected, items InfoChar3 & 4 were dropped from the scale. The new factor analysis resulted in four factors (Table 31b).

Table 31b

Factor Analysis for the Moderator Variable - II

Items	*Components*			
	Information Needs 1	*Decision Types 1*	*Decision Types 2*	*Decision Types 3*
InfoChar5	.781	.067	.157	.074
InfoChar2	.737	.017	-.067	-.055
InfoChar6	.629	.032	-.201	.174
InfoChar1	.490	-.136	.047	.313
DecType2_coded	-.004	.865	-.139	.153
DecType4_coded	-.053	-.753	-.221	.394
DecType1	.067	-.156	.827	-.219
DecType3	-.166	.238	.762	.360
DecType5	.239	-.035	.002	.882

Examining the questions measuring decision types, DecType 4 item was dropped due to possible cross loading between Decision Types 1 and Decision Types 3. Table 31c shows the new factor analysis after dropping this item.

Table 31c

Factor Analysis for the Moderator Variables - III

Items	Components		
	Information Needs 1	Decision Types 1	Decision Types 2
InfoChar5	.741	.119	.027
InfoChar2	.663	-.126	-.058
InfoChar6	.639	-.203	.108
InfoChar1	.600	.046	-.082
DecType5	.523	.167	.436
DecType3	-.055	.837	.270
DecType1	.003	.759	-.349
DecType2_coded	-.065	-.054	.850

Item DecType 2_coded (I make decision without higher level manager involvement) loaded as a single factor. Its wording was deemed to be ambiguous because involvement from the higher level managers in a decision may not imply the decision type made by the decision maker. After dropping this item, another factor analysis was run; table 31d shows the results.

Table 31d

Factor Analysis for the Moderator Variables - IV

Items	*Components*	
	Information Needs	*Decision Types*
InfoChar5	.739	.099
InfoChar2	.642	-.143
InfoChar6	.640	-.223
DecType5	.590	.138
InfoChar1	.585	.023
DecType3	.012	.836
DecType1	-.024	.764

Although this analysis resulted in two factors, one of the items thought to measure decision types (DecType5) loaded with the items thought to measure information needs. This item (the decisions I make require computational complexity and precision) was dropped from the scale because it seemed to tap something other than information needs and because it also seems to tap two different things; precision and computational complexity. Thus, it was deemed to be a poor indicator. The resulting factors for the moderator shows high factor loadings, yet low internal consistency (Table 31e). Reporting Cronbach's Alpha for two-item scales have been criticized (Cudeck, 2001), thus the correlations between items and their significance is also reported (Table31f). Although the correlations are significant, they and the

Cronbach's Alpha for Decision Types were deemed too low to retain the factor. Thus, only Information Needs is used in subsequent analyses.

Table 31e

Factor Analysis for the Moderator Variables - V

Items	*Components*	
	Information Needs	*Decision Types*
InfoChar5	.768	.146
InfoChar2	.711	-.083
InfoChar6	.651	-.199
InfoChar1	.578	.036
DecType1	.027	.809
DecType3	-.071	.804
Mean	3.819	2.806
Variance Explained	31.260%	22.570%
Cronbach's Alpha	0.601	0.494

Table 31f

Correlations for Decision Type Items

		DecType1	*DecType3*
DecType1	Pearson Correlation	1	.330**
	Sig. (2-tailed)		.000
DecType3	Pearson Correlation	.330**	1
	Sig. (2-tailed)	.000	

** Correlation is significant at the 0.01 level (2-tailed).

PLS Analysis and Assessment of Validity

PLS path modeling was used to analyze and assess the proposed research model and to test the hypotheses suggested. PLS has several advantages compared to other statistical techniques such as regression and analysis of variance. PLS has the capability to concurrently test the measurement and structural model and does not require the homogeneity and normal distribution of the data set (Chin et al., 2003). PLS can also handle smaller sample sizes better than other techniques, although PLS is not a panacea for unacceptably low sample sizes (Marcoulides and Saunders, 2006). PLS requires a minimum sample size that is 10 times greater of either the number of independent constructs influencing a single dependent construct, or the number of items comprising the most formative construct (Chin, 1998; Wixom and Watson, 2001; Garg et al., 2005). This dissertation examines eight BI capabilities as independent variables, thus requires 80 as the minimum sample size. Although a priori power analysis yielded that for an effect size of .2, an α level of .05, and a power of .8, a minimum sample size of 132 is needed, the collected and cleaned data of 116 respondents satisfies the PLS requirement. SmartPLS version 2.0.M3 (Ringle, Wende & Will, 2005) is used to analyze the research model.

The acceptability of the measurement model was assessed by the model's construct validity as well as the internal consistency between the items (Au et al., 2008). Internal consistency, a form of reliability, was assessed using Cronbach's alpha and exploratory factor analysis was used to assess dimensionality (Beatty et al., 2001). All Cronbach's alpha values were satisfactory after item purifications, as presented in the previous section.

The independent and dependent variables were assessed for construct validity through convergent and discriminant validity as well as composite reliability (Hair et al, 1998; Kerlinger and Lee, 2000). Convergent validity is assessed by the average variance extracted (AVE) and communality. Both communality and AVE values for all constructs are suggested to be higher than the recommended threshold value of 0.5 (Rossiter, 2002; Fornell and Larker, 1981). This required further item purifications in the model. The items that share a high degree of residual variance with other items in the instrument were eliminated (Au et al., 2008; Gefen et al., 2000; Gerbing and Anderson, 1988) to increase the AVE and communality values above 0.5. The resulting item loadings and related statistics are given in Table 32 below.

Discriminant validity was assessed by comparing the square root of AVE associated with each construct with the correlations among the constructs and observing that square root of AVE is a greater value (Chin, 1998). As suggested for discriminant validity, the values on the diagonal were all larger than the off-diagonal values. Composite reliability measures "the internal consistency of the constructs and the extent to which each item indicates the underlying construct" (Moores and Chang, 2006, p. 173). Composite reliability values were well above the recommended level (0.70) for all constructs (Bagozzi and Yi, 1988; Fornell and Larker, 1981). Table 33 shows the composite reliability, average variance extracted (AVE), the square root of AVE, and the correlations between constructs.

Table 32

Item Statistics and Loadings

Item <- Construct it measures	*Loading*	*Std. dev.*	*Mean*
BIsat1 <- BI Success	0.85663	0.035	3.767
BIsat2 <- BI Success	0.889508	0.022	3.879
BIsat3 <- BI Success	0.86678	0.030	3.646
BIsat4 <- BI Success	0.786284	0.043	3.620
BIsat5 <- BI Success	0.93116	0.015	3.663
InfoChar1 <- Decision Environment	0.437519	1.099	3.470
InfoChar2 <- Decision Environment	0.803038	0.829	4.010
InfoChar5 <- Decision Environment	0.847287	0.938	3.910
InfoChar6 <- Decision Environment	0.406642	0.934	3.880
ExtDataReliability1 <- Data Reliability	0.632047	0.204	3.207
ExtDataReliability3 <- Data Reliability	0.43458	0.258	3.293
ExtDataSrcQ2 <- Data Source Quality	0.648588	0.164	2.828
ExtDataSrcQ3 <- Data Source Quality	0.587863	0.202	2.819
IntDataReliability1 <- Data Reliability	0.82271	0.147	3.871
IntDataReliability3 <- Data Reliability	0.857347	0.135	3.733
IntDataSrcQ2 <- Data Source Quality	0.806969	0.078	3.698
IntDataSrcQ3 <- Data Source Quality	0.781245	0.101	3.379
IntDataSrcQ4 <- Data Source Quality	0.774343	0.120	3.198
QualDataQuality2 <- Data Quality	0.590387	0.105	3.336
QuantDataQuality1 <- Data Quality	0.909218	0.023	3.931
QuantDataQuality3 <- Data Quality	0.89763	0.038	3.845
QuantDataQuality4 <- Data Quality	0.916249	0.025	3.776
UserAccess_qual1 <- user access quality	0.903284	0.021	3.586
UserAccess_qual2 <- user access quality	0.660236	0.114	3.853
UserAccess_qual3 <- user access quality	0.91113	0.019	3.776
flex1 <- Flex	0.676308	0.075	3.853
flex2 <- Flex	0.913582	0.014	3.293
flex3 <- Flex	0.86401	0.027	3.259
flex8 <- Flex	0.814945	0.045	3.362
interaction1 <- interaction	0.858283	0.033	3.414
interaction3 <- interaction	0.87544	0.032	3.233
interaction4 <- interaction	0.803407	0.056	3.043
intuition4 <- intuition	0.780321	0.295	3.974
intuition5 <- intuition	0.832241	0.268	3.759
risk2 <- risk	0.726962	0.088	3.440
risk3 <- risk	0.896195	0.030	3.767
risk4 <- risk	0.854442	0.039	3.741

Table 33

Inter-Construct Correlations: Consistency and Reliability Tests

Construct	*Composite Reliability*	**AVE*	*Risk*	*Flexibility*	*Intuition*	*Data Quality*	*Data Source Quality*	*Data Reliability*	*Interaction*	*User Access Quality*	*Decision Environment*	*BI Success*
Risk	0.867	0.687	0.829									
Flexibility	0.892	0.676	0.591	0.822								
Intuition	0.788	0.651	0.133	0.127	0.807							
Data Quality	0.903	0.705	0.453	0.411	0.127	0.840						
Data Source Quality	0.845	0.526	0.414	0.496	0.007	0.426	0.725					
Data Reliability	0.791	0.500	0.419	0.442	0.063	0.551	0.521	0.707				
Interaction	0.883	0.716	0.565	0.517	0.020	0.447	0.472	0.454	0.846			
User Access Quality	0.870	0.694	0.608	0.599	0.126	0.674	0.605	0.548	0.536	0.833		
Decision Environment	0.747	0.518	0.158	0.069	0.123	0.385	0.078	0.224	0.536	0.181	0.720	
BI Success	0.938	0.752	0.523	0.569	0.144	0.546	0.385	0.336	0.526	0.719	0.192	0.867

The shaded numbers on the diagonal are the square root of the variance shared between the constructs and their measures.
Off-diagonal elements are correlations among constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements.

* Average Variance Extracted

Hypotheses Testing Results

Hypothesis 1 and Hypothesis 2

Hypotheses 1a-e and 2a-c posit that technological and organizational BI capabilities impact BI success (Table 34).

Table 34

Hypotheses 1 & 2

H1a	The better the quality of data sources in an organization, the greater its BI success.
H1b	The better the quality of different types of data in an organization, the greater its BI success.
H1c	The higher the data reliability in an organization, the greater its BI success.
H1d	The higher the quality of interaction of BI with other systems in an organization, the greater its BI success.
H1e	The higher the quality of user access methods to BI in an organization, the greater its BI success.
H2a	The level of BI flexibility positively influences BI success.
H2b	The level of intuition allowed in analysis by BI positively influences BI success.
H2c	The level of risk supported by BI positively influences BI success.

In order to obtain reliable results and t-values, 500 random samples of 116 responses (Chin, 1998) were generated using the bootstrapping procedure available in the SmartPLS software. The significance of the hypotheses was evaluated by assessing the significance and the sign of the inner model path coefficients using *t*-tests. To evaluate the predictive validity of the relationship between the constructs, R^2 values were assessed. Table 35 shows the path coefficients between BI capabilities and BI success, as well as the t values associated with these paths. Figure 5 shows the PLS results along with the t values of both the inner and the outer models. Figure 5 also shows the R^2 value for the dependent variable, BI success. Results show that the total variance (R^2) for BI success explained by eight constructs is 60 percent.

Table 35

Path Coefficients, t Values and p Values for BI Capabilities (H1 & H2)

Constructs	*Path coefficients*	*t value*	*p-value*
Flexibility	0.197927	2.918918	0.003671***
Intuition	0.046332	0.426293	0.670146
Risk	0.027724	0.183228	0. 854716
Data Source Quality	-0.103309	1.506560	0.066286 **
Data Quality	0.130787	1.475176	0.070408 **
Data Reliability	-0.131662	1.862048	0.031588*
Interaction with Other Systems	0.175194	2.367860	0.009137***
User Access Quality	0.537448	5.407056	0.000000***

* Significant at the p = 0.5 level
** Significant at the p = 0.1 level
*** Significant at the p = 0.01 level

Results show that H1a-e and H2a are supported. This means that the higher the quality of data sources, data types, user access methods, higher the interaction with other systems, data reliability and flexibility, the better the BI success. But results do not show any support that the level of intuition used in analysis and level of risk supported by BI influences BI success.

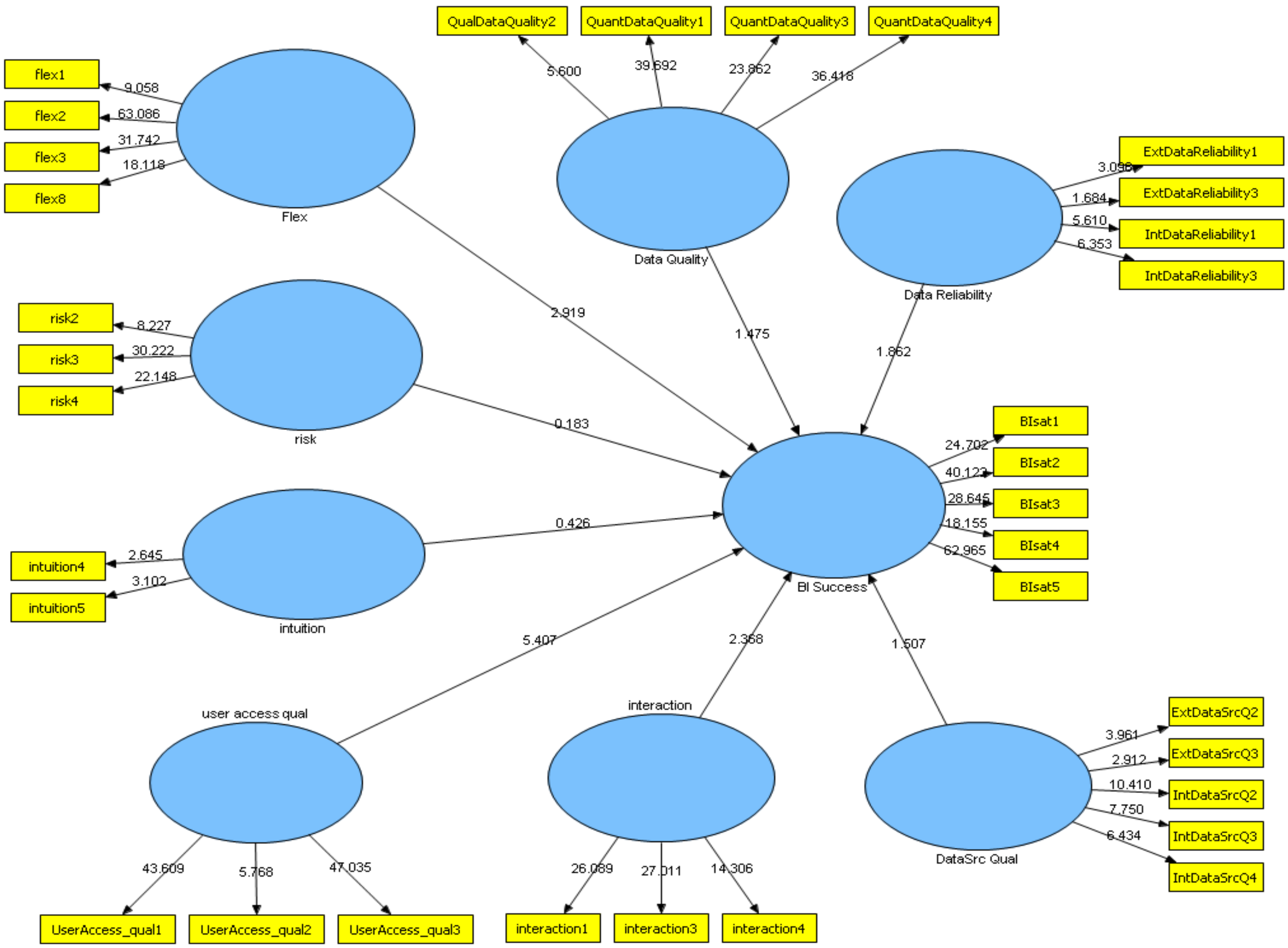

Figure 5. PLS results – H1 and H2.

Hypothesis 3 and Hypothesis 4

H3 and H4 posit that the decision environment moderates the relationship between the BI capabilities and BI success. As explained above, one dimension of the moderator was retained for subsequent analysis; information processing needs. Information processing needs are operationalized based on Anthony's (1965) management activities framework, and the items measuring this construct were developed based on Gorry and Scott Morton (1971), Kirs et al. (1989), Klein et al. (1997) and Shim et al. (2002). As recommended by Goodhue et al. (2007), a multiple regression approach was employed to test whether significant interactions exist. Although PLS was stated as the main analysis method for this dissertation, using regression is suggested instead of PLS in the case of sample size or statistical significance is of concern (Goodhue et al., 2007). Although the sample size for this study exceeds the minimum sample size requirements for PLS analysis (calculated as 80), the requirement set by the a priori power analysis is not met (calculated as 132). Hence, because of the sample size is of concern for testing a moderator effect, a multiple regression approach was employed to test H3 and H4.

The interactions between BI capabilities and the decision environment are tested by creating cross-product variables and testing the statistical significance of these cross-product variables in the regression equation (Keith, 2006). The cross-product variables are created by multiplying the moderator variable with each BI capability. Before the multiplication, all BI capabilities and the decision environment measures were centered by subtracting the mean score of the variable from that variable (Aiken and West, 1991; Cohen et al., 2003). Centering continuous variables helps with reducing the multicollinearity (Keith, 2006; Aiken and West, 1991).

The moderator related hypotheses, H3a-i and H4a-c, were tested with separate regression models. Rather than testing all possible interactions, it is suggested that one should focus on a single interaction and test one hypothesis at a time (Keith, 2006). Thus, to test the statistical significance of the interaction, BI success was regressed on each BI capability and the decision environment variables as the first step in a sequential regression i.e., H3a was tested separately, then H3b, and so on. However, for clarity, the set of H3 hypotheses is presented and discussed first, then the set of H4 hypotheses is presented and discussed. As the second step, the interaction term was added to the equation. Then, the change in R^2 between the two equations was examined. A significant change in R^2 means a significant interaction term (Keith, 2006). This method of testing interaction is equivalent to dividing the sample into two groups based on the moderator, conducting separate regressions for each group, and comparing the regression coefficients (Keith, 2006). Table 36 shows the hypotheses H3a-i.

Table 36

Hypothesis 3

H3a	The influence of high quality internal data sources on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.
H3b	The influence of high quality external data sources on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.
H3c	The positive influence of high quality quantitative data on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.
H3d	The positive influence of high quality qualitative data on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.
H3e	The positive influence of high data reliability at the system level on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.
H3f	The positive influence of high data reliability at the individual level on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.
H3g	The positive influence of high quality interaction of BI with other systems in the organization on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.
H3h	The positive influence of high quality shared user access methods to BI on BI success is moderated by the decision environment, such that the effect is stronger for structured decision types and operational control activities.
H3i	The positive influence of high quality individual user access methods to BI on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.

Only H3c was supported. High quality quantitative data has a greater impact on BI success for operational control activities. Because these activities are largely based on quantifiable data, the quality of that data is critical to the guidance that a BI provides the decision maker. However, H3d, which posits that higher quality qualitative data has a greater impact on BI success in a strategic decision environment, was not supported. One possible explanation is that these respondents rely more heavily on quantitative or quantifiable data than on qualitative data. Thus, they are not as concerned with the quality of qualitative data in the strategic decision environment.

None of the other hypothesized moderator effects were significant for this set of hypotheses. This suggests that the decision environment does not moderate the ability of BI to support decision making. It does not moderate the relationship between BI success and the influence of data sources (H3a & b), data reliability (H3 e & f), or user access methods (H3h & i) regardless of whether the environment is one of operational activities or strategic activities. One possible explanation for this is that the data sources are consistent across respondents i.e., the data they use is drawn from transactional data that is filtered into data warehouses and data marts, regardless of the decision environment. Similarly, although data reliability impacts BI success, all decisions must be based on reliable data regardless of the decision environment. With regard to user access methods, these findings indicate that higher quality user access methods positively impact BI success regardless of decision environment. Table 37 shows regression results for H3, where the significant hypotheses are highlighted.

Table 37

Multiple Regression Results – H3

	Variables	*β*	*t-value*	*p-value*	*R Square Change*	*F Change*	*Sig. F Change*
H3a	Internal Data Source Quality Decision Environment	.311 .180	3.559 1.551	.001 .124	.118	7.546	.001
	Internal Data Source Quality Decision Environment IntDatSrcQ X DecEnv	.317 .172 -.075	3.596 1.472 -.602	.000 .144 .549	.003	.362	.549
H3b	External Data Source Quality Decision Environment	.165 .165	2.142 1.371	0.34 .173	.057	3.428	.036
	External Data Source Quality Decision Environment ExtDatSrcQ X DecEnv	.164 .171 -.084	2.120 1.418 -.726	.036 .159 .469	.004	.528	.469
H3c	Quantitative Data Quality Decision Environment	.557 -.067	6.311 -.592	.000 .555	.275	21.390	.000
	Quantitative Data Quality Decision Environment QuantDatQ X DecEnv	.509 -.065 .298	5.779 -.593 2.600	.000 .554 .011	.041	6.759	.011
H3d	Qualitative Data Quality Decision Environment	.242 .128	3.156 1.083	.002 .281	.098	6.165	.003
	Qualitative Data Quality Decision Environment QualDatQ X DecEnv	.225 .138 .077	2.798 1.155 .752	.006 .250 .454	.005	.565	.454
H3e	Internal Data Reliability Decision Environment	.404 .112	4.047 .966	.000 .336	.143	9.436	.000
	Internal Data Reliability Decision Environment IntDatRel X DecEnv	.369 .126 .153	3.468 1.079 .949	.001 .283 .345	.007	.900	.345
H3f	External Data Reliability Decision Environment	.164 .159	1.760 1.309	.081 .193	.045	2.668	.074
	External Data Reliability Decision Environment ExtDatRel X DecEnv	.170 .155 .069	1.801 1.270 .464	.074 .207 .644	.002	.215	.644
H3g	Interaction Decision Environment	.479 .232	6.605 2.222	.000 .028	.292	23.322	.000
	Interaction Decision Environment Interaction X DecEnv	.478 .232 .006	6.523 2.208 .056	.000 .029 .956	.000	.003	.956
H3h/H3i	User Access Quality Decision Environment	.671 .069	9.912 .767	.000 .445	.475	51.156	.000
	User Access Quality Decision Environment UserAccQ X DecEnv	.668 .067 .021	9.385 .736 .180	.000 .463 .858	.000	.032	.858

To further assess the substantive impact of the significant moderator effect in H3c, regression equations were calculated for low and high values of independent variables by substituting the desired values in the overall regression equation. Research suggests substituting the value of -1 standard deviation, the mean, and +1 standard deviation on the moderator variable (Aiken and West, 1991). Because I am specifically interested in the implications of this research for operational and strategic decision environments (low and high values of the decision environment variable), a regression equation was calculated using -1 standard deviation, mean and +1 standard deviation of the decision environment. The mean and the standard deviation for the decision environment are shown below in Table 38. Table 39 presents the calculated regression equations.

Table 38

Descriptive Statistics for the Decision Environment

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
Average Decision Environment - Centered	116	-1.818966	1.181034	.00000000	.644024546

Table 39

Regression Equations for High and Low Values of the Decision Environment

Moderator Values	*Corresponding Decision Environment*	*Independent Variable*	*Regression Equation for BI Success*
+1 Standard Deviation	Operational	Quantitative Data Quality	BI Success = 3.596 + (0.807 * QuantitDataQ)
Mean	Between Operational and Strategic	Quantitative Data Quality	BI Success = 3.661 + (0.509 * QuantitDataQ)
-1 Standard Deviation	Strategic	Quantitative Data Quality	BI Success = 3.726 + (0.211 * QuantitDataQ)

The above regression equations show that quantitative data quality has stronger effect on BI success for operational decision environments, where the decisions are structured and management activities are operational. Below Figure 6 show the graphical representation of the above mentioned regression lines. This figure depicts that quantitative data quality appears to have a substantive positive effect on BI success. As this variable increases, BI success for an operational decision environment exhibits greater increase than for a strategic decision environment. Thus, the effect of moderation is significantly and substantively greater for the operational decision environment.

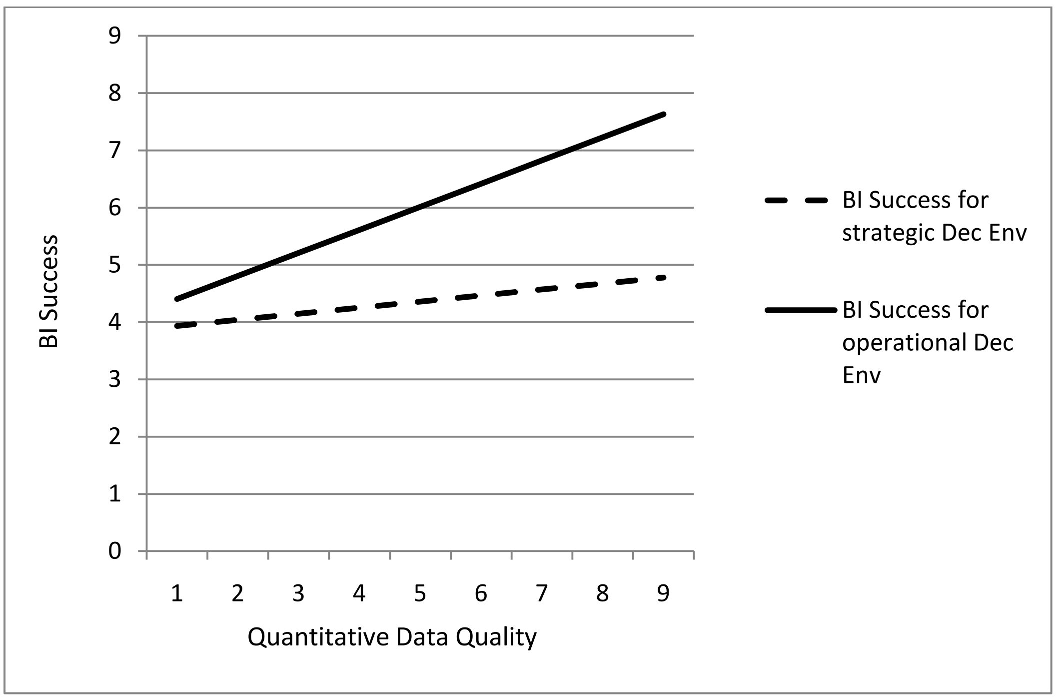

Figure 6. Interaction effect on the quantitative data quality.

The interaction effect of the decision environment on the relationship between organizational BI capabilities and BI success (H4a - c) were each tested separately using multiple regression. These hypotheses examine only the moderator effect of an unstructured/strategic decision environment (Table 40). Results show that none of the R^2 changes are significant, thus the interaction effects are not significant (Table 41). The strength of the impact of flexibility, risk, and intuition on BI success is not impacted by the decision environment. Only flexibility and risk impact BI success in the absence of the moderator. This suggests that the degree of intuition involved in the decision is not related to the success of the BI in supporting decisions. One reason for this may be that BI users do not heavily rely on intuition for decision making. This is consistent with research that indicates that BI helps to reduce the amount of intuition involved in decision making (Howson, 2006). A possible explanation for the findings surrounding flexibility and risk may also relate to the way BI is used. Research suggests that BI may be more useful in helping decision makers grapple with decisions involving higher risk and where flexibility is needed (Clark et al 2007). Therefore, the impact of flexibility and risk on BI success is strong across decision environments.

Table 40

Hypotheses 4

H4a	The influence of BI flexibility on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.
H4b	The influence of the intuition allowed in analysis on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.
H4c	The influence of tolerating risk on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.

A summary of all hypotheses testing results is provided in Table 42. Overall, BI success is greater with higher quality data sources, data types, data reliability, interaction of BI with other systems, user access methods, and higher flexibility. Thus, technological BI capabilities are largely more influential in BI success than organizational. This is somewhat surprising given the importance of organization readiness (capabilities) called for in much of the BI literature (Clark, et al. 2007; Watson and Wixom, 2007). The implications of these findings are discussed further in Chapter 5.

Table 41

Multiple Regression Results – H4

	Variables	β	*t*-value	*p*-value	R^2 Change	*F* Change	Sig. F Change
H4a	Flexibility	.554	7.344	.000	.336	28.575	.000
	Decision Environment	.178	1.769	.080			
	Flexibility	.558	7.321	.000	.001	.211	.647
	Decision Environment	.182	1.795	.075			
	Flexibility X DecEnv	-.050	-.460	.647			
H4b	Risk	.490	6.208	.000	.268	20.728	.000
	Decision Environment	.176	1.664	.099			
	Risk	.485	5.825	.000	.000	.035	.852
	Decision Environment	.174	1.622	.108			
	Risk X DecEnv	.022	.187	.852			
H4c	Intuition	.095	.733	.465	.024	1.363	.260
	Decision Environment	.176	1.438	.153			
	Intuition	.089	.668	.505	.000	.049	.825
	Decision Environment	.173	1.403	.163			
	Intuition X DecEnv	.043	.222	.222			

Table 42

Summary of Hypothesis Testing

	Hypothesis	*Results*
Technological BI Capabilities Direct Effects	H1a: The better the quality of data sources in an organization, the greater its BI success.	Supported
	H1b: The better the quality of different types of data in an organization, the greater its BI success.	Supported
	H1c: The higher the data reliability in an organization, the greater its BI success.	Supported
	H1d: The higher the quality of interaction of BI with other systems in an organization, the greater its BI success.	Supported
	H1e: The higher the quality of user access methods to BI in an organization, the greater its BI success.	Supported
Organizational BI Capabilities Direct Effects	H2a: The level of BI flexibility positively influences BI success.	Supported
	H2b: The level of intuition allowed in analysis by BI positively influences BI success.	Not Supported
	H2c: The level of risk supported by BI positively influences BI success.	Not Supported
Technological BI Capabilities Interaction Effects	H3a: The influence of high quality internal data sources on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.	Not Supported
	H3b: The influence of high quality external data sources on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.	Not Supported
	H3c: The positive influence of high quality quantitative data on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.	Supported

(table continues)

Table 42 *(continued)*.

Technological BI Capabilities Interaction Effects	H3d: The positive influence of high quality qualitative data on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.	Not Supported
	H3e: The positive influence of high data reliability at the system level on BI success is moderated by the decision environment such that the effect is stronger for structured decision types and operational control activities.	Not Supported
	H3f: The positive influence of high data reliability at the individual level on BI success is moderated by the decision environment such that the effect is stronger for unstructured decision types and strategic planning activities.	Not Supported
	H3g: The positive influence of high quality interaction of BI with other systems in the organization on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	Not Supported
	H3h: The positive influence of high quality shared user access methods to BI on BI success is moderated by the decision environment, such that the effect is stronger for structured decision types and operational control activities.	Not Supported
	H3i: The positive influence of high quality individual user access methods to BI on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	Not Supported
Organizational BI Capabilities Interaction Effects	H4a: The influence of BI flexibility on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	Not Supported
	H4b: The influence of the intuition allowed in analysis on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	Not Supported
	H4c: The influence of tolerating risk on BI success is moderated by the decision environment, such that the effect is stronger for unstructured decision types and strategic planning activities.	Not Supported

* Significant at the p = 0.1 level
** Significant at the p = 0.05 level
*** Significant at the p = 0.01 level

CHAPTER 5

DISCUSSION AND CONCLUSIONS

This dissertation studies the relationship between various business intelligence (BI) capabilities and BI success, and whether this relationship is affected by different decision environments. This chapter starts with providing a discussion of the findings and presenting the limitations of the study. It then proceeds with theoretical and managerial implications of the study, and concludes by providing future research directions.

Discussion of Research Findings

This dissertation proposes a framework for examining technological and organizational BI capabilities and how they impact BI success. This framework also considers that different BI capabilities may have a more significant impact on BI success for different decision environments. The decision environment consists of different information characteristics required to make decisions. Each of the constructs and their relevant findings are discussed below.

Technological BI Capabilities and BI Success

Hypotheses 1a-e propose that the quality of technological BI capabilities positively impact BI success. The technological BI capabilities examined in this dissertation are data sources (H1a), different types of data (H1b), data reliability (H1c), interaction of BI with other systems (H1d) and user access methods to BI (H1e). These hypotheses suggest that the higher the quality of technological BI capabilities, the greater the BI success. All of these hypotheses (H1a-e) were confirmed by the positive significant relationship between all technological BI capabilities and BI success.

These results suggest that technological BI capabilities are critical elements for a successful BI. Organizations, as they are going through BI implementations, should make sure that they have these technological capabilities implemented. But, just implementing these capabilities is not enough; the difference in the quality of these capabilities is one of the factors that may explain why some organizations are successful with their BI initiative while some are not. Organizations should work towards maintaining the quality of these capabilities, because as the quality of technological BI capabilities increases, the BI success in an organization also increases.

These results are also consistent with prior research. Research shows that clean, high quality and reliable data is one of the most important BI success factors (Eckerson, 2003; Howson, 2006). Research also implies that the sources where the organizations obtain their data from play a critical role for the success of a BI initiative (Howson, 2006). Especially for organizations that use multiple data sources and multiple information systems, it is critical to integrate these technologies and information to avoid inconsistencies and inaccuracies (Swaminatha, 2006; Sabherwal and Becerra-Fernandez, 2010). Different user access methods are also critical for BI success; providing high quality user access methods increases the decision making effectiveness (Hostmann et al., 2007) as well as the effectiveness of presenting the appropriate information based on user specific needs and tasks. Because the overall goal is to enable users access and navigate through data based on their requirements (Sabherwal, 2007, 2008).

Organizational BI Capabilities and BI Success

Hypotheses 2a-c propose that organizational BI capabilities positively impact BI success. The organizational BI capabilities examined in this dissertation are flexibility (H2a), the level of intuition involved in analysis (H2b) and level of risk supported by BI (H2c). These hypotheses suggest, regardless of their levels, these organizational BI capabilities significantly impact BI success. Results of data analysis showed that H2a was confirmed by the positive significant relationship between flexibility and BI success, but H2b and H2c were not confirmed. There was not a significant relationship between BI success and intuition involved in analysis or level of risk supported by BI. This is somewhat surprising considering research emphasizing the importance of organizational readiness (Clark, et al. 2007; Watson and Wixom, 2007). Although organizational readiness and organizational capabilities are not the same thing, organizational capabilities play a critical role in achieving organizational BI readiness (Williams and Williams, 2007).

The significance of flexibility as an organizational BI capability suggests that in order to be successful, a BI initiative should be able to accommodate a certain amount of variation in the business processes, environment or the technology (Gebauer and Schober, 2006; Clark et al., 2007). This finding is also consistent with the literature. Prior research suggests that flexibility is one of the most important factors to consider while selecting a BI application (Dreyer, 2006). Considering that change is inevitable in the current business environment, the organization should be able to modify its BI easily and quickly to adapt to the changing business (Sabherwal and Becerra-Fernandez, 2010).

The non-significance of the level of intuition involved in analysis may indicate two things. First, it may mean that decision makers do not involve their intuition in their decision making process with BI and make decisions purely on data and analysis. In support of this argument, prior research suggests that organizations making decisions based on data and analysis are more likely to succeed with their BI initiative compared to the organizations making decisions based on intuition (Howson, 2008; Sabherwal and Becerra-Fernandez, 2010). The non-significance of the level of intuition involved in analysis may also mean that BI success is more dependent on how decision makers use the system rather than "what is going on in their head." While experience based intuition is important, gut instinct based on experiences is not as useful as it used to be in less dynamic events (Bresnahan, 1999). This is consistent with research that indicates that BI helps to reduce the amount of intuition involved in decision making (Howson, 2006).

A possible explanation for the findings about risk may also relate to the way BI is used. Research suggests that BI may be more useful in helping decision makers deal with decisions involving higher risk (Clark et al 2007). BI has been studied as a risk analysis and mitigation platform, with the overall goal of managing and reducing it (Azvine et al., 2007). Given internal and external risks that an organization deals with and how they can harm organizational performance, the role of BI should be to manage risk by attempting to minimize it and providing an integrated view of performance and risk (Azvine et al., 2007). Thus, users may not be aware of the level of risk surrounding the decisions they make because their BI is already managing that risk. It is also possible that different organizations as well as different groups within an organization may be facing different levels of risk during their decision making process, and the majority of respondents to the survey were from a group that does not have to deal with a lot of risk. This is not surprising considering that majority of the respondents are middle and operational level managers. By definition, middle and operational level managers deal with less risky situations compared to strategic level managers.

Technological BI Capabilities and the Decision Environment

Hypotheses 3a-i propose that the relationship between technological BI capabilities and BI success is moderated by the decision environment. Results of data analysis showed that only the influence of high quality quantitative data on BI success is moderated by the decision environment such that the effect is stronger for operational decision environments (H3c). This finding is not surprising considering that operational management activities largely rely on quantifiable data (Gorry and Scott Morton, 1971; Anthony, 1965; Keen and Scott-Morton, 1978), and that the quality of that data is critical for the decision maker. The rest of the hypotheses positing interaction effects were not supported. More specifically, the findings suggest that high quality internal data sources (H3a), high quality quantitative data (H3c), high data reliability at the system level (H3e), and high quality shared user access methods (H3h) do not have a stronger impact on BI success for operational decision environments.

The results also suggest that high quality external data sources (H3b), high quality qualitative data (H3d), high data reliability at the individual level (H3f), high quality interaction (H3g), and high quality individual user access methods (H3i) do not have a stronger impact on BI success for strategic decision environments. One possible explanation for the non-significance of H3d is that respondents rely more heavily on quantitative or quantifiable data than on qualitative data. Thus, they are not as concerned with the quality of qualitative data in the strategic decision environment. It is also a possibility that there were not enough respondents representing the strategic decision environment to account for a significant statistical impact.

The non-significance of the other hypothesized moderator effects suggests that the decision environment does not moderate the relationship between technological BI capabilities and BI success. One possible explanation for this is that respondents refer to the same data sources, use consistently reliable data, access the BI and experience same level of interaction with other systems, regardless of decision environment. Thus, these technological BI capabilities influence BI success regardless of whether the environment is one of structured decisions/operational activities or unstructured decisions/strategic activities.

Organizational BI Capabilities and the Decision Environment

Hypotheses 4a-c proposes the relationship between organizational BI capabilities and BI success is moderated by the decision environment. More specifically, they suggest that the positive impact of flexibility (H4a), intuition allowed in analysis (H4b) and level of risk supported by BI (H4c) on BI success is stronger for strategic decision environments. Results of data analysis showed that none of the interaction effects hypothesized is significant. This indicated that the decision environment does not impact the strength of the relationship between BI success and organizational BI capabilities.

The non-significance of the interaction effect associated with intuition is not surprising in the light of the non-significance of its main effects (H2b). Thus, it may mean that decision makers do not involve their intuition in the decision making process, regardless of the decision environment. Research also suggests that the role of BI is to minimize the use of intuition in the decision making process (Howson, 2006; Sabherwal and Becerra-Fernandez, 2010). Similarly, the main effect of the level of risk was not significant, and the interaction effect associated with risk is not significant either. It means that there is no difference between decision environments in terms of the impact level of risk supported by BI has on BI success. This may indicate that regardless of the decision environment, BI is more successful as long as it can support high risk decisions.

Flexibility impacts BI success in the absence of the moderator. The interaction effect of the decision environment on the relationship between flexibility and BI success is not significant. This indicates that the level of BI flexibility is as important for operational decision environments as it is for strategic decision environments. This is consistent with research suggesting that BI is more successful dealing with situations where flexibility is needed (Clark et al 2007).

Limitations

This study is subject to several possible limitations in terms of sample size and scales used. First, the sample size does not allow for a more comprehensive analysis. The results might have been more significant if the sample size had been larger and a more thorough analysis could have been employed. Also, the respondents are not as diverse as I would like. For instance, only 11 respondents are female, and only 24 of the respondents are executive level managers. Response rate is another limitation for this study. Although the survey link was broadcasted to over 8,000 people, less than 1% actually filled out the survey. There can be possible reasons for the low response rate. First of all, there was no incentive for taking the survey and considering the busy business life, recipients possibly did not feel compelled to take the survey. Also, the length of the survey (20 to 30 minutes) might be another reason why the recipients did not want to complete the survey.

Common method variance is another possible limitation of the study. Common method variance refers to the fact that potential respondent biases might constitute a systematic error. This is common when using survey responses from the same source because a single respondent for each survey can only yield one perspective. Thus, there might be spurious correlation (Bagozzi, 1980). Several precautions were taken to minimize the effects of common method variance. The dependent and independent variables were separated into different sections of the survey instrument, using different question formats.

Another possible limitation is the items used to measure some of the constructs. The reliability analysis was not satisfactory for the level of intuition involved in analysis and decision types constructs. It is possible that items measuring intuition was not clear enough or did not tap well enough into the level of intuition the respondents use during their decision making process. Although the analysis of the responses show that more than 65% of the respondents involve their gut feeling and put emphasis on their past experiences when making decisions, this was not reflected in the BI success factor. Similarly, three out of five items that were supposed to measure decision types were dropped from the scale, because they were either tapping into multiple different things (e.g., DecType5, “the decisions I make require computational complexity and precision”) or their wording was deemed to be ambiguous (e.g., DecType2_coded, “I make decision without higher level manager involvement”) because they were not necessarily measuring the decision type made by the decision maker.

The items measuring user access quality were deemed problematic. It was posited that the user access methods consist of two types; individual user access and shared user access. The goal with the survey was to measure the extent of satisfaction of the BI user with both user access methods. Yet, the items in the survey only measure the overall quality of the user access methods. Thus, whether these two different user access methods have different impacts on BI success, for different decision environments could not be measured. Instead, the impact of the overall user access quality on BI success for different decision environments was measured.

Although scale related issues may pose as limitations for the current study, this may also be considered as a starting point for developing a BI success model and its scale. The wording of some of the questions was ambiguous and mistakes such as using conjunctives have been made. There are some questions that should have been divided into two and asked as two different questions.

Research Contributions

The BI success model suggested in this study contributes to the information systems (IS) literature in several ways. First, it proposes to extend current research in BI and provide a parsimonious and intuitive model for explaining the relationship between BI success and BI capabilities in the presence of different decision environments, based on theories from decision making and organizational information processing. This dissertation contributes to academic research by providing richer insight in the role of the decision environment in BI success and providing a framework with which future research on the relationship between BI capabilities and BI success can be conducted.

Another research contribution is the inclusion of the decision environment in the BI success model. The moderating effect of the decision environment has not been studied in the IS literature before. The decision environment is operationalized based on Gorry and Scott Morton's (1971) framework for DSS and Anthony's (1965) framework for management activities. Although these are two established theories, they have not been used for BI research before and also have not been operationalized to measure with survey items. This study is a first attempt in creating survey items to operationalize these frameworks. Also, this dissertation is a first attempt to develop a scale for BI capabilities and BI success. The BI capabilities have not been measured to date and they all have shown good validity and reliability. All capabilities has an internal consistency of .768 or above, with the exception of the intuition involved in analysis, which had an acceptable level of internal consistency of .605 for newly developed instruments (O'Leary-Kelly and Vokurka, 1998). Similarly, the BI success scale was a first attempt and had a Cronbach's alpha of .914, indicating an internally consistent scale (Nunnally and Bernstein, 1994).

The findings of this study indicate that technological BI capabilities impact BI success significantly, regardless of the decision environment. This may imply that technology drives the BI initiatives. While the technologies used or the platform BI is built upon is undeniable critical for BI success, factors such as top management support, alignment between business strategy and BI, a strong BI team and available resource are as important (Eckerson, 2006; Wason and Wixom, 2007). These non-technological capabilities are mostly referred to as organizational readiness issues and discussed widely in the IT literature as critical success factors for IT implementation (Rud, 2009; Williams and Williams, 2007; Abdinnour-Helm et al., 2002).

Although these have substantial impact on how BI is used within an organization, there are still enabling technologies that need to be implemented in order to benefit from these factors (Sabherwal and Becerra-Fernandez, 2010). This may be the reason behind findings suggesting that technological capabilities impact BI success more significantly. For example, intuition was non-significant in the results, implying that it does not substantially impact BI success. Consistent with this finding, literature suggests not to make decisions based on intuition, yet, both academic and practitioners' literature emphasize that so many business decisions today are made based on the decision maker's gut feeling (Davenport and Harris, 2007; Bonabeau, 2003). As a solution, converting intuition into a tangible strategy is suggested, through using decision support tools (Bonabeau, 2003) and analytics (Davenport and Harris, 2007). This exemplifies that it is critical to have the necessary enabling technologies to be able to benefit from the organizational capabilities.

Only one of the three organizational BI capabilities, flexibility, was found to be significant by the analysis. This indicates that technology is the most eminent factor that decision makers associate with BI success, and that BI success is mostly driven by technology rather than organizational factors. Although research suggests that organizational BI capabilities are important for BI success (Watson and Wixom, 2007; Watson, 2008) the results of this study suggest that some organizational BI capabilities are more important than the others. The significance of flexibility as an organizational BI capability shows that it is a strategically important element for managing the unpredictable, especially in the technology-intensive settings (Evans, 1991). This suggests that flexibility can be tied to the frequently sought after agility by the companies. Agility can be defined as a measure of an organization's ability to change and adapt to new environments (Neumann, 1994). The more change in the business environment, the more the organization requires agility and BI provides the opportunities for the organization to be more agile and adopt innovation (Sabherwal and Becerra-Fernandez, 2010). It is possible that organizations strive to achieve agility, and flexibility of BI may be the most important capability of BI in order to achieve that agility. Literature has suggested IT capabilities as a potential source for agility (Weill et al., 2002; Fink and Neumann, 2007), and findings of this study is consistent with the previous research findings about flexibility being one of the most important factors for achieving agility (Swafford et al., 2008; Erol et al., 2009).

Another contribution of this dissertation is that it shows the relationship between quantitative data quality, decision environment and BI success. The results show that the influence of high quality quantitative data on BI success is moderated by the information processing needs such that the effect is stronger for operational control activities. Literature suggests that operational management activities largely rely on quantifiable data (Gorry and Scott Morton, 1971; Anthony, 1965; Keen and Scott-Morton, 1978), and that the quality of that data is critical for the decision maker. This indicates that, based on the information requirements of a decision maker, the quality of the quantitative data significantly impacts BI success. Especially for those decision makers who deal with operational control related management activities, this impact becomes even more obvious because they mostly rely on this type of data. Although the importance of data quality and to be more specific, the quality of the quantitative data has been studied (Baars and Kemper, 2008; Sabherwal and Becerra-

Fernandez, 2010), the fact that it is more critical for the operational control activities has not been investigated previously.

This study provides significant findings for practitioners. The practitioner oriented contribution of this study is that it helps users and developers of BI understand how to better align their BI capabilities with their decision environments and presents information for managers and users of BI to consider about their decision environment in assessing BI success. Although it is the only significant interaction effect, the fact that quantitative data quality has a stronger effect on BI success for operational decision environments rather than strategic decision environments provides an important insight for BI users and managers. Also, the scale used for this study can be worked up and extended into a much broader BI success survey, which can be used in the industry to assess organizations' BI success.

Conclusion and Future Research Directions

Research on BI success and its relationship with BI capabilities is scarce. This study introduces a new BI success model and provides understanding regarding how different BI capabilities can improve BI success within an organization. Prior to this study, BI success research included topics such as critical success factors for BI implementation (Wixom and Watson, 2001; Solomon, 2005), measurement of BI success (Gessner and Volonino, 2005; Lonnqvist and Pirttimaki, 2006), and case studies focusing on success or failure stories of specific BI technologies implemented by specific companies (Cooper et al., 2000; Watson and Donkin, 2005; Anderson-Lehman et al., 2004).

This study adds to the existing body of knowledge by introducing technological and organizational BI capabilities and how they can impact BI success. In addition, this study also introduces the decision environment as a moderator for BI success. The findings of this dissertation suggest that technological capabilities positively impact BI success. However, hypotheses testing the moderating effect of the decision environment are not supported with one exception. Results show that the quality of quantitative data indeed impacts BI success stronger for operational decision environment than strategic decision environments, as hypothesized. Using a different sampling frame and a larger sample size may yield more significant findings. Thus, this is one of the future research directions. Another future research direction may be to expand the capabilities. The technological and organizational BI capabilities studied in this research are by no means exhaustive. Reexamining the ones studied in this dissertation, expanding capabilities and even possible redefining grouping of the constructs maybe another future research direction.

Having the right BI capabilities within the proper decision environment is important for an organization to realize maximum benefits from its BI investment. This study may serve as a starting point in investigating how different BI capabilities may impact BI success, for different decision types and different information requirements for those decisions. Future research on BI success would benefit from the inclusion of different BI capabilities as well as the inclusion of other organizational characteristics, such as the organizational structure or organizational culture. Incorporating environmental characteristics such as the uncertainty and equivocality (Tushman and Nadler, 1978) in the model may also increase understanding of BI success.

APPENDIX A

COVER LETTER

Dear Participant,

I would like to invite you to participate in this research project, which is being conducted as part of the requirements for me to earn my Ph.D. in Business Computer Information Systems from the University of North Texas. The project aims to measure Business Intelligence (BI) success by examining the BI capabilities used in your organization and how they are influenced by your decision environment.

Your honest responses to each statement and question are extremely important to this project’s outcome. You can be assured of complete confidentiality – no individual responses will be published and the raw information will be accessible only to me and the University of North Texas faculty on my dissertation committee. This survey contains sections addressing your satisfaction with BI, the types of decisions you make, your information processing needs, the capabilities of BI you use, and some information about yourself.

It will take you approximately 30 minutes to complete the survey. In addition, your participation is voluntary. You may decline to answer any particular question that you are uncomfortable with or feel is not appropriate. Submitting the survey will indicate that you have given your consent for us to use your data. The study has been reviewed and approved by the UNT Committee for the Protection of Human Subjects (940.565.3940). If you have questions concerning this study, please feel free to contact me.

Thank you again for your consideration.

Sincerely,

Oyku Isik

APPENDIX B

SURVEY INSTRUMENT

1. What is the highest education level you have completed? ***(Analysis Label: HighestEdLevel)***

- ❑ High School
- ❑ Some college
- ❑ Two-year college degree
- ❑ Four-year college degree
- ❑ Graduate degree
- ❑ Post-graduate degree

2. What is your gender? ***(Analysis Label: Gender)***

- ❑ Male
- ❑ Female

3. How long have you been in your current organization? ___ years ***(Analysis Label: TimeInOrg)***

4. Do you hold a managerial position? ***(Analysis Label: ManagerialPosition)***

- ❑ Yes
- ❑ No

5. What is your functional area? ***(Analysis Label: FunctArea)***

- ❑ General management
- ❑ Corporate communications
- ❑ Finance / Accounting / Planning
- ❑ Human resources / Personnel
- ❑ Information technology
- ❑ Legal
- ❑ Manufacturing / Operations
- ❑ Marketing
- ❑ Sales
- ❑ Supply chain
- ❑ Other (please specify) ___________________________

6. What is your level in the organization? ***(Analysis Label: LevelInOrg)***

- ❑ Executive management
- ❑ Middle management
- ❑ Operational management
- ❑ Other (please specify) ___________________________

7. What is your job title? __________ ***(Analysis Label: JobTitle)***

8. What is the approximate number of employees in your organization? ***(Analysis Label: NumEmployees)***

- ❑ Less than 100
- ❑ 100-499
- ❑ 500-999
- ❑ 1,000 -4,999
- ❑ 5,000- 9,999
- ❑ 10,000 or more

9. Which below best describes your industry? ***(Analysis Label: Industry)***

- ❑ Manufacturing
- ❑ Finance
- ❑ Education
- ❑ Wholesale & retail trade
- ❑ Transportation
- ❑ Banking
- ❑ Manufacturing
- ❑ Utilities
- ❑ Government
- ❑ Insurance
- ❑ Other (Please specify) ______

For the purposes of this research, Business Intelligence (BI) is defined as the following;

"BI is a system comprised of both technical and organizational elements that presents historical information to its users for analysis, to enable effective decision making and management support, for the overall purpose of increasing organizational performance."

Please answer the following questions about a specific BI application you use for your everyday business decision making purposes. If you are using more than one BI application, please focus only on one of them and answer the questions only based on that specific application.

Please choose the response which best describes your satisfaction with each of the following:

LABEL	**CONSTRUCT: BI Success**	Strongly dissatisfied	Somewhat dissatisfied	Neither satisfied or dissatisfied	Somewhat satisfied	Strongly satisfied
BIsat1	How well the BI that I am using supports my decision making	❍	❍	❍	❍	❍
BIsat2	How well the BI that I am using provides precise information I need	❍	❍	❍	❍	❍
BIsat3	How well the BI that I am using provides information I need in time	❍	❍	❍	❍	❍
BIsat4	How user friendly the BI that I am using is	❍	❍	❍	❍	❍
BIsat5	The BI that I am using overall	❍	❍	❍	❍	❍

Please indicate how well each statement below describes the decisions you make:

LABEL	**CONSTRUCT: Decision Types**	Almost never	Rarely	Sometimes	Frequently	Almost always
DecType1	I make routine, repetitive decisions	❍	❍	❍	❍	❍
DecType2_coded	I make decisions without higher level manager involvement	❍	❍	❍	❍	❍
DecType3	The decisions I make could be automated	❍	❍	❍	❍	❍
DecType4_coded	The decisions I make require judgment and intuition	❍	❍	❍	❍	❍
DecType5	The decisions I make require computational complexity and precision	❍	❍	❍	❍	❍

Please answer the following about the nature of the information you use to make decisions;

LABEL	**CONSTRUCT: Information Processing Needs**	Low 1	2	3	4	5 High
InfoChar1	The granularity is ...	❍	❍	❍	❍	❍
InfoChar2	Accuracy of information is ...	❍	❍	❍	❍	❍
		Wide 1	2	3	4	5 Narrow
InfoChar3	The scope of information is...	❍	❍	❍	❍	❍
		1 Qualitative	2	3	4	5 Quantitative
InfoChar4	Type of information is ...	❍	❍	❍	❍	❍
		1 Infrequent	2	3	4	5 Frequent
InfoChar5	Frequency of use is...	❍	❍	❍	❍	❍
		1 Older	2	3	4	5 Current
InfoChar6	Age of information is ...	❍	❍	❍	❍	❍

Please choose the response that best describes each of the following statements;

LABEL	CONSTRUCT: Data Sources	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
IntDataSrcQuality1	The **internal** data sources used for my BI are readily available	❍	❍	❍	❍	❍
IntDataSrcQuality2	The **internal** data sources used for my BI are readily usable	❍	❍	❍	❍	❍
IntDataSrcQuality3	The **internal** data sources used for my BI are easy to understand	❍	❍	❍	❍	❍
IntDataSrcQuality4	The **internal** data sources used for my BI are concise	❍	❍	❍	❍	❍
ExtDataSrcQuality1	The ***external*** data sources used for my BI are readily available	❍	❍	❍	❍	❍
ExtDataSrcQuality2	The ***external*** data sources used for my BI are readily usable	❍	❍	❍	❍	❍
ExtDataSrcQuality3	The ***external*** data sources used for my BI are easy to understand	❍	❍	❍	❍	❍

Please choose the response that best describes each of the following statements;

LABEL	CONSTRUCT: Data Types	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewha t agree	Strongl y agree
QuantDataQuality1	My BI provides accurate **quantitative** data	❍	❍	❍	❍	❍
QuantDataQuality2	My BI provides comprehensive **quantitative** data	❍	❍	❍	❍	❍
QuantDataQuality3	My BI provides consistent **quantitative** data	❍	❍	❍	❍	❍
QuantDataQuality4	My BI provides high quality **quantitative** data	❍	❍	❍	❍	❍
QualDataQuality1	My BI provides high quality ***qualitative*** data	❍	❍	❍	❍	❍
QualDataQuality2	My BI provides accurate ***qualitative*** data	❍	❍	❍	❍	❍
QualDataQuality3	My BI provides comprehensive ***qualitative*** data	❍	❍	❍	❍	❍
QualDataQuality4	My BI provides consistent ***qualitative*** data	❍	❍	❍	❍	❍

Please choose the response that best describes each of the following statements;

LABEL	CONSTRUCT: Intuition Involved	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
intuition1_coded	Using my BI, I make decisions based on facts and numbers	❍	❍	❍	❍	❍
intuition2	Although I use my BI for decision making, I still involve my gut feeling for the decisions I make	❍	❍	❍	❍	❍
intuition3	With my BI, it is easier to use my intuition to make better informed decisions	❍	❍	❍	❍	❍
intuition4	The decisions I make require a high level of thought	❍	❍	❍	❍	❍
intuition5	Although I use my BI for decision making , I still put emphasis on my past experiences for the decisions I make	❍	❍	❍	❍	❍

Please choose the response that best describes each of the following statements;

LABEL	CONSTRUCT: Data Reliability	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
IntDataQuality1	**Internal** data collected for my BI is reliable	❍	❍	❍	❍	❍
IntDataQuality2_Coded	There are inconsistencies and conflicts in the **internal** data for my BI	❍	❍	❍	❍	❍
IntDataQuality3	**Internal** data collected for my BI is accurate	❍	❍	❍	❍	❍
IntDataQuality4	**Internal** data for my BI is updated regularly	❍	❍	❍	❍	❍
ExtDataQuality1	***External*** data collected for my BI is reliable	❍	❍	❍	❍	❍
ExtDataQuality2_Coded	There are inconsistencies and conflicts in the ***external*** data for my BI	❍	❍	❍	❍	❍
ExtDataQuality3	***External*** data collected for my BI is accurate	❍	❍	❍	❍	❍
ExtDataQuality4	***External*** data for my BI is updated regularly	❍	❍	❍	❍	❍

Please choose the response that best describes each of the following statements;

LABEL	**CONSTRUCT: User Access**	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
UserAccess _qual1	I am satisfied with the quality of the way I access my BI	❍	❍	❍	❍	❍
UserAccess _qual2	I am authorized to access to all information I need with BI	❍	❍	❍	❍	❍
UserAccess _qual3	The way I access my BI is fits well to the types of decisions I make using my BI	❍	❍	❍	❍	❍

Please choose the response that best describes each of the following statements;

LABEL	**CONSTRUCT: Interaction with Other Systems** **My BI provides ...**	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
interaction1	… a unified view of business data and processes	❍	❍	❍	❍	❍
interaction2	… links among multiple business applications	❍	❍	❍	❍	❍
interaction3	… a comprehensive electronic catalog of the various enterprise information resources in the organization	❍	❍	❍	❍	❍
interaction4	… easy and seamless access to data from other applications and systems	❍	❍	❍	❍	❍

Please choose the response that best describes each of the following statements;

LABEL	CONSTRUCT: Flexibility My BI ...	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
flex1	… is compatible with other tools that I use (e.g., Microsoft Office Suite, security infrastructure, portal technology or databases)					
flex2	… can accommodate changes in business requirements quickly					
flex3	… makes it easier to deal with exceptional situations					
flex4	… is highly scalable with regards to transactions					
flex5	… is highly scalable with regards to data					
flex6	… is highly scalable with regards to users					
flex7	… is highly scalable with regards to infrastructure					
Flex8	The manner in which the components of my BI are organized and integrated allows for rapid changes					

Please choose the response that best describes each of the following statements;

LABEL	CONSTRUCT: Risk Level My BI ...	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
risk1	… supports decisions associated with high level of risk (e.g., entering a new market, hiring a new manager)					
risk2	… supports decisions motivated by exploration and discovery of new opportunities (e.g., starting a new business line, creating a new product design)					
risk3	… helps me minimize uncertainties in my decision making process					
risk4	… helps me manage risk by monitoring and regulating the operations (e.g., monitoring key performance indicators (KPIs), customizing alerts or creating dashboards)					

REFERENCES

Abdinnour-Helm, S., Lengnick-Hall, M. L. and Lengnick-Hall, C. A. (2003). Pre-implementation attitudes and organizational readiness for implementing an enterprise resource planning system. *European Journal of Operational Research*, *146* (2), 258-273.

Aiken, L. S., and West, S. G. (1991). Multiple regression: testing and interpreting interactions. Newbury Park, CA: Sage.

Al-Busaidi, K. A. and Olfman, L. (2005). An investigation of the determinants of knowledge management systems success in omani organizations. *Journal of Global Information Technology Management*, *8* (3), 6-27.

Alexander, J. W. and Randolph, W. A. (1985). The fit between technology and structure as a predictor of performance in nursing subunits. *Academy of Management Journal*, *28* (4), 844-859.

Alter, A. (2004). A work system view of DSS in its forth decade. *Decision Support Systems*, *38* (3), 319-327.

Anandarajan, M. and Arinze, B. (1998). Matching client/server processing architectures with information processing requirements: A contingency study. *Information & Management*, *34* (5), 265-276.

Anderson-Lehman, R., Watson, H. J., Wixom, B. H., and Hoffer, J. A. (2004). Continental Airlines flies high with real-time business intelligence. *MIS Quarterly Executive 3* (4), 163-176.

Antebi, O., (2007, January 16). Managing by exception [web log post]. Retrieved from http://www.panorama.com/blog/?p=13.

Anthony, R. N. (1965). *Planning and control systems: A framework for analysis.* Boston, MA: Harvard Business School Press.

Applegate, L. M., F. W. McFarlan, and J. L. McKenney. (1999). Corporate information systems management: The challenges of managing in an information age (5th ed). Boston, MA: Irwin/McGraw-Hill.

Armstrong, J. S., and Overton, T. S. (1971). Brief vs. comprehensive descriptions in measuring intentions to purchase. *Journal of Marketing Research*, *8* (1), 114-117.

Armstrong, J. S., and Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, *14*, 396-402.

Arnott, D. (2004). Decision support systems evolution: Framework, case study and research agenda," *European Journal of Information Systems, 13* (4), 247-259.

Arnott, D., and Pervan, G. (2005). A critical analysis of decision support systems research. *Journal of Information Technology*, *20* (2), 67-87.

Ashill, N. J. and Jobber, D. (2001). Defining the information needs of senior marketing executives: An exploratory study. *Qualitative Market Research*, *4* (1), 52-61.

Au, N., Ngai, E. W. T. and Cheng, T. C. E. (2008). Extending the understanding of end user information systems satisfaction formation: An equitable needs fulfillment model approach," *MIS Quarterly*, *32* (1), 43-66.

Azvine, B., Cui, Z., Majeed, B. and Spott, M. (2007). Operational risk management with real-time business intelligence. *BT Technology Journal*, *25* (1), 154-167.

Baars, H. and Kemper, H.G. (2008). Management support with structured and unstructured data-an integrated business intelligence framework. *Information Systems Management*, *45* (2), 132-148.

Bagozzi, P. (1980). Causal methods in marketing. New York, NY: John Wiley & Sons.

Baloh, P. (2007). The role of fit in knowledge management systems: Tentative propositions of the KMS design. *Journal of Organizational and End User Computing*. *19* (4), 22-41.

Baron, R. M. and Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations," *Journal of Personality and Social Psychology. 51* (6), 1173-1182.

Bartlett, J. E., Kotrlik, J. W., and Higgins, C. C. (2001). Organizational research: determining appropriate sample size in survey research. *Information Technology, Learning, and Performance Journal*, *19* (1), 43-50.

Basi, R. K. (1999). WWW response rates to socio-demographic items. *Journal of the Market Research Society*, *41* (4), 1999, 397-401.

Beach, L. R. and Mitchell, T. R. (1978). A contingency model for the selection of decision strategies. *The Academy of Management Review*, *3* (3), 439 -451.

Bell, R. (2007, July 11). Gut instincts give business intelligence a new flavor. *Financial Times*, p.2.

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly*, *24* (1), 169–196.

Bharadwaj, A. S., Sambamurthy, V. and Zmud, R. W. (1999, December). *IT Capabilities: Theoretical perspectives and empirical operationalization.* Paper presented at the 20th International Conference on Information Systems (ICIS), Charlotte, North Carolina.

Bhatt, G. D. and Grover, V. (2005). Types of information technology capabilities and their role in competitive advantage: An empirical study. *Journal of Management Information Systems, 22* (2), 253-277.

Blumberg, R. and Atre, S. (2003). The problem with unstructured data. *DM Review*. Retrieved from http://dmreview.com/master.cfm?NavID=55&EdID=6287.

Bonde, A. and Kuckuk, M. (2004, April). Real world business intelligence: The implementation perspective. *DM Review.* Retrieved from http://www.dmreview.com.

Bonabeau, E. (2003). Don't trust your gut. *Harvard Business Review*, *81* (5), 116-123.

Bresnahan, J. (1998, July). Legal espionage. *CIO Enterprise*.

Briggs, L. L. (2006). BI case study: Power company draws new energy. *Bi Solution Third*, *11* (3). Retrieved from http://www.tdwi.org/Publications/BIJournal/display.aspx?ID=8119m_page=1.

Buchanan, L. and O'Connell, A. (2006). A brief history of decision making. *Harvard Business Review*, *84* (1), 32-40.

Burns, T., and Stalker, G. M. (1961). The Management of Innovation. London: Tavistock.

Burton, B., Geishecker, L., Schelegel, K., Hostmann, B., Austin, T., Herschel, G., Soejarto, A., and Rayner, N. (2006). *Business intelligence focus shifts from tactical to strategic*. Retrieved from Gartner database.

Burton, B. and Hostmann, B. (2005). *Findings from Sydney symposium: Perceptions of business intelligence*. Retrieved from Gartner database.

Busemeyer, J. R. and Jones, L. E. (1983). Analysis of multiplicative combination rules when the causal variables are measured with error. *Psychological Bulletin, 93*, 549-563.

Busenitz, L. W. (1999). Entrepreneurial risk and strategic decision making. *The Journal of Applied Behavioral Science*, *35* (3), 325-340.

Chin, W.W. (1998). Issues and opinions on structural equation modeling. *MIS Quarterly, 22* (1), 7-16.

Chin, W. W. (2004). Frequently asked questions – partial least squares & PLS graph [Web log post]. Retrieved from: http://disc-nt.cba.uh.edu/chin/plsfaq/multigroup.htm.

Chung W., Zhang, Y., Huang, Z., Wang, G., Ong, T. and Chen H. (2004). Internet searching and browsing in a multilingual world: An experiment on the Chinese business intelligence portal (CbizPort). *Journal of the American Society for Information Science and Technology, 55* (9), 818-831.

Chung, W., Chen, H., and Nunamaker, J. F., Jr. (2005). A visual framework for knowledge discovery on the web: An empirical study of business intelligence exploration. *Journal of Management Information Systems 21* (4), 57-84.

Churchill, G. A. (1979). A paradigm for developing better measures of marketing constructs. *Journal of Marketing Research, 16*, 64-73.

Clark T. D., Jones, M. C., and Armstrong, C.P. (2007). The dynamic structure of management support systems: Theory development, research focus and direction. *MIS Quarterly*, *31* (3), 579-615.

Cody, W. F., Kreulen, J. T., Krishna, V. and Spangler. W. S. (2002). The integration of business intelligence and knowledge management. *IBM Systems Journal, 41* (4), 697-715.

Cohen, J. (1998). *Statistical power analysis for the behavioral sciences* (2nd ed). Hillsdale, NJ: Erlbaum.

Cooper, B. L., Watson, H. J., Wixom, B. H., and Goodhue, D. L. (2000). Data warehousing supports corporate strategy at first American corporation. *MIS Quarterly*, *24* (4), 547-567.

Cooper, R. B. and Wolfe, R. A. (2005). Information processing model of information technology adaptation: An intra-organizational diffusion perspective. *Database for advances in information systems*, *36* (1), 30-48.

Cooper, R. B. and Zmud, R. W. (1990). Information technology implementation research: A technological diffusion approach. *Management Science, 36* (2)*,* 123-141.

Cronbach, L.J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*, 297-334.

Cudeck R. (2001). Cronbach's Alpha on two-item scales. *Journal of Consumer Psychology, 10* (1/2), 55-69.

Daft, R. L. and Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, *32* (5), 554-571.

Daft, R. L. and Machintosh, N. B. (1981). A tentative exploration into the amount and equivocality of information processing in organizational work units. *Administrative Science Quarterly*, *26* (2), 207-224.

Damianakis, S. (2008, June). The ins and outs of imperfect data. *DM Direct*. Retrieved from http://www.dmreview.com/dmdirect/2008_77/10001491-1.html?portal=data_quality.

Davenport, T. H. and Harris, J. G. (2007). *Competing on analytics: The new science of winning*. Boston, MA: Harvard Business School Press.

Davison, L. (2001). Measuring competitive intelligence effectiveness: Insights from the advertising industry. *Competitive Intelligence Review, 12* (4), 25-38.

DeLone, W.H. and McLean, E.R. (1992) “Information system success: The quest for the dependent variable. *Information Systems Research*, *3* (1), 60–95.

Delone, W.H. and McLean, E.R. (2003). The DeLone and McLean model of information system success: A ten-year update. *Journal of Management Information Systems, 19* (4), 9–30.

Dennis, A. R., Wixom, B. H., and Vandenberg, R. J. (2001). Understanding fit and appropriation effects in group support systems via meta-analysis. *MIS Quarterly, 25* (2), 167-193.

Dillman, D.A. (2000). *Mail and internet surveys: The tailored design*. New York: John Wiley and Sons.

Doll, W. J. and Torkzadeh, G (1988). The measurement of end-user computing satisfaction. *MIS Quarterly, 12* (2), 259-274.

Douglas, B. S. (1998). Information processing theory: implications for health care organizations. *International Journal of Technology Management*, *15* (3-5), 211-223.

Dreyer, L. (2006, May). The “right time” for operational business intelligence? *TDWI What Works*. Retrieved from http://www.tdwi.org/Publications/WhatWorks/display.aspx?id=7976.

Duncan, R. B. (1972). Characteristics of organizational environment and perceived environmental uncertainty. *Administrative Science Quarterly*, *17*, 313-327.

Eckerson, W. (2003). Smart companies in the 21st century: The secrets of creating successful business intelligence solutions. *TDWI The Data Warehousing Institute Report Series*, 1-35. Retrieved from http://www.tdwi.org.

Eckerson, W. W. (2004). Gauge your data warehouse maturity. *DM Review*, *51*, 34–37. Retrieved from http://www.tdwi.org/publications/display.aspx?ID=7199.

Eckerson, W. W. (2006). *Performance dashboards: Measuring, monitoring, and managing your business.* Hoboken, NJ: Wiley & Sons.

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *The Academy of Management Review*, *14* (1), 57-76.

Erdfelder, E., Faul, F., and Buchner, A. (1996). GPOWER: A general power analysis program. *Behavior Research Methods, Instruments, & Computers*, *28*, 1-11.

Erol, O., Sauser, B. J., and Boardman, J. T. (2009). Creating enterprise flexibility through service oriented architecture. *Global Journal of Flexible Systems Management, 10* (1), 11-16.

Evans, J. S. (1991). Strategic flexibility for high technology manoeuvres: A conceptual framework. *Journal of Management Studies*, *28* (1), 69-89.

Evelson, B., McNabb, K., Karel, R., and Barnett, J. (2007). *It's time to reinvent your BI strategy.* Retrieved from Forrester database.

Fairbank, J.F., Labianca, G., Steensma, H.K. and Metters, R.D. (2006). Information processing design choices, strategy and risk management performance. *Journal of Management Information Systems*, *23*, 293-319.

Feeney, D. and Willcocks, L. (1998). Core IS capabilities for exploiting information technology. *Sloan Management Review*, *39* (3), 9–21.

Fink, L. and Neumann, S. (2007). Gaining agility through IT personnel capabilities: The mediating role of IT infrastructure capabilities. *Journal of the Association for Information Systems*, *8* (8), 440-458.

Finlay, P. N. and Forghani, M. (1998). A classification of success factors for decision support systems. *The Journal of Strategic Information Systems*, *7* (1), 53-70.

Forgionne, G. A. and Kohli, R. (2000). Management support system effectiveness: further empirical evidence. *Journal of the Association of Information Systems 1* (3), 1-37.

Fryman, H. (2007). Taking a user-centric approach to the information challenge. *Business Intelligence Journal, 12* (2). Retrieved from http://www.tdwi.org/Publications/BIJournal/display.aspx?ID=8475.

Galbraith, J. (1977). *Organizational design*. Reading, MA: Addison-Wesley.

Gallegos, F. (1999). Decision support systems: An overview. *Information Strategy, 15* (2), 42-47.

Garg, A.K., Joubert, R.J.O., and Pelisser, R. (2005). Information systems environmental alignment and business performance: A case study. *South African Journal of Business Management*, *36* (4), 33-53.

Gattiker, T. F. and Goodhue, D. L. (2004). Understanding the local-level costs and benefits of ERP through organizational information processing theory. *Information & Management*, *41* (4), 431.

Gebauer, J. and Schober, F. (2006). Information system flexibility and the cost efficiency of business processes. *Journal of the Association for Information Systems*, *7* (3), 122-145.

Gefen, D., Straub, D. W., and Boudreau, M. C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, *4* (7), 1-70.

Gefen, D., and Straub, D. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the AIS*, *16*, 91-109.

Gelderman, M. (2002). Task difficulty, task variability and satisfaction with management support systems. *Information & Management, 39* (7), 593-604.

Gerbing, D. W., and Anderson, J. C. (1988). An updated paradigm for scale development incorporating unidimensionality and its assessment. *Journal of Marketing Research, 25* (2), 186-192.

Gessner, G.H., and Volonino, L. (2005). Quick response improves on business intelligence investments. *Information Systems Management, 22* (3), 66-74.

Gile, K., Kirby, J. P., Karel, R., Teubner, C., Driver, E. and Murphy, B. (2006). *Topic overview: business intelligence*. Retrieved from Forrester database.

Gonzales, M. L. (2005, August). What's your BI environment IQ? *DM Review Magazine*. Retrieved from http://www.dmreview.com/issues/20050801/1033572-1.html.

Goodhue, L, D., Wybo, D, M. and Kirsch, J. L. (1992). The impact of data integration on the costs and benefits of information systems. *MIS Quarterly*, *16* (3), 293.

Dale Goodhue, D., Lewis, W., and Thompson, R. (2007). Statistical power in analyzing interaction effects: Questioning the advantage of PLS with product indicators. *Information Systems Research*, *18* (2), 211-227.

Gorry, G. A., Scott Morton, M. S. (1971). A framework for management information systems. *Sloan Management Review, 13* (1), 55-72.

Graham, P. (2008, August). Data quality: You don't just need a dashboard! Strategy execution. *DM Review Magazine*. Retrieved from http://www.dmreview.com/issues/2007_50/10001727-1.html?portal=data_quality.

Guimaraes, T., Igbaria, M. and Lu, M.T. (1992). The determinants of DSS success: An integrated model. *Decision Sciences, 23* (2), 409-432.

Hair, J.F, Anderson, R.L., Tatham, R., and Black, W. (1998). *Multivariate data analysis* (5th ed). New York: Prentice Hall.

Hannula, M. and Pirttimaki V. (2003). Business intelligence empirical study on the top 50 Finnish companies. *Journal of American Academy of Business, 2* (2), 593-599.

Harding, W. (2003). BI crucial to making the right decision. *Financial Executive, 19* (2), 49-50.

Hartono, E., Santhanam, R. and Holsapple, C.W. (2007). Factors that contribute to management support system success: An analysis of field studies. *Decision Support Systems, 43* (1), 256-268.

Havenstein, H. (2006, October). QlikTech looks to broaden access to BI data. *ComputerWorld*, Retrieved from http://www.computerworld.com/action/article.do?command=viewArticleBasic&articleId=9004369.

Henderson, J. C, and Venkatraman, N. (1993). Strategic alignment: Leveraging information technology for transforming organizations. *IBM Systems Journal*, *32* (1), 4-19.

Herring, J. (1996). Measuring the Value of Competitive Intelligence: Accessing & Communicating CI's Value to Your Organization. Alexandria, VA: SCIP Monograph Series.

Hong, K and Kim, Y. (2002). The critical success factors for ERP implementation: An organizational fit perspective. *Information and Management*, *40*, 25-40.

Hostmann, B.,Herschel, G. and Rayner, N. (2007). *The evolution of business intelligence: The four worlds*. Retrieved from Gartner database.

Howson, C. (2004, 2nd quarter). Ten mistakes to avoid when selecting and deploying BI tools. *TDWI Quarterly Ten Mistakes to Avoid Series.* Retrieved from http://www.bi-bestpractices.com/view-articles/4741.

Howson, C. (2006, September). The seven pillars of BI success. *Intelligent Enterprise.* Retrieved from http://www.intelligententerprise.com/showArticle.jhtml?articleID=191902420.

Howson, C. (2008). *Successful business intelligence: Secrets to making BI a killer app*. New York, NY: McGraw-Hill.

Huck, S. W. (2004). *Reading statistics and research*, (4th ed). Boston, MA: Pearson Education.

Hung, S.Y., Ku, Y. C., Liang, T. P. and Lee, C. J. (2007). Regret avoidance as a measure of DSS success: An exploratory study. *Decision Support Systems, 42* (4), 2093-2106.

Imhoff, C. (2005, August). Risky business! Using business intelligence to mitigate operational risk. *DM Review Magazine*. Retrieved from http://www.dmreview.com/issues/20050801/1033577-1.html.

Jain, H., Vitharana, P. and Zahedi, F. (2003). An assessment model for requirements identification in component-based software development. *Database for Advances in Information Systems*, *34* (4), 48-63.

Jarvenpaa, L. S. and Ives, B. (1993). Organizing for global competition: The fit of information technology. *Decision Sciences, 24* (3), 547-580.

Jourdan, Z., Rainer, R. K. and Marshall, T. E. (2008). Business intelligence: An analysis of the literature. *Information Systems Management*, *25* (2), 121–131.

Kanuk, L. and Berenson, C. (1975). Mail surveys and response rates: A literature review. *Journal of Marketing Research, 12* (4), 440-453.

Karahanna, E., Straub, D.W., and Chervany, N.L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly, 23* (2), 183-213.

Karimi, J., Somers, T.M. and Gupta, Y. P. (2004). Impact of environmental uncertainty and task characteristics on user satisfaction with data. *Information Systems Research, 15* (2), 175-195.

Kearns, G. S. and Lederer, A. L. (2003). A resource-based view of strategic IT alignment: How knowledge sharing creates competitive advantage. *Decision Sciences*, *34* (1), 1-29.

Keen, P. G. W. and Scott Morton, *M. S.* (1978). *Decision support systems: An organizational perspective*. Reading, MA: Addison-Wesley.

Keith, T. Z. (2006). *Multiple regression and beyond*. Boston, MA: Allyn & Bacon.

Keller, R. T. (1994). Technology-information processing fit and the performance of R&D project groups: A test of contingency theory. *Academy of Management Journal*, *37* (1), 167-179.

Kerlinger, F.N. and Lee, H.B. (2000). *Foundations of behavioral research* (4^{th} ed). New York: Thomson Learning.

Kirs, P. J., Sanders, G. L., Cerveny, R. P., and Robey, D. (1989). Experimental validation of the Gorry and Scott Morton framework. *MIS Quarterly*, *13* (2), 183-197.

Klein, G., Jiang, J. J. and Balloun, J. (1997). Information system evaluation by system typology. *Journal of Systems and Software*, *37* (3), 181-186.

Kulkarni, U. R., Ravindran, S. and Freeze, R. (2006). A knowledge management success model: Theoretical development and empirical validation. *Journal of Management Information Systems, 23* (3), 309-347.

Kviz, F. J. (1977). Toward a standard definition of response rate. *The Public Opinion Quarterly*, *41* (2), 265-267.

Lakshminarayan, K., Harp, S.A., Goldman, R. and Samad, T. (1996). Imputation of missing data using machine learning techniques. *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*. Portland, OR. Retrieved from http://www.aaai.org/Papers/KDD/1996/KDD96-023.pdf.

Lewis, G. J. (2004). Uncertainty and equivocality in the commercial and natural environments: The implications for organizational design. *Corporate Social Responsibility and Environmental Management, 11* (3), 167-177.

Loftis, L. (2008, November). Getting data in, getting information out. *DM Review Magazine,* 2008. Retrieved from http://www.dmreview.com/issues/2007_53/10002146-1.html.

Lonnqvist, A., and Pirttimaki, V. (2006). The measurement of business intelligence. *Business Intelligence, 23* (1), 32-40.

Lovelace, K. and Rosen, B. (1996). Differences in achieving person-organization fit among diverse groups of managers. *Journal of Management, 22* (5), 703-722.

Malone, R. (2005). Data warehousing: Information under control. *Forbes*. Retrieved from http://www.forbes.com/logistics/2005/12/23/cardinal-data-warehouse-cx_rm_1222cardinal.html.

Mangione, T. W. (1995). *Mail surveys: Improving the quality*. Thousand Oaks, CA: Sage Publications.

Manglik, A. (2006). Increasing BI adoption: An enterprise approach. *Business Intelligence Journal, 11* (2). Retrieved from http://www.tdwi.org/Publications/BIJournal/display.aspx?ID=8038.

Manglik, A. and Mehra, V. (2005). Extending enterprise BI capabilities: New patterns for data integration. *Business Intelligence Journal, 10* (1). Retrieved from: http://www.tdwi.org/research/display.aspx?ID=7486.

Marcoulides, G. A. and Saunders, C. (2006). PLS: A silver bullet? *MIS Quarterly*, *30* (2), iii-x.

Martinich, L. (2002). Managing innovations, standards and organizational capabilities*. IEEE International Engineering Management Conference*, *1*, 58- 63.

McMurchy, N. (2008). *Take these steps to develop successful BI business cases*. Retrieved from Gartner database.

McKnight, W. (2004, April). Business intelligence return on investment issues. *DM Review, 62*. Retrieved from: www.dmreview.com.

Miller, D. (2007, October). Measuring BI success: business goals and business requirements. *DM Review*. Retrieved from: http://www.dmreview.com/news/10000100-1.html.

Millet, I. and Gogan, J. L. (2006). A dialectical framework for problem structuring and information technology. *The Journal of the Operational Research Society*, *57* (4), 434-442.

Moss, L. T. and Atre, S. (2003). *Business intelligence roadmap: The complete project lifecycle for decision-support applications*. Boston, MA: Addison-Wesley.

Munro, M. C. and Davis, G. B. (1977). Determining management information needs: A comparison of methods. *MIS Quarterly*, *1* (2), 55-67.

Negash, S. (2004). Business intelligence. *Communications of the Association for Information Systems*, *13*, 177-195.

Nelson, R. R., Todd, P. A., and Wixom, B. H. (2005). Antecedents of information and system quality: Within the context of data warehousing. *Journal of Management Information Systems, 21* (4), 199-235.

Neumann, S. (1994). *Strategic information systems: Competition through information technologies*. New York, NY: Macmillan College Publishing.

Nunnally, J.C. and Bernstein, I.H. (1998). *Psychometric theory,* New York: McGraw-Hill.

O'Leary-Kelly, S.W. and Vokurka, R.J. (1998). The empirical assessment of construct validity. *Journal of Operations Management*, *16* (4), 387-405.

Olszak, C. M. and Ziemba, E. (2003). Business intelligence as a key to management of an enterprise. *Proceedings of Informing Science And IT Education.* Santa Rosa, CA. Retrieved from http://proceedings.informingscience.org/IS2003Proceedings/docs/109Olsza.pdf.

Oltra, V. (2005). Knowledge management effectiveness factors: The role of HRM. *Journal of Knowledge Management*, *9* (4), 70-86.

Parikh, A. A. and Haddad, J. (2008, October). Right-Time information for the real-time enterprise timely information drives business. *DM Direct*. Retrieved from http://www.dmreview.com/dmdirect/2008_92/10002003-1.html?portal=data_quality.

Pirttimaki, V., Lonnqvist, A., and Karjaluoto, A. (2006). Measurement of business intelligence in a Finnish telecommunications company. *Electronic Journal of Knowledge Management, 4* (1), 83-90.

Power, D. J. (2002). *Decision support systems: Concepts and resources for managers*. Westport, CT: Quorum Books.

Power, D. J. (2003, May). A brief history of decision support systems [Web log post]. Retrieved from http://dssresources.com/history/dsshistory.html.

Premkumar, G., Ramamurthy, K., and Saunders, C. S. (2005). Information processing view of organizations: An exploratory examination of fit in the context of interorganizational relationships. *Journal of Management Information Systems, 22* (1), 257-294.

Rai, A., Lang, S. S., and Welker, R. B. (2002). Assessing the validity of IS success models: An empirical test and theoretical analysis. *Information Systems Research, 13* (1), 50-69.

Ray, G., Muharma W. A., and Barney J. B. (2005). Information technology and the performance of the customer service process: A resource-based analysis. *MIS Quarterly 29* (4), 625-652.

Raymond L. (2003). Globalization, the knowledge economy, and competitiveness: A business intelligence framework for the development SMES. *Journal of American Academy of Business*, *3* (1/2), 260-269.

Ross, J. W., Beath C. M., and Goodhue D. L. (1996). Develop long-term competitiveness through IT assets. *Sloan Management Review, 38* (1), 31-44.

Rouibah, K., and Ould-ali, S. (2002). Puzzle: A concept and prototype for linking business intelligence to business strategy. *Journal of Strategic Information Systems*, *11* (2), 133-152.

Rud, O. P. (2009). *Business intelligence success factors: Tools for aligning your business in the global economy*. Hoboken, NJ: John Wiley and Sons.

Ryan, A. M. and Schmit, M. J. (1996). An assessment of organizational climate and P-E fit: A tool for organizational change. *International Journal of Organizational Analysis*, *4* (1), 75-95.

Ryan, S.D., Harrison, D.W., and Schkade, L.L. (2002). Information-technology investment decisions: When do costs and benefits in the social subsystem matter?" *Journal of Management Information Systems, 19* (2), 85-127.

Saaty, T. L. and Kearns, K. P. (1985). *Analytical planning: The organization of systems*. Oxford: Pergamon Press.

Sabherwal, R. and Kirs, P. (1994). The alignment between organizational critical success factors and information technology capability in academic institutions. *Decision Sciences, 25* (2), 301-331.

Sabherwal, R. (2007). Succeeding with business intelligence: Some insights and recommendations. *Cutter Benchmark Review*, *7* (9), 5-15.

Sabherwal, R. (2008). KM and BI: From mutual isolation to complementarity and synergy. *Cutter Consortium Executive Report*, *8* (8), 1-18.

Sabherwal, R. and Becerra-Fernandez, I. (2010). *Business intelligence: Practices, technologies, and management*. Hoboken, NJ: John Wiley & Sons.

Sambamurthy, V., and Zmud, R. W. (1992). *Managing IT for success: The empowering business partnership.* Morristown, NJ: Financial Executives Research Foundation.

Sanders, G. L. and Courtney, J. F. (1985). A field study of organizational factors influencing DSS success. *MIS Quarterly, 9* (1), 77-95.

Sanders, N. R., Premus, R. (2005). Modeling the relationship between firm IT capability, collaboration, and performance. *Journal of Business Logistics*, *26* (1), 1-25.

Sauer, C. and Willcocks, L. (2003). Establishing the business of the future: The role of organizational architecture and information technologies. *European Management Journal*, *21* (4), 497–508.

Sawka, K. (2000). Are we valuable? *Competitive Intelligence Magazine*, *3* (2). Retrieved from http://www.scip.org/Publications/CIMArticleDetail.cfm?ItemNumber=1191.

Schuman, H., and Pressor, S. (1981). *Questions and answers in attitude survey.* New York, NY: Academic Press.

Schwab, D. P. (1980). Construct validity in organizational behavior. In L. L. Cummings & B. M. Staw (Eds.), *Research in Organizational Behavior* (pp. 3-43). Greenwich, CT: JAI Press.

Scott Morton, M. S. (1984). The state of the art of research. In F. W. McFarlan (Ed.), *The Information Research Challenge* (pp. 13-41). Boston, MA: Harvard University Press.

Seeley, C.P. and Davenport, T.H. (2006). KM meets business intelligence. *Knowledge Management Review*, *8* (6), 10-15.

Setia, P., Sambamurthy, V., and Closs, D. J. (2008). Realizing business value of agile IT applications: Antecedents in the supply chain networks. *Information Technology and Management, 9* (1), 5-19.

Shim, J.P., Warkentin, M., Courtney, J.F., Power, D.J., Sharda, R. and Carlsson, C. (2002). Past, present, and future of decision support technology. *Decision Support Systems*, *33* (2), 111–126.

Silver, M. S. (1991). *Systems that support decision makers: Description and analysis*. Chichester, United Kingdom: Wiley & Sons.

Simon, H. A. (1960). *The new science of management decision*. New York: Harper and Row.

Soelberg, P. O. (1967). Unprogrammed decision making. *Industrial Management Review*, *8* (2), 19-29.

Solomon, M.D. (2005). Ensuring a successful data warehouse initiative. *Information Systems Management, 22* (1), 26-36.

Sommer, D. (2008). *Report highlight for market trends: Business intelligence, worldwide, 2008*. Retrieved from Gartner database.

Srinivasan, A. (1985). Alternative measures of system effectiveness: Associations and implications. *MIS Quarterly*, *9* (3), 243-253.

Srivastava, J. and Cooley, R. (2003). Web business intelligence: Mining the web for actionable knowledge. *INFORMS Journal on Computing, 15* (2), 191-207.

Stock, G. N. and Tatikonda, M. V. (2008). The joint influence of technology uncertainty and interorganizational interaction on external technology integration success. *Journal of Operations Management, 26* (1), 65-80.

Swafford, P. M., Ghosh, S. and Murthy, N. (2008). Achieving supply chain agility through IT integration and flexibility. *International Journal of Production Economics, 116* (2), 288-297.

Swoyer, S. (2008, September 24). Lyza empowers new class of BI consumers. *TDWI*. Retrieved from http://www.tdwi.org/News/display.aspx?id=9129.

Tatikonda, M. V. and Rosenthal, S. R. (2000). Technology novelty, project complexity, and product development project execution success: A deeper look at task uncertainty in product innovation. *IEEE Transactions on Engineering Management*, *47* (1), 74-87.

Tatikonda, M. V. and Montoya-Weiss, M. M. (2001). Integrating operations and marketing perspectives of product innovation: The influence of organizational process factors and capabilities on development performance. *Management Science, 47* (1), 151-172.

Teo, T. S. H. and King, W. R. (1997). Integration between business planning and information systems planning: An evolutionary-contingency perspective. *Journal of Management Information Systems, 14* (1), 185-216.

Tsai, C.H. and Chen, H. Y. (2007). Assessing knowledge management system success: An empirical study in Taiwan's high-tech industry. *Journal of American Academy of Business*, *10* (2), 257-264.

Tuggle, F. D, and Gerwin, D. (1980). An information processing model of organizational perception, strategy and choice. *Management Science*, *26* (6), 575-592.

Tushman, M. L. and Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. *The Academy of Management Review*, *3* (3), 613-624.

Vitt, E., Luckevich, M, and Misner, S. (2002). *Business intelligence: Making better decisions faster,* Redmond, WA: Microsoft Corporation.

Wang, E.T.G. (2003). Effect of the fit between information processing requirements and capacity on organizational performance. *International Journal of Information Management, 23* (3), 239-247.

Watson, H. J. (2008). Why some firms' BI efforts lag. *Business Intelligence Journal*, *13* (3), 4-7.

Watson, H. J. (2005). Are data warehouses prone to failure? *Business Intelligence Journal*, *10* (4), 4-7.

Watson, H. J., Annino, D. A., Wixom, B. H., Avery, K. L., and Rutherford, M. (2001). Current practices in data warehousing. *Information Systems Management, 18* (1), 47-55.

Watson, H.J. and Donkin, D. (2005). Editorial preface: Outstanding BI and data warehousing practice exists around the world: The Absa Bank in South Africa. *Journal of Global Information Technology Management*, *8* (4), 1-6.

Watson, H. J., Goodhue, D. L., and Wixom, B. H. (2002). The benefits of data warehousing: Why some organizations realize exceptional payoffs. *Information and Management*, *39* (6), 491-502.

Watson, H.J., Abraham, D.L., Chen, D., Preston, D., and Thomas, D. (2004). Data warehousing ROI: Justifying and assessing a data warehouse. *Business Intelligence Journal, 9* (2), 6-17.

Watson, H. J., Fuller, C., and Ariyachandra, T. (2004). Data warehouse governance: Best practices at Blue Cross and Blue Shield of North Carolina. *Decision Support Systems,* 38 (3), 435-450.

Watson, H.J., Wixom, B.H., Hoffer, J.A., Anderson-Lehman, R., and Reynolds, A. M. (2006). Real-time business intelligence: Best practices in Continental Airlines. *Business Intelligence, 23* (1), 7-18.

Watson, H. J., and Wixom, B. H. (2007). The current state of business intelligence*.* *Computer*, *40* (9), 96-99.

Watson, H. J. and Wixom, B. H. (2007). Enterprise agility and mature BI capabilities. *Business Intelligence Journal*, *12* (3), 13-28.

Weier, M.H. (2007). QUERY: What's next in BI? *Information Week, 1128*, 27-29.

Weill, P., M. Subramani, and Broadbent, M. (2002). Building IT infrastructure for strategic agility. *MIT Sloan Management Review*, *44* (1), 57-65.

Wells, D. (2003, April). Ten best practices in business intelligence and data warehousing. *TDWI FlashPoint*. Retrieved from https://www.tdwi.org/Publications/display.aspx?id=6638&t=y.

White, C. (2005, May). The next generation of business intelligence: Operational BI. *Information Management Magazine*. Retrieved from http://www.dmreview.com.

White, C. (2004, September). Now is the right time for real-time BI. *Information Management Magazine*. Retrieved from http://www.dmreview.com.

Williams, S. and Williams, N. (2007). *The profit impact of business intelligence*, San Francisco, CA: Morgan Kaufmann.

Wixom, H. and Watson, H. J. (2001). An empirical investigation of the factors affecting data warehousing success. *The Journal of Business Strategy*, *25* (1), 17-41.

Wu, J. H. and Wang, Y. M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information & Management, 43* (6), 728-739.

Wunsch, D. (1986). Survey research: Determining sample size and representative response. *Business Education Forum*, *40* (5), 31-34.

Yoon, Y., Guimaraes, T. and O'Neal, Q. (1995). Exploring the factors associating with expert systems success. *MIS Quarterly, 19* (1), 83-106.

Zack, M. H. (2007). The role of decision support systems in an indeterminate world. *Decision Support Systems, 43* (4), 1664-1674.

Zaltman, G., Duncan, R. and Holbek, J. (1973). *Innovation and organizations.* New York: John Wiley and Sons.

Zhang, M. and Tansuhaj, P. (2007). Organizational culture, information technology capability, and performance: The case of born global firms. *Multinational Business Review*, *15* (3), 43-77.