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A MODEL OF ORGANIZATIONAL COMPETENCIES FOR BUSINESS INTELLIGENCE SUCCESS

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

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Abstract

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A Dissertation submitted in partial fulfillment of the requirements for the degree of Ph.D. at Virginia Commonwealth University.

Virginia Commonwealth University, 2009

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Business intelligence (BI) systems comprise one of the largest and fastest growing areas of IT expenditure in companies today. Companies' experiences with deriving benefits from these systems are still mixed. One of the differences between BI and other types of information systems is that how BI systems are used, not just whether they are used, can have a major impact on the benefits derived. Therefore the characteristics of BI users and the organizations within which they work can have a disproportionate impact on the benefits derived from investments in BI.

Organizational competence is one way to evaluate the characteristics of individuals and organizations relative to their ability to achieve organizational goals. This dissertation examines the characteristics of BI users and their organizations within the framework of

organizational competences. Models representing those competences at both the individual and organizational level are presented. A combined competency model and resulting emerging competences are proposed that, if adopted, can improve the likelihood of organizations realizing benefits from their BI investments.

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1. Introduction

1.1 Background

Companies spend billions of dollars annually on implementation and maintenance of information systems (IS). Estimates are that IS expenses constitute the largest portion of organizational expenditures (Carr 2004; Nash 2008). Given the size of these expenditures one would hope that companies were gaining benefits commensurate with the money being spent. Unfortunately recent figures estimated that nearly half of IS projects did not result in the anticipated benefits (Nash 2008). It is therefore important to understand what can help companies gain benefits from the investments in these systems.

Early information systems were used to automate otherwise manual processes, such as maintaining accounting ledgers or processing financial transactions. The benefits from these types of systems resulted from increases in efficiency or effectiveness of the underlying processes resulting in measurable cost savings or revenue increases (Zuboff 1988). BI systems provide benefits by supporting analytical processes that provide recommendations for changing products or processes in ways that improve their competitiveness or operational efficiency (Scheps 2008). These benefits are therefore dependent on the ability of the individuals using BI to do so effectively and the organizational ability to support the implementation of the resulting recommendations. Another way to describe organizational abilities to perform tasks or functions effectively is competence (Javidan 1998). This dissertation will develop a model to help understand how an organization can gain benefits via BI systems by understanding the competencies necessary for effective BI use and the relationship between those competencies and realizing BI benefits.

1.2 Definitions:

1.2.1 Business Intelligence:

Business intelligence has been defined as "business information and business analyses within the context of key business processes that lead to decisions and actions and that result in improved business performance" (Williams et al. 2007). Another definition is "a set of processes and technologies that transform raw, meaningless data into useful and actionable information" (Evelson 2007). BI implementations encompass many different technologies including data warehousing, online analytical processing (OLAP), data visualization, dashboards, extraction transformation and load (ETL), data quality (DQ) (Evelson 2007). Yet these technologies by themselves do not constitute business intelligence. Business Intelligence is the combination of organizational and technological capabilities that allow an organization to use information to support business processes and/or related decisions. Put another way, "business intelligence allows people at all levels of an organization to access, interact with, and analyze data to manage the business, improve performance, discover opportunities, and operate efficiently" (Howson 2008).

In recent years Business Intelligence systems have consistently been rated as one of the highest priorities of IS and business leaders (Evelson 2007; Friedman et al. 2004; Hertzberg 2007). A significant portion of company's IT budgets are being spent on BI and related technology. Estimates of the amount spent on BI in 2006 range from $14 to $20 Billion, with growth estimates of from 10% to 11% per year for the foreseeable future (Gantz et al. 2007; Howson 2008). In spite of these investments only 24% of BI implementations were identified as being very successful in a recent survey of companies using BI systems (Howson 2008). If companies are investing this much in BI they must expect to achieve benefits from these investments. Why then do some organizations benefit while others don't? What is different about those organizations that achieve benefits from BI implementations? Unfortunately, while much has been written about how to effectively implement and use business intelligence technology (Davenport et al. 2007; Howson 2008; Liebowitz 2006; Williams et al. 2007), research on BI and specifically detailing how an organization can achieve benefits from BI is sparse (Arnott et al. 2008; Jourdan et al. 2008).

1.2.2 BI Success:

In order to be able to research how BI can be considered successful we must be able to articulate what we mean by success. As BI is a class of information system, we will start by looking at how success is measured for IS in general. A large volume of IS research has attempted to evaluate success (DeLone et al. 2003; Ein-Dor et al. 1978; Grover et al. 1996; Kwon et al. 2006; Mirani et al. 1998; Seddon et al. 1999). Early work looking at measures of IS success considered multiple criteria including "profitability, application to major problems of the organization, quality of decisions or performance, user satisfaction and wide-spread use" (Ein-Dor et al. 1978). The appropriate success measure depended upon the perspective of those evaluating success or the nature of the problem being addressed (Melville et al. 2004).

While it was recognized that there were multiple criteria by which an information system would be considered a success in an organization, many of those criteria are difficult to measure. As a result, much of the work on IS success has focused on system use as a proxy for success (Davis 1999; Dedrick et al. 2003; DeLone 1988). In other words, these studies suggested that a way to evaluate if a system was successful was to determine whether it was being used. Still it was recognized that "a better measure of [IS] success would probably be some weighted average of the criteria" (Ein-Dor et al. 1978).

The most commonly referenced model of information systems success, proposed by DeLone and McLean (1992), was an attempt to synthesize the various measures of IS success into a single model. This model suggests that the use of an information system and user satisfaction with that information system lead to net benefits attributed to that system. It also states that the antecedents to intention to use and satisfaction are information quality, system quality, and service quality (DeLone et al. 2003). A key concept mentioned here is that of "net benefits." Net benefits refers to the impact of a system at an operational or organizational level (DeLone et al. 2003). The authors state that "n*et benefits* are the most important success measures as they capture the balance of positive and negative impacts of the [IS]…" (DeLone et al. 2003, pg 24).

Reviews of research based on this model have shown that the net benefits accrued from an information system are also context specific (Grover et al. 1996; Seddon et al. 1999).

In other words, the benefits realized from IS differ depending on the type of system being implemented and the stakeholder for whom the benefits are being measured. This suggests that success measures for this research need to be based on BI specific characteristics. BI systems are implemented to provide analytical capability to provide recommendations to improve operational or strategic processes or product characteristics (Howson 2008; Williams et al. 2007). The benefits of these systems are only realized if the resulting recommendations are the "right" ones and if they are ultimately implemented. This means that just using a BI does not mean that it is successful, but whether that use results in recommendations that provide net benefits is the key factor. Therefore this research will consider the achievement of organizational benefits to be the appropriate measure of BI success.

1.2.3 Competence

There are two basic conceptions of competence used in organizational research. One operates at the firm level while the other addresses both individual and organizational characteristics. The firm level perspective considers something called "core competence" as a characteristic or set of idiosyncratic characteristics of a firm that can inform that firm's strategic planning in a way that can provide a sustainable competitive advantage, as exemplified by the work of Prahalad and Hamel (1990). This conception of competence can be used to examine firms' overall competitive strategy relative to the marketplace, but is not useful when examining the impact of a system such as business intelligence.

The other organizational research related to competence examines more micro level processes and the impact of associated competence on an organization. The conception of competence used in this research is more related to a traditional dictionary definition such as; "possession of required skill, knowledge, qualification, or capacity" (RandomHouse 2009). This research seeks to understand how competence embodied in individuals and in organizational structure and culture impact an organization's ability to achieve specific goals and is exemplified by the work of McGrath, MacMillan, and Venkataraman (1995). It is this conception of competence that will be used to inform this research.

1.3 Research Objectives:

There are business books that discuss organizational factors for successful BI. Williams and Williams (2007) identified seven factors defining "business intelligence readiness" as being "Strategic Alignment, Continuous Process Improvement Culture, Culture Around the Use of Information and Analytics, BI Portfolio Management, Decision Process Engineering Culture, BI & DW Technical Readiness, and Business/IT Partnership" (Williams et al. 2007, pg 202). They suggested that only when an organization has this BI readiness would they be able to realize the benefits of BI.

Davenport and Harris in their book "Competing on Analytics," looked at the impact of BI systems on organizations. They identified something they called an analytical capability, which was their conception of the ability of an organization to use BI and as consisting of organizational acumen and technology factors (Davenport et al. 2007). They suggest that for an organization to benefit from an analytical capability that both organizational and technology factors must exist in that organization. They provide a high level view of the organizational factors, but they haven't defined the detailed competencies that an organization must possess in order to exploit these capabilities.

Research in information systems is generally focused on either developing theories that explain related phenomena or on verifying existing theories (Hevner et al. 2004). This research is directed towards developing a theoretical model of BI success. Competence has been shown to be an important element in the success of information systems, and appears to have the potential to be of particular value in explaining the attainment of benefits from BI. However, a framework that explains competence for successful BI does not exist. This research will therefore seek to develop a framework to help explain the organizational competencies that would support the attainment of business value from BI.

1.4 Structure of the thesis:

This dissertation is divided into seven chapters. The first chapter introduces some key concepts that provided the motivation for this research and introduces the basic objective of this work. The second chapter contains a review of the literature that informs the research and provides a foundation for the remainder of the work. Chapter three provides the theoretical underpinnings and research methodology taken in studying the key research questions and provides a summary of the key questions to be addressed. Chapter four provides an exposition of the evidence collected during the research and presents the initial models that relate the key concepts that emerge from the evidence. In chapter five a framework for evaluating the fundamental research question is presented and evaluated.

Chapter six provides a synthesis of all of the findings in this research, and chapter seven summarizes the entire document and outlines limitations and potential future directions.

2. Literature Review

2.1 Introduction:

This section will review the research that informs this dissertation. Any research must begin with an understanding of the literature relevant to the key concepts being explored. The objective of this research is to understand the nature of organizational factors that impact the benefits from BI, with a perspective that one of the key factors is organizational competence. The questions being asked relate to business intelligence systems and how competence can enable those systems to provide benefits to an organization. The key concepts embodied in these questions relate to BI, competence, and organizational benefits from BI. The extant literature in each of these areas will be reviewed and its relationship to the questions posed by this dissertation examined.

2.2 Business Intelligence:

Introduction:

Early information systems were focused on automating routine computational tasks. Computers were viewed as tools to help perform routine tasks done faster than was previously possible. However, as computers grew more capable, and in particular data storage became more accessible and flexible, the use of information technology expanded from purely an automation perspective to something that has been called "informating" (Zuboff 1988). Zuboff suggested that technology can "informate, empowering ordinary working people with overall knowledge…, making them capable of critical and collaborative judgments…" (Zuboff 1988, pg 243). The term that is used for systems of this type is Decision Support Systems (DSS) (Barki et al. 1985).

Early DSS were typically single function (Arnott et al. 2008). They supported a particular decision making process for a particular part of an organization. The underlying data was specific to the application and the user interfaces were often customized for a particular purpose. This changed with the emergence of data warehousing (Inmon 1992). As organizations began to build data warehouses they often started by trying to create a large, centralized, analytic repository for all of their historical data. These early data warehouses were often built without clear objectives as to how this data was to be used. Organizations began to recognize that even when cleansed and centralized, a large scale data warehouse would not provide organizational benefits without clearly defined business needs for the data (Inmon 1992; Kimball et al. 1998). The term that was coined in 1989 for the class of applications designed to take advantage of these data warehouses was Business Intelligence (BI) (Rajesh 2008).

The emergence of BI as a concept caused organizations to begin to see these types of systems as part of a larger framework of analytical capabilities enabled by technology. Several definitions of BI were given in the preceding chapter. BI has also been defined as "an active, model-based, and prospective approach to discover and explain hidden, decision-relevant aspects in large amounts of business data to better inform business decision processes" (Liebowitz 2006). There are probably as many different definitions of business intelligence as there are authors, but consistent among the definitions is the use of an analytic data store coupled with analysis software and reporting/visualization tools to solve business problems (Golfarelli et al. 2004 ; Negash et al. 2003; Rajesh 2008). The problems that BI has been applied to vary and include most aspects of a company's operations and marketing (Davenport et al. 2006). An important part of any BI implementation is how the system will be used by people to achieve its goals (Jourdan et al. 2008; Rajesh 2008). Put another way, "BI converts data into useful information and, *through human analysis*, into knowledge" [emphasis added] (Negash et al. 2003, pg. 3191). While the human analysis component of this definition is important, very little research has looked at it in any level of detail.

Combining the various BI definitions we will use the following definition for BI in this research: Business Intelligence consists of the use of analytical technologies and data stores by people in an organization to analyze business problems and produce related business recommendations to improve business performance. The key technologies that make up the technological components of BI are data warehousing, and related extraction transformation and load (ETL) tools; analysis tools, including statistical analysis and online analytical processing (OLAP) tools; and reporting/visualization tools. Based on this definition it becomes clear that the people/organizational component of BI is as important as the technological.

Since BI is a relatively new topic, research specifically referring to BI is still sparse. However, the volume of DSS research is much larger. BI is considered a subset of DSS research by some (Arnott et al. 2005; Arnott et al. 2008), while others have suggested that

DSS is a component of BI (Negash et al. 2003; Rajesh 2008). However you look at it, BI related research is still one of the least studied areas of DSS. BI related research accounted for only 7% of all of the DSS articles published between 1990 and 2004 (Arnott et al. 2008). We will examine the key research relative to DSS success and the major BI research that does exist. Research in DSS and BI can be categorized into four main areas; effectiveness, tools and technologies, algorithms and data mining, and organizational impacts. The next sections will examine research in each of these areas.

Effectiveness:

A large volume of work has looked for sources of DSS effectiveness. Researchers have looked at characteristics of the systems (Cody et al. 2002; Goslar 1986; Rouibah et al. 2002), the nature of post-implementation support (Foster et al. 2005; Watson et al. 1987; Zeid 2006), the nature of the decisions for which the system was designed (Guimaraes et al. 1992; Sanders et al. 1985), the level of end-user participation in development (Kasper 1985), and some combination of the above (Alavi et al. 1992; Guimaraes et al. 1992). Some research has examined organizational factors' impact on DSS outcomes. Some early work suggested that changing work processes can be necessary to benefit from new systems implementations, and that this was more important for DSS as Ginzberg found "systems vary in the degree of individual change they imply, and that DSS's require substantially greater change than do "conventional" systems" (Ginzberg 1978, pg. 48). Subsequently others have found that how the organization adapts to an information system is an important aspect of that system's success (Elbashir et al. 2008; Hong et al. 2002; Rainer et al. 1995).

A meta-analysis of 33 studies that looked at user factors identified four types of user factors that have been studied in terms of DSS success; "cognitive style, personality, demographics, and user-situational variables" (Alavi et al. 1992). Cognitive style has been considered a potential factor influencing the effectiveness of decision support for a long time (Chakraborty et al. 2008; Huysmans 1970). Cognitive style represents a measure of how individuals approach decision making, therefore it would be logical to assume that it could impact the effectiveness of individuals' use of an IS that supports decision making processes. A number of different classification methods have been used to categorize cognitive style including analytic-heuristic (Huysmans 1970), adaptive-innovative (Chakraborty et al. 2008), and the Myers-Briggs type indicator (Green et al. 1986; Keen et al. 1981). Cognitive style would seem to be an important factor supporting DSS effectiveness.

A number of early works on DSS looked at using cognitive style as a criterion to help govern the development of those systems (Er 1988; Green et al. 1986; Huysmans 1970; Keen et al. 1981; Ramaprasad 1987; Zmud 1979). Subsequently it was suggested that cognitive style was not an effective criteria to use in systems design (Huber 1983). Although concluding that cognitive style was not an effective criterion for designing an information system, Huber (1983) did acknowledge that it was part of the set of individual characteristics that influenced how DSS systems are used. While a meta-analysis of DSS research that included cognitive style dimensions found that the impact of cognitive style on DSS effectiveness was significant, but with a small effect size (Alavi et al. 1992), recent research found that cognitive style had a significant impact on individuals' tendency to use such systems (Chakraborty et al. 2008). All of this research points to the need to consider cognitive style as one of the potential characteristics indicating the likeliness of BI success.

The one area of user factors that appeared to have the largest impact on DSS effectiveness was that of "user-situational factors" (Alavi et al. 1992). Three elements made up user-situational factors in the studies included in this meta-analysis, involvement, training, and experience. These factors were found to be significant in several studies of DSS success (Green et al. 1986; Guimaraes et al. 1992; Sanders et al. 1985). Another word that has been used to describe this combination of experience and involvement is competence. It appears that for DSS, competence has the potential for improving effectiveness.

Tools and Technology:

Much of the research related to BI is associated with the underlying technologies supporting BI and not the integrated concept and implementation that are BI. A review of 167 articles about BI published between 1997 to 2006 clearly illustrates this point (Jourdan et al. 2008). Only one article included in this review actually has BI in its title (Chung et al. 2005). The remainder of the articles can be categorized as being related to technology, process, or organization. The technology research generally is looking for improvements to the technological components of which BI systems are comprised. In this research, organizational factors that might improve effectiveness of system use were generally not included.

One of the most complex and most studied of these components is data warehousing (DW). Many articles have been published on data warehousing (Ballou et al. 1999; Bontempo et al. 1998; Chen et al. 2000; Gorla 2003; Jukic 2006; Little et al. 2003; Nelson et al. 2005; Wixom et al. 2001). This research looked at data warehouse design methods and architectures, data quality, ongoing maintenance issues, performance, and planning and development, but the majority of DW research is focused on technical aspects of designing or building a data warehouse. Wixom and Watson (2001) modified the DeLone and McLean (1992) model to develop a comprehensive conceptualization of the elements that contribute to DW success. Their research uses "perceived net benefits" as their measure of success, and directly relates this measure with data and systems quality, bypassing the use and satisfaction measures in the Delone & McClean (1992) model. Looking in detail at the factors in this model reveals that they are primarily related to the technology or the implementation of the technology. Organizational factors that are included relate to such factors as the existence of a champion for the project, or organizational commitment, but the model does not consider characteristics that could impact appropriate use of the system once it is in place (Wixom et al. 2001). While this is an important finding regarding one technology that is a component of BI, it does not consider the impact of the users of a DW or the process by which it is used, nor does it examine BI as an integrated system.

Algorithms and Data Mining:

The largest research area that could be considered a subset of BI research is that of data mining (Jourdan et al. 2008). Data mining consists of a number of different algorithmic approaches to discovering relationships in data or drawing inferences from data. It is just one family of statistical techniques that may be used within the analytical subsystem of a BI solution. Although there has been research into organizational aspects of implementing and using data mining (Apte et al. 2002; Hirji 2001; McCarthy 2000), the majority of data mining research is focused on algorithm development (Ahn et al. 2008; Busygin et al. 2008; Chen-Fu et al. 2009; Chen et al. 2008; Subramanyam et al. 2005; Vityaev et al. 2008a). As noted "currently, the strong focus of most DM-researchers is still only on technology-oriented topics" (Vityaev et al. 2008b, pg. 237). While some data mining research has looked at application of data mining techniques (Apte et al. 2002; Cheng et al. 2005; Datta 2008; Hirji 2001), this research primarily focuses on how to apply data mining to specific business problems, not the organizational antecedents to the successful application of these techniques.

Organizational Impact:

There is just beginning to be research published that addresses the overall impact of BI. The majority of the work published on BI has come from practitioners and vendors since it is a practitioner driven initiative (Evelson 2007; Gantz et al. 2007; Howson 2006 ; Howson 2008; Williams 2004; Williams et al. 2007). The academic work that has begun to appear is primarily definitional/conceptual (Gnatovich 2007; Golfarelli et al. 2004 ;

Jourdan et al. 2008; Kohavi et al. 2002; Negash et al. 2003; Rajesh 2008), but two case studies of business intelligence have been published that can provide some guidance in investigating the questions being raised in this research (Gibson et al. 2005; Wixom et al. 2008). Gibson et. al. (2005) identified a need for what they called "a BI engagement model" for effective BI. This refers to the need for an organization to understand how BI fits within its organizational structure and for employees to embrace BI as a natural part of their work. Another way to describe this would be that the organization needs to have competence to effectively interact with their BI environment. However, they do not provide specific guidelines as to what such an engagement model should look like.

Wixom et. al. (2008) identified a couple of key elements that improved Continental airline's effectiveness in using their BI environment. Specifically they found "a culture of data" within the company that supported the use of data driven decision tools at all levels of the organization, and they found what they called "business-IT hybrid" skills among employees. By this they mean that technical personnel had more business savvy and business personnel had more technical skills that would exist in most companies. (Wixom et al. 2008). This hybridization of the workforce appears to support the concept that there is a unique set of competencies necessary for a company to make effective use of BI. They do not however, provide details as to the nature of the competencies.

Another stream of research that has been identified as business intelligence is actually focused on competitive intelligence (Ghoshal et al. 1986; Powell et al. 2000). Competitive intelligence has been defined as the process by which companies track the activities of their competitors in various areas of activity (Rouach et al. 2001). While competitive intelligence efforts often use business intelligence technology, competitive intelligence is not the focus of this research.

Summary:

The volume of research in the types of decision support systems with which BI is identified is limited. Research does support the idea that competence is necessary for effective use of BI, but the specifics of the nature of this competence have not been studied. The research that does exist can provide valuable guidance for the research which is the focus of this effort. In particular the measures of success used in Wixom et. al. (2001), Guimaraes et. al. (1992), and Sanders et. al. (1985) support the concept that the most appropriate measure of BI success should be net benefits realized.

2.3 IS Success:

Introduction:

This research seeks to understand mechanisms that can support the attainment of benefits from BI. Attainment of benefits is one of the key elements that determine the success of information systems, including BI, which is a category of IS. If the objective of this research is to understand BI success, we must understand the research that has looked at models of IS and/or BI success to understand its relevance to and potential impact on our research questions. In this section we will start by examining the key models that have been proposed for determining IS success. These models can provide a foundation upon which our research questions can be examined. We will then look specifically at research that looks at aspects of BI success. Finally we will looks at research that has studied the impact of interactions between organizations individuals and information systems on IS success.

Models of IS Success:

The concept of information systems success has been used as the dependent variable in many studies of IS related phenomena. However, many different concepts of success have been used. Some have used characteristics of the technological artifact itself, such as information quality or system quality (Gable et al. 2003; Goslar 1986), others looked at whether the resulting information system was used by its intended users (DeLone 1988; Ein-Dor et al. 1981; Raymond 1985; Raymond 1990; Sabherwal et al. 2006). Another measure of success was the level of user satisfaction with the resulting system (Gallagher 1974; Ives et al. 1983; Kaye 1990; Melone 1990; Raymond 1985; Raymond 1990; Sabherwal et al. 2006), still others looked at outcomes such as impact on the organization using financial or operational measures (Ahituv 1980; Dedrick et al. 2003; DeLone 1988; Gallagher 1974; Kwon et al. 2006; Meier 1995; Melville et al. 2004; Mirani et al. 1998; Oh et al. 2007; Ross et al. 1996; Wang et al. 2008). Many have used multiple criteria as determinants of IS success (Caldeira et al. 2003; Gable et al. 2003; Gallagher 1974; Ives et al. 1983; Raymond 1985; Sabherwal et al. 2006). DeLone and McLean (1992) evaluated nearly 200 articles that included some measure of success and identified six factors that had been used as measures of IS success as, system quality, information quality, use, user satisfaction, individual impact and organizational impact.

These can be categorized into three broad areas of system characteristics, user characteristics, and system impact. They suggest that while many researchers had used a single criterion, or just a few criteria, one must understand all of these constructs in order to effectively measure success of an information system. Ten years later they revised their model of IS success to add service quality to the system characteristics and to combine individual impact and organizational impact into a single construct they called net benefits (DeLone et al. 2003).

BI Success:

Researchers have found that IS context can impact success and the appropriate measures to be used (Ein-Dor et al. 1982; Grover et al. 1996; Montazemi 1988; Seddon et al. 1999). Context can refer to the level of analysis (individual, group, firm, organization, industry (Ein-Dor et al. 1982; Seddon et al. 1999)), the type of system being studied (operational, DSS, ERP, inter-organizational, network, web, etc. (Seddon et al. 1999)), the size of the organization (Caldeira et al. 2003; DeLone 1988), and even the country in which the study is taking place (Caldeira et al. 2003). Given the complex and varying definitions of IS success, the questions for this research are what are the appropriate measures of IS success to use when studying BI and what factors has research shown to have potential for impacting those measures?

BI systems are focused on providing guidance to help people in organizations make better decisions. There are real-time BI systems that are designed to use analytical techniques to make automated decisions regarding things like product pricing or promotional offers (Azvine et al. 2005; Watson et al. 2006), but those are specialized cases of BI and not the focus of this research. The decisions that BI systems are built to help support are varied. BI has been used in just about every aspect of an organization (Negash et al. 2003). Because of this diversity, a single measure of BI effectiveness, such as increased profitability, or improved competitive position, would be too narrow. However, BI is built specifically to provide some benefit to an organization. Whether the BI system is built with high reliability, is easy to maintain, or even whether it is used or users are happy with it do not insure that these benefits will be realized. Ultimately, the measure of this type of system is whether the organization gains net benefits from it.

A number of researchers have used net benefits as the criteria for determining the effectiveness of the IS phenomenon being researched (Ahituv 1980; Gable et al. 2003; Melville et al. 2004), yet the specific criteria used have varied. Often the benefits are determined by some self reported measure of benefits perceived by the users of the system (DeLone 1988; Wixom et al. 2001). This type of measure is attractive because it's relatively simple to evaluate, but doesn't provide information about the details of the nature of the benefits received. Mirani and Lederer (1998) developed a 25 item instrument that solves this problem of providing a detailed measure of "organizational benefits of IS". Their instrument included specific items in the three main categories of strategic benefits, informational benefits, and transactional benefits as shown below:

Strategic Benefits

Competitive Advantage

Enhance competitiveness or create strategic advantage.

Enable the organization to catch up with competitors.

Alignment

Align well with stated organizational goals.

Help establish useful linkages with other organizations.

Enable the *organization* to respond more quickly to change.

Customer Relations

Improve customer relations.

Provide new products or services to customers.

Provide better products or services to customers.

Informational Benefits

Information Access

Enable faster retrieval or delivery of information or reports.

Enable easier access to information.

Information Quality

Improve management information for strategic planning.

Improve the accuracy or reliability of information.

Improve information for operational control

Information Flexibility

Present information in a more concise manner or better format.

Increase the flexibility of information requests.

Transactional Benefits

Communications Efficiency

Save money by reducing travel costs.

Save money by reducing communications costs.

Systems Development Efficiency

Save money by reducing system modification or enhancement costs.

Allow other applications to be developed faster

Allow previously infeasible applications to be implemented.

Provide the ability to perform maintenance faster.

Business Efficiency

Save money by avoiding the need to increase the work force.

Speed up transactions or shorten product cycles.

Increase return on financial assets.

Enhance employee productivity or business efficiency.

Figure 2.1, “Organizational Benefits of IS” (Mirani et al. 1998, pg 833)

While these items provide a comprehensive list of potential benefits of information systems, not all systems can be expected to support all of these benefits. In particular BI, because it is not focused on transaction processing, would not normally be expected to provide transactional benefits. Still, this model provides a comprehensive instrument that can provide a rich set of information to describe IS benefits. This research will therefore use this model to inform the questions to be asked in our data collection relative to the benefits derived from BI systems.

Organizational/User success factors:

How an organization interacts with an information system has been shown to have an impact on success (Sabherwal et al. 2006). Some of the organizational factors that have been suggested as impacting IS success are: “Size of the organization, Organizational structure, Organizational time frame, Extra-organizational situation, Organizational resources, Organizational maturity, The Psychological climate, Rank of the responsible executive, Locations of the responsible executive, The [existence of a] steering committee" (Ein-Dor et al. 1978). In this case the authors used "use" of a system as a proxy for success because they found that the two measures were correlated in the literature that they reviewed and the measurement of success itself was difficult. However, they also observed that this relationship, and their propositions in general, were dependent on the type of system under study (Ein-Dor et al. 1978).

Success of IS has been related to factors associated with the people who use them (Seddon et al. 1999). Organizations are made up of individuals and although they may have procedures, structure, and culture that transcend individuals, interaction with any system is done by individuals. Those individuals bring their own skills, knowledge, and perspectives to their work. The success of an IS must therefore also consider the characteristics of the individuals that make up an organization.

Soh and Markus (1995) examined five theories of business value creation through IT and developed an integrated model with the following form:

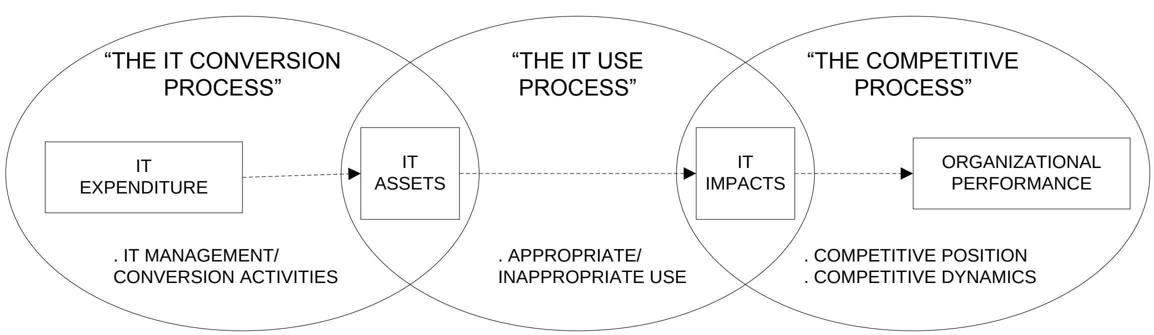

Figure 2.2, "How IT Creates Business Value" (Soh et al. 1995)

This model suggests that IT investments can lead to competitive advantage, but the process by which that happens is separate from the use of the technology. They are specifically referring to the impacts of investments in technology as opposed to a broader view of IS, but their model operates at the level of IS since it includes organizational aspects operating on the technology. They suggest that many other factors can have an impact on competitive performance and while effective use of technology may be a necessary condition for competitive advantage, it is not by itself a sufficient condition for this advantage to occur (Soh et al. 1995).

An important finding of this work is that in order for an organization to realize benefits from IT investments, not only must the associated system be used, but it must be used "appropriately" and effectively. The authors observe that "user skill – what users actually know how to do with their applications and infrastructure – is also a critical IT asset, since without user skill, the potential of the portfolio and the infrastructure can never be realized" (Soh et al. 1995). User skill is one of the components of competence identified in the competence model that informs this research. This model clearly suggests that competence can impact organizational performance resulting from the use of information systems.

Summary:

The research we have examined provides s foundation for understanding the how benefits may be derived from BI. The use of BI systems is different from that of operational systems, such as billing or logistics systems (Davenport et al. 2005; Premkumar 1989).

Users of these systems use the data and associated tools to develop models and make recommendations specific to the type of problem being addressed (Rosenberger et al. 2009; Scheps 2008). Even for so called operational BI systems, the people developing the system must be able to use the necessary analytical tools and understand the underlying data to be able to develop these systems in a way that provides the appropriate outputs (Watson et al. 2006; Wixom et al. 2008). All of this points to a need for a set of characteristics associated with those who will be working with BI different from those associated with other types of systems. While some of the practitioner literature has provided some high level guidance as to what these characteristics may be (Howson 2008; Miller et al. 2006; Williams et al. 2007), there is a need for a comprehensive model to define these competences both for practical guidance and to provide a theoretical base from which to begin researching BI.

2.4 Competence Research:

Introduction:

This research looks at competence as a key to the attainment of benefits from BI. In order to incorporate competence into our model it is important to understand the research that has been done relative to competence in organizations and specifically relative to BI and IS. In this section we will start with a review of general competence research in business. We will then examine the IS research that relates competence to organizational benefits, and then finally identify a competence model that will be specifically used to inform this study.

The origins of competence in business research:

The resource based view (RBV) of the firm suggests that organizational resources are what differentiate a firm from other organizations in their industry (Barney 1991). The RBV takes the position that the primary factor impacting differences in individual firm performance are the resources that make that firm unique. Barney (1991) defined resources as:

> …all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness (Barney 1991).

While RBV has its origins in work from the 1950's (Wernerfelt 1984), it really came to the fore in the early 1990s, and is therefore still a relatively young perspective. The initial research in this area was primarily conceptual (Barney 1991; Barney 1999; Chmielewski et al. 2007; Grant 1991; Wernerfelt 1984). These works refined the definitions of resources and their relationship to firm performance. One of the key resources identified by this perspective is competence (Barney 1986; Hitt et al. 1985; Hitt et al. 1986; Wernerfelt 1984). One definition of competence is the ability to "create and transfer knowledge within an organizational context" (Kogut et al. 1992). Key to this definition is the concept of knowledge. Kogut and Zander (1992) have provided a good description of knowledge as consisting of "information and know-how." The figure below illustrates the dimensions of each of these elements of knowledge.

	Individual	**Group**	**Organization**	**Network**
Information	-facts	-who knows what	-profits -accounting data -formal & informal structure	-prices -whom to contact -who has what
Know-How	-skill of how to communicate -problem solving	-recipes of organizing such as Taylorist methods or craft production	-higher-order organizing principles of how to coordinate groups and transfer knowledge	-how to cooperate -how to sell and buy

Figure 2.3 - Dimensions of information and know-how (Kogut et al. 1992).

As this figure illustrates, knowledge exists at various levels of an organization, ranging from individuals to inter-organizational networks. It is this knowledge that BI systems seek to allow organizations to use to provide financial benefits.

IS research on competence and organizational benefits:

Competence has been mentioned as a source of organizational benefits by a number of authors (Bassellier et al. 2003; Dhillon 2005; Feeny et al. 1998; Gottschalk et al. 2005; Peppard et al. 2004; Piccoli et al. 2005; Ravichandran et al. 2005; Ross et al. 1996; Weill et al. 2006). The competence to which the majority of these authors refer is primarily related to the implementation of information technology. Bassellier, Benbasat, and Reich (2003) present a model that focuses on IT knowledge and IT experience and relate them to the intention of managers to champion IT. They define competence as “the set of inter-related knowledge and experience that a business manager possesses” (Bassellier et al. 2003, pg. 317). This competence seems to be focused on the individual rather than at an organizational level. Their conclusion is that greater managerial knowledge of and experience with information technology lead to greater intent to champion IT. This then leads to management support for a particular technology implementation resulting in greater organizational benefits. While this is an important finding, they have not examined the mechanism by which this knowledge leads to benefits.

Feeny and Willcocks (1998) suggest that there are nine "core" IS capabilities that a firm must maintain in order to effectively exploit IT capabilities. These capabilities support three categories of IT processes; business and IT vision, design of IT architecture, and delivery of IS services. This model can provide guidance as to competencies that a firm must demonstrate in order to be able to benefit from the information systems investments. Their argument is that this capabilities model can help a company benefit from technology and continue to maintain those benefits as technology changes (Feeny et al. 1998). Their model also focuses on the management of the process by which the technological components of an information system are implemented and maintained, and not on the effective use construct.

Peppard, Lambert and Edwards (2000) looked at organizational factors that influence how information can add value to an organization. They developed a model of six "macro competencies" that support IS value consisting of strategy formulation, resource design, resource development, solution development, exploitation and monitoring of the solution, and process and information design. (Peppard et al. 2000) Within these macro competencies they identified 25 micro competencies that provide a more detailed view of the competencies necessary to realize value from IT investments by an organization. Yet they suggest that even this framework is just a start when they say that "the micro competencies developed in this paper require further study to identify their component elements" (Peppard et al. 2000). This framework primarily focuses on the technology aspects of an IS, not on the organizational use. While the competence to plan, design, and build the appropriate technological components of an IS is important to the utility of those systems, this model does not provide a look at the details of the interactions of people and organizations with a system after it's built.

A recent study examined the impact of the linkage between information systems resources and a firm's core competencies on firm performance. The authors found that IT can improve firm performance when the IT capabilities that are deployed are focused on a firm's core competencies. They found that what matters is not necessarily the technology deployed, but the complimentarity of the technology with capabilities that the firm uses to support their core business. Further, a firm must develop IS capabilities consisting of human, technological, and relationship nature linking the IS function with the business and supporting the IS function itself. This research supports the idea that an organization must have the requisite capabilities to effectively use the technology that is deployed, but does not provide a detailed model of what those competencies are (Ravichandran et al. 2005).

Weill and Aral (2006) looked at companies return on their IT investments to determine what factors can lead to increased value from those investments. They identified something they called "IT Savvy" that can allow companies to gain tangible benefits from their investments. The five characteristics of IT savvy presented are grounded in practice and competencies, and need to exist throughout an organization to improve the chances that payoffs from IT investments can be realized. These characteristics are generic skills and knowledge related to specific types of technology, but they can serve to inform a study of organizational capabilities that could support beneficial use of other types of technology.

Competence has been related to BI in practitioner literature primarily though a concept known as a BI competency center (BICC) (Miller et al. 2006; Stodder 2008; Zeid 2006). A BICC is a way that practitioners have recommended organizing individuals with certain skills to support the development and support of BI in an enterprise. The skills that are generally considered when suggesting elements of a BICC are primarily technical in nature, relating to the building and maintenance of the information technology associated with BI (Miller et al. 2006). Still this literature supports the concept that there are unique competences necessary for an organization to benefit from BI.

Competence models informing this research:

McGrath, MacMillan, and Venkataraman (1995) proposed a process model regarding the development of competence in an organization. They suggest that competence is learned by an organization over time and identify two antecedents, comprehension and deftness, that are necessary to develop competence as shown below.

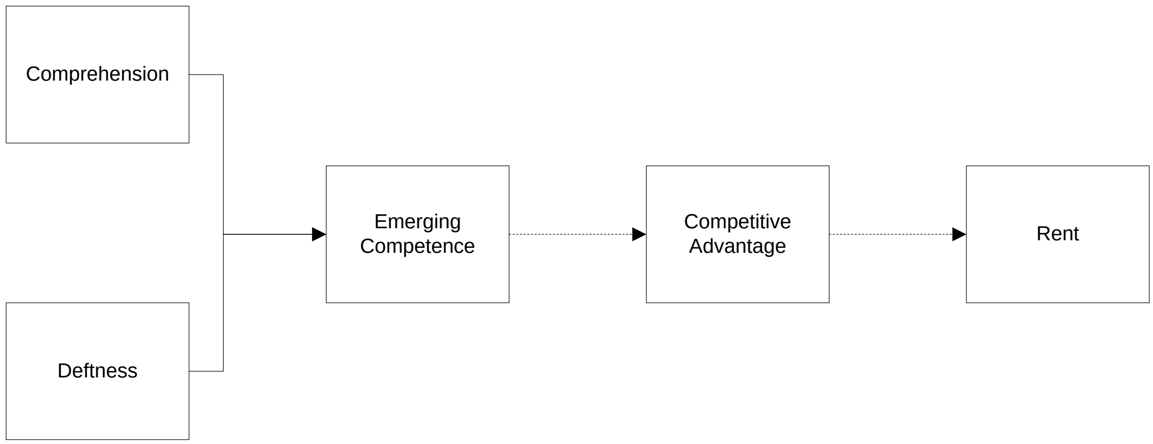

Figure 2.4 – Conceptual model of organizational competence (McGrath et al. 1995).

The authors concepts of comprehension and deftness were taken from the work of Weick and Roberts (1993). By comprehension they are referring to "the outcome of a process by which individual know-how and skill become linked." This conception of comprehension is viewed as an organizational construct. Although understanding takes place at the individual level, individuals work together to produce results beyond those that would normally be able to be achieved by an individual operating on their own (McGrath et al. 1995).

Deftness refers to the ability of a group to act together, with a single purpose, as if they were a single entity rather than a number of individuals (McGrath et al. 1995). Weick and Roberts (1993) refer to this as "heedful" interacting. They differentiate heedful interactions from un-heedful ones by illustrating that when groups interact heedfully they work together as if they were of one mind even though there may be many individuals involved (Weick et al. 1993). This model of organizational competence can provide a framework within which to study those competencies necessary to exploit BI technology to gain organizational benefits.

Dhillon (2008) used this model to specifically study the competence necessary to harness IT. His model however reclaimed the constructs of comprehension and deftness originally conceived by Weick and Roberts (1993) of individual know-how and skills; and purposeful heedful interactions as illustrated below:

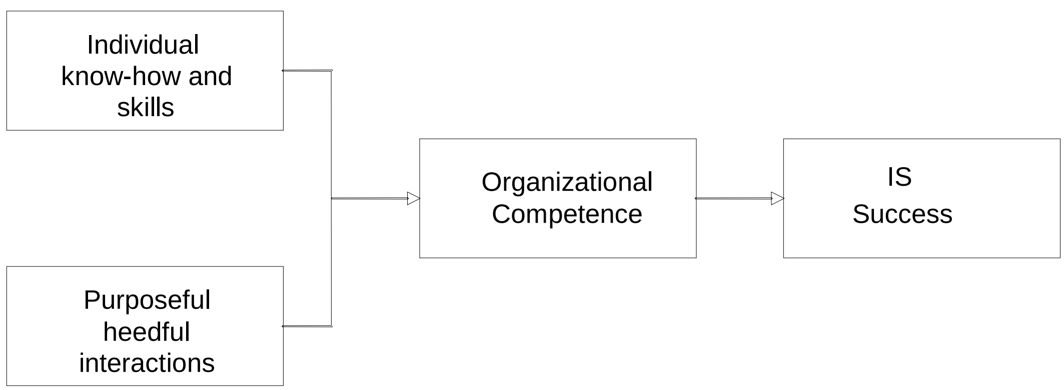

Figure 2.5 – Model of competence for Harnessing IT (Dhillon 2008).

As this model specifically relates the McGrath et. al. (1995) model to IS success, this is the framework through which competence for effective use of BI will be studied in this dissertation.

Summary:

Competence has been found to have the potential to impact organizational success and relative to BI in particular. Specifically it has been related to an organization's ability to derive benefits from their investments in IS. Competence has been found to impact user and organizational ability to harness IS in general, yet the literature does not address provide a specific model of competence to help understand its detailed nature, nor has such a model been examined relative to BI. The literature suggests that the development of such a model would provide a valuable new foundation with which to study BI. In addition, the Dhillon model (2008) provides a theoretical foundation on which to base this dissertation.

2.4 Conclusions:

The research record regarding BI is still sparse. The research that does exist primarily focuses on aspects of tools and technology or algorithms. Research that can begin to add to the body of work on this important technology would be of both theoretical and practical value. BI success has been said to be related to organizational capabilities (Watson et al. 2007). This section has identified many models of organizational capabilities and success that can provide valuable insight to inform this research. We will build on two of those models (Dhillon 2008; Mirani et al. 1998) to examine how factors relating to individuals and organizations can contribute to a model of BI success.

3. Research Philosophy and Methodology

3.1 Introduction:

The goal of social science research is to explain social phenomena in one of three ways, to describe the phenomena in a way that allows further study, to examine the underlying cause of the phenomena of interest, or to understand the process by which change occurs as a result of or to the phenomena (Blaikie 2007). The approach taken to examine the phenomenon under study will vary based on the nature of which of these types of understanding the researcher seeks. Describing ones research goals must be included in any discussion of research approach and is therefore an important part of this section.

Any researcher brings to their work particular ontological and epistemological perspectives. Ontology refers to “assumptions which concern the very essence of the phenomena under investigation” (Burrell et al. 1979, pg 1). The ontological perspective underlying specific research both informs and determines the epistemological and methodological approaches of that research. As such a clear understanding of the ontology underlying the research must exist and be articulated. Another goal of this section will therefore be to articulate the ontological perspective underlying this work.

Epistemology has to do with a researcher’s conception of knowledge. An epistemology “is a theory of how human beings come to have knowledge of the world around them (however this is regarded), of how we know what we know” (Blaikie 2007, pg 18). A researcher must be able to articulate the epistemological perspective from which their research is being performed to provide context for their research. Epistemology is one factor in determining the appropriate research methodology to be employed. Methodologies are ways that scientists can investigate various phenomena. A researcher's ontology and epistemology determine the set of methodologies appropriate to those perspectives. Further certain methods are used within a methodology to actually perform the research in question. In this chapter I will explore the research objectives and the ontology, epistemology, methodologies and methods underlying this research.

3.2 Research Philosophy:

Ontology:

The ontological perspective underlying this research is realism. In realism "both natural and social phenomena are assumed to have an existence that is independent of the activities of the human observer" (Blaikie 2007, pg 13). Realism as articulated by Bhaskar (1998) considers that "men in their social activity produce knowledge which is a social product much like any other, which is no more independent of its production and the men who produce it than motor cars, armchairs or books…" Yet he also observes that there is a 'knowledge of objects' that is independent of human activity. (Bhaskar 1998, pg 16). This perspective considers that there is an objective reality that would exist no matter whether it were observed or able to be described, but that in the study of such reality people create descriptions that are based on perceptions and are not necessarily equivalent to the objective reality being described.

Another way to describe this is that realism assumes "the further stratification of reality into the domains of the real, the actual, and the empirical. The last of these is in a contingent relationship to the other two; to be (either for an entity or structure or for an event) is *not* to be perceived" (Outhwaite 1998, pg 282).

> The *empirical* domain is the world that we experience through the use of our senses; the *actual* domain includes events whether or not anyone is there to observe them; and the *real* domain consists of the process that generate events (Blaikie 2007, pg 16).

While these concepts are embodied in Bhaskar's (1998) critical realism, Blaikie (2007) defines this form of realism as the depth realist ontology.

Epistemology:

When adopting a depth realist ontology, the associated epistemology is that of *neo-realism* (Blaikie 2007). Neo-realism suggests that finding underlying patterns in phenomena is only part of what is required for explanation. Under this epistemological perspective a researcher must understand the underlying mechanisms by which the observed phenomena occur. In order to do this a researcher may have to "postulate entities and processes that have never been observed in order to get beyond the surface appearances to the nature and essences of things" (Blaikie 2007, pg 22). This research seeks to do just that, to not only identify the competences that lead to benefits being realized from BI systems, but to also begin to develop an understanding of the mechanisms by which these competences lead to those benefits.

Methodology:

This research will use a retroductive methodology. Retroduction "refers to the process of building hypothetical models of structures and mechanisms that are assumed to produce empirical phenomena" (Blaikie 2007, pg 83). Bhaskar (1998) suggests that retroduction is the appropriate method to use when exploring social phenomena from a realist perspective. Retroduction starts with a model of the constructs to be studied. These models are then tested to determine if they represent the reality that the researcher is attempting to uncover. These tests are then used to modify the model based on understanding developed through testing. Finally a new model is postulated based on the revisions suggested by the evidence discovered during testing (Blaikie 2007).

3.3 Research Method:

This research seeks to understand the specific competencies that would allow an organization to gain business value from business intelligence systems. The question being studied is concerned with "how" and "why" questions regarding the relationship between competencies and BI. These types of questions can most effectively be addressed, especially in the early phases of a stream of research, via a case study approach (Benbasat et al. 1987; Yin 2003). A case study approach also allows one to examine a real world phenomenon in detail in a real life setting. Such an examination can lead to insights that could subsequently be used to develop generalized theories about the phenomenon in question.

One of the shortcomings noted with regard to Decision Support System (DSS) research is the limited amount of this research that has addressed business intelligence in spite of the prevalence of this topic in the popular press (Arnott et al. 2005). Arnott observes:

> The low practical relevance of DSS research is in part a symptom of research inertia… It is paradoxical that while DSS publication rate has fallen to early 1990s levels, in practice DSS is one of the only areas of commercial IT that is booming. DSS research is simply focusing on the wrong application areas. … To overcome this disconnect, DSS researchers must engage the data warehousing and business intelligence domains (Arnott et al. 2005, pg 83).

He goes on to say that "another strategy for improving the relevance of DSS research is to increase the number of case studies" (Arnott et al. 2005, pg 83). This research seeks to address both issues.

By using a case study approach this work will be able to examine a phenomenon in a detailed real world setting to be able to identify important relationships that can be used to begin to develop a generalized theory of the discipline. Therefore the first phase of this research will be to perform a case study to help identify the emergent constructs of competence for effective use of BI systems. The multiple-holistic case study approach will be used (Yin 2003). Multiple organizations that have implemented and use BI will be included. While the data will be collected from individuals who may work in a particular unit of the organization, the analysis will focus on the organization as a whole rather than individual business units, because our focus is on overall benefits from BI to the organization, not necessarily to a single entity within the organization.

Data will be collected through semi-structured interviews with key members of the organization under study. These interviews will examine the nature of comprehension, deftness, and competence relative to the organization's use of BI. The specific measures to be investigated will be informed by the constructs identified in McGrath, Macmillan, and Venkataraman (1995) and in Dhillon (2008). The respondents to be used will be identified through solicitation of graduate students at VCU and through the researcher's direct industry contacts. Those asked to participate will be people who through their regular work have frequent interaction with BI systems, either as a user or developer. Interviews will continue until the responses reach a saturation point, that is until the responses from each additional respondent no longer provide unique or new information regarding the questions being asked (Strauss et al. 1998). A list of the respondents, their industry and the date of the initial interview are listed in Appendix A.

In their work McGrath et. al. identified competence as "the extent to which *ex post* results are in the neighborhood of or above *ex ante* expectations" (McGrath et al. 1995, pg 254). They identified ten measures for the construct competence as "meeting budget objectives, meeting staffing objectives, meeting major deadlines, meeting quality objectives, meeting reliability objectives, meeting cost objectives, meeting efficiency objectives, meeting user/client satisfaction objectives, meeting service objectives, meeting objectives overall" (McGrath et al. 1995, pg 271). These measures however appear to be outcomes, not the processes or capabilities that lead to these outcomes. Their definition of competence and these associated items don't provide guidance to an organization as to how to achieve their goals. They are in effect saying that an organization must have competence if they meet their business objectives. This is a different definition of competence than is typically used where competence refers to specific skills and learning of a firm that allow them to realize superior performance (Prahalad et al. 1990). As such our research will seek to identify emerging competence for BI based on the evidence collected in the interviews and the antecedents, not building on the McGrath et. al. (1995) elements of emerging competence.

The antecedents to competence in the model we are using include comprehension and deftness. Sixteen measures of comprehension were proposed by McGrath et. al. (1995) Dhillon used this definition as a starting point in developing the construct of individual know-how and skill as an antecedent of organizational competence (Dhillon 2008). These measures will be used to inform our data collection on individual know-how and skill. The questions developed from these measures as an interview guide are shown in Appendix B.

The construct of deftness also had 16 measures that were evaluated on a scale from "less deft" to "more deft" (McGrath et al. 1995). These measures relate to the nature of the interactions among individuals in the organization otherwise known as purposeful heedful interactions. Deftness is dependent on formal organizational structures and organizational culture (Drejer 2000). Organizational structures define the "official" method of interaction between individuals or organizational units. Culture represents the "shared values and norms" of individuals that impact the informal interactions (Drejer 2000, pg 208). This will be evaluated similarly to the comprehension construct.

3.4 Data Analysis Approach:

In order to ensure validity of the data collected in this case study it is necessary to follow a structured approach to data analysis. While the data collection is being done from the perspective of existing theory, it is still important to structure analysis that ensures a deep understanding of underlying meanings. This will be accomplished by using the techniques of open and axial coding (Strauss et al. 1998).

Open coding is the process by which "concepts are identified and their properties and dimensions are discovered in data" (Strauss et al. 1998, pg 102). Through this process underlying themes embodied in the interviews should emerge. These themes will be evaluated within the theoretical constructs of individual know-how and skills and purposeful heedful interactions.

Once themes have emerged from the data, axial coding will be performed to align emergent themes within the overall theoretical model. Axial coding relates the categories identified through open coding "to subcategories along the lines of their properties and dimensions" (Strauss et al. 1998, pg 124). From these coding steps should emerge a model of competencies that will begin to explain successful BI.

As the coding of data is being performed new concepts may emerge that are not necessarily represented in the original theoretical model. These concepts will be explored by referring back to the literature to examine whether they have been studied. This iterative review of the research data and associated literature should provide insights that can be used to develop a theoretical model (Strauss et al. 1998).

3.5 Developing an assessment tool:

An additional goal of this research is to develop a preliminary assessment tool that can be used to determine an organization's level of competence for BI. The tool will be created using the individual elements of competence that emerge from the coding of the interview data. These elements should represent the various items that have been identified as antecedents to BI competence in our evaluation. Respondents will be asked to evaluate each of the elements in terms of the status of their organization on each item and the importance of each item.

This process will allow the evaluation of the potential for this tool to be used by an organization to determine their current likelihood of attaining BI benefits and provide direction for steps to take to increase their BI success. Evaluating how respondents use this tool can provide insight into how it can be used and its potential impact.

3.6 Conclusions:

The main objective of this research is to understand the characteristics of an organization that allow it to be successful in deriving benefits from business intelligence systems. This research poses the proposition that beneficial use of BI requires certain competences to be present in an organization. The specific questions that describe this proposition based on the model with which we are starting would therefore be:

Question one: What are the characteristics of individual know-how and skill for BI?

Question two: What are the characteristics of purposeful and heedful interactions for BI?

Question three: What is the relationship between individual know-how and skills and BI success?

Question four: What is the relationship between purposeful heedful interactions and BI success?

Given the researcher's ontological and epistemological perspective, a retroductive methodology will be used as realized though a case study method.

4. Defining antecedents to BI Competence

4.1 Introduction:

This research seeks to understand the competences necessary for an organization to benefit from the use of business intelligence systems. We are using a competency model proposed by McGrath et. al. (McGrath et al. 1995; Weick et al. 1993) as the theoretical model with which to understand these competences. This model suggests that competences emerge from the interaction of "comprehension" at the individual level; and "deftness" at the organizational level. Comprehension is defined as "the outcomes of a process by which elements of individual know how and skill become linked" (McGrath et al. 1995, pg 255). While deftness is a process, if one were to look for organizational characteristics as antecedents to competences one would also need to understand the underlying skills and knowledge of individuals in the organization.

Deftness is defined as "the operational characteristics we might expect to find associated with a group which operates 'heedfully'" (McGrath et al. 1995, pg 256). Deftness is the process by which heedful and purposeful interactions develop, but those heedful and purposeful interactions are the organizational level elements that lead to organizational competence. Heedful and purposeful interactions refer to the fact that an organization consists of individuals who interact in the course of performing their duties. For competence to exist at the organizational level these interactions need to take place in a way that is effective and appropriate to reinforce the goals of the organization (Weick et al. 1993). Individuals may interact in ways that tend to reduce the value of their individual contributions. Only when they interact heedfully can the real value of their performance be realized.

The interaction of comprehension and deftness leads to emerging competences, defined as “a purposive combination of firm-specific assets (or resources) which enables it to accomplish a given task,” (McGrath et al. 1995, pg 254) that then impact an organization’s success.

Dhillon (2008) used this model to develop an associated model specifically associated with “harnessing IT” as shown in Figure 4.1 below:

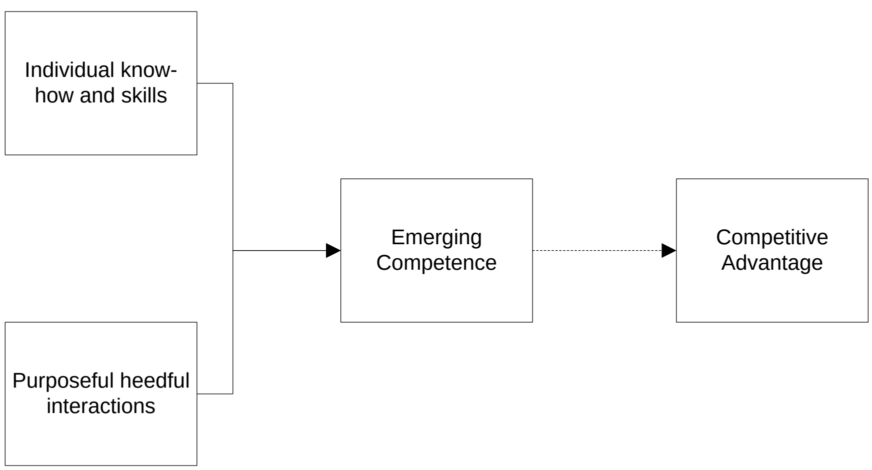

Figure 4.1 Competence model for harnessing IT (Dhillon 2008).

While this model addresses the competences necessary to harness IT in general, we are seeking to develop a version of this model specific to business intelligence systems. In order to do this, the first step was to interview individuals who had specific experience with business intelligence. The objective was to begin to develop an understanding of the competences that are necessary for the effective use of business intelligence capabilities to provide benefits to an organization. These interviews were conducted in a semi-structured manner, using an interview guide (appendix B), but letting the respondent drive the direction of the discussion (Marshall et al. 2006). Although the guide was structured in a way to elicit information about competences for BI at both the individual and organizational levels, the specifics of these two concepts were allowed to emerge from the discussion. This research was done as a multiple case study of firms known to have experience with implementing and using business intelligence.

In this chapter we will review the results emerging from these interviews. This chapter is organized into four sections. This first will discuss the individual level constructs, i.e. individual know how and skills emerging from the data collected. A model of competence emerging from this information will then be developed and described. The second section will describe the organizational level findings describing characteristics that lead to purposeful and heedful interactions and then a model that explains these findings. The next section will provide a perspective on the emerging competences that emerged from the individual level and organizational level information. Finally we will describe how all of these concepts fit into an overall competence model.

4.2 Individual Know-How and Skills:

4.2.1 Definitions:

Competences are necessary at an organizational level in order to have an impact on organizational performance. However, an organization is not a monolithic entity. Any organization consists of individuals whose combined actions lead to organizational outcomes. In talking about competence development Drejer (2000) noted, “human beings are to us the most obvious part of competence: if no humans use the technologies, then nothing will happen. Therefore human beings are the focal point of competence development" (Drejer 2000, pg 208).

Competence at an individual level consists of both skills and knowledge. Another term for skills would be "know-how," vs. knowledge, which constitutes "know-that" (Dhillon 2008). For example, one may know the process of how to hit a baseball. They may know that one holds a bat and waits for the ball to come to them and then swings to make contact with the ball. This would constitute knowledge or know-that. But to play on a Major league baseball team one must also have skill or know-how, which enables one to consistently hit the ball with power and placement. Knowledge by itself is not sufficient to be able to effectively perform a function; one must have skill to go along with the knowledge.

The way that one acquires skill and knowledge is through learning. Learning takes place at both an individual level and at an organizational level (Shrivastava 1983; Skerlavaj et al. 2007). Individual level learning is commonly referred to as training. It is the process by which individuals acquire skills and knowledge. For organizational learning to take place there needs to be a culture that supports learning and the learning needs to be embodied at the organizational level, not just in individuals (Huber 1991; Miller 1996; Miner et al. 1996). The concept of organizational learning and a learning organization will be discussed in more detail as we examine our findings.

Yet skill, or ability, is not only learned. As in the case of hitting a baseball, one can learn how, and practice regularly to improve skill at performing this ability, but certain people will be able to learn certain abilities faster or with more proficiency than others. These inherent skills are also important for building competence. In this section we will review the findings relative to skills, both learned and inherent, and knowledge associated with an organization's ability to gain benefits from business intelligence systems.

4.2.2 Evidence:

Cognitive Ability:

One of the first concepts to emerge from the data was that of cognitive ability. The generally accepted measure of cognitive ability is "g," representing general intelligence (Bowman et al. 2001; Gottfredson 1997). This measure represents an individual's ability to perform certain intellectually based tasks. It is generally measured and quantified through one of several tests that provide a measure of Intelligence Quotient (IQ), although IQ represents an approximation of the underlying value of g.

The data collected for this research recognized a number of characteristics of cognitive ability as important for effective BI. For example, a director of data management noted "*on average we have a very smart company, [because] we screen for intelligence*." A data stewardship director noted "*we trust everyone to be braniacs.*" A data warehousing director commented on the fact that general cognitive ability was more important than understanding of the business in which the person was to work: "*Maybe you didn't have the syntax of the business, but you had the brain capacity of saying how do I solve* *problems. ...if you're smart enough we can teach you the syntax of the business, that's easy. But you can't teach people to be smarter."* While one of his peers said *"In terms of this company using intelligence at the individual level, more than most corporations we have historically screened on individual intelligence. What you may think of as IQ or whatever. On average we have a very smart company.*"

The emergence of cognitive ability on the effectiveness of individual's performance on BI related tasks should not be a surprise, since a significant volume of research has identified a relationship between cognitive ability and job performance (Bajema 1968; Barrett et al. 1991; Gottfredson 1997; Hunter 1986; Sternberg et al. 2002). While some have argued that specific job skills or competence would be a better predictor of overall job performance (McClelland 1973), evidence indicates that general cognitive skill, not specific job skills is a better predictor of job performance (Barrett et al. 1991; Hunter 1986).

Cognitive ability is not a unitary concept. It was originally developed via factor analysis of measures of individuals' abilities to learn from experience, to understand relationships and to understand correlations (Bowman et al. 2001). Cognitive ability represents a combination of a number of different concepts. The respondents mentioned a number of them. Part of cognitive ability is general numerical and verbal reasoning. This was specifically mentioned by a number of people. The following comment by a business analyst was typical:

…first would be both numerical and verbal problem solving. The numerical would be … the standard math screening test, but now we have added a verbal reasoning test. While some of them [the employment screening tests] *have a little math they're really more verbal reasoning without that. The reason we're doing that is because it broadens the construct of intelligence and also we're trying to get in place some tools for that are really not that analytical, art jobs and such, we can still measure their problem solving, but kind of in a softer and more accessible way.*

The following statement by an HR analyst embodies the broader concept of cognitive ability's impact on BI:

…it's one of the weaknesses I see in our society in general is understanding relationships. I really blame that on people's lack of training and understand of… you know the fraction is the simplest form of the relationship and it's amazing how few people can convert even a fraction to a decimal. Extend this to the concept of understanding cause and effect relationships and I think another thing is our society… we tend to be very myopic and weak on causal chains that are more than one or 2 steps, or take this to the concept of systems thinking and understanding all of those relationships. Because a lot of times what's happening, people will pull data out of a data set, but if they don't understand how all the

different tables are related you can get a data set that looks right and they may think it's right and if you're the user and don't know better you may think it's right as well, but they can miss out on data or add in a lot of data or even do something stupid like truncate a number that you need more information out of or something because they don't understand the relationships they don't understand the needs of the user.

These broader elements of cognitive ability have been recognized by organizational researchers as contributing to job performance. The ability to understand relationships has been shown to be an element of tacit knowledge, sometimes referred to as practical intelligence, and related to job performance (Bowman et al. 2002; Sternberg 1997; Sternberg et al. 2002; Young et al. 2000). This research suggests that there is an ability that is not consciously learned or understood by them that exists in individuals that allows them to solve problems effectively in a particular setting, consistent with our findings.

While general cognitive ability clearly seems to be perceived as a factor in the ability to effectively benefit from BI systems, cognitive ability by itself is not sufficient. There are other abilities that are not necessarily inherent that support successful BI. A data stewardship director noted *"…being smart is only part of the story …it's really more screening out for people who aren't good problem solvers…[we look for people who] can view the problem, structure it, and come up with an approach to solve it."*

Cognitive Style:

In addition to cognitive ability, or general intelligence, individuals differ in their cognitive style. Cognitive style refers to the preferred ways that a person processes information and makes decisions. While cognitive style can change for each person over time, people have generally been shown to have a preferred cognitive style that changes only slowly. A number of different measures of cognitive style have been used but in general they refer to "systematic differences among individuals in terms of perception, thinking, and judgment that significantly influence their choice of and response to information" (Keen et al. 1981, pg 21). Mason and Mitroff (1973) suggested that cognitive style was an important aspect of MIS research when they said "*an information system consists of at least one PERSON of a certain PSYCHOLOGICAL TYPE who faces a PROBLEM within some ORGANIZATIONAL CONTEXT for which he needs EVIDENCE to arrive at a solution (i.e., to select some course of action) and that the evidence is made available to him through some MODE OF PRESENTATION"* (emphasis retained) (Mason et al. 1973, pg 475). They went on to explain that by "psychological type" they were referring to the dimensions of the Myers-Briggs type indicator (Mason et al. 1973), a common measure of cognitive style (Keen et al. 1981). Cognitive style was used extensively in early MIS research (Benbasat et al. 1978), yet its use has also been criticized (Huber 1983). In spite of criticism of its use, cognitive style continues to be studied in MIS and has recently been found to impact individual's tendency to use decision support tools (Chakraborty et al. 2008; Fox 2003; Green et al. 1986).

Concepts related to cognitive style were mentioned by a number of respondents as being important for BI success. The respondents described this as having a preference for making decisions based on data or facts versus an intuitive style. Fact based decision makers use analytical tools and try to have a tangible reason for each major decision that they make (Choo et al. 2008; Davenport et al. 2007). This is consistent with using BI tools for making decisions, since BI tools support providing data and supporting analysis of that data for decision making. Intuitive decision makers use facts, but they tend to make a final decision based on some intangible, at least to them, sense of what is correct based on the entire spectrum of information and experience available to them (Curry et al. 2003). Typical of the comments on cognitive style was this statement by a financial analyst *"The whole culture is that people use data to make decisions. I remember somebody told me that [a large competitor] had like three analysts developing all account management strategies for the entire company. We have an entire department of analysts that manages the entire function."*

There are a number of different aspects of cognitive style (Chakraborty et al. 2008; Huysmans 1970; Keen et al. 1981). In general though, cognitive style refers to the way that people process information. Huysmans (1970) taxonomy separates cognitive style into two aspects, heuristic and analytic. In this model, analytic reasoning is defined as follows:

> This type of reasoning reduces problem situations to a core set of underlying causal relationships. All effort is directed towards

> manipulating the decision variables (behavior) in such a manner that some 'optimal' equilibrium is reached with respect to the objectives. A more or less explicit model, often stated in quantitative terms, forms the basis for each decision (Huysmans 1970, pg 94).

The contrasting cognitive style is called heuristic reasoning and is defined as:

> This type of reasoning emphasizes workable solutions to total problem situations. The search is for analogies with familiar problems rather than for a system of underlying causal relationships, which is often thought illusory. Common sense, intuition, and unquantified 'feelings' about future developments play an important role to the extent they are applied to the totality of the solution as an organic whole, rather than as built up from clearly identifiable separate parts. It is extremely difficult, if not impossible, to uncover the mechanisms that lead to a decision under heuristic reasoning (Huysmans 1970, pg 95).

While Huysmans is careful to note that these cognitive styles represent ends of a continuum, they are useful for categorizing individuals relative to their tendencies regarding their decision making processes.

Non-Cognitive Skills:

A number of skills that could be categorized as non-cognitive were also identified. Communications was one of the key non-cognitive skills. An individual may be able to analyze a problem and come up with a solution, but if they are unable to articulate the meaning and importance of their proposed solution both verbally and in written form the organization for which the analysis was completed is less likely to adopt the proposed solution (Amidon 2005). As noted by a data stewardship director:

> *[our employees must have the] ability to communicate technical issues in non-technical way. The way our folks explain our results…analysts and statisticians are actually very good at simplifying and boiling down the results so you can tell that this whole model gives better results for us, and not have to go into the details of the model.*

This result is consistent with research on the impact of knowledge management systems where it has been recognized that the explanatory capabilities of such systems have an impact on the ability of such systems to provide benefits (Arnold et al. 2006; Dhaliwal et al. 1996; Mackay et al. 1992). The ability to provide adequate explanation of the results of BI systems was noted by the respondents as determining the likelihood that such results would be used in the same way that explanation are key to an organization’s ability to use the information embodied in knowledge management systems (Gregor et al. 1999).

Other non-cognitive skills have to do with the ability to perform the type of analysis for which BI tools are typically implemented. These skills have been identified as something called “analytic capability.’ Analytic capability refers to skills beyond basic cognitive abilities. A person may be intelligent, but not have learned the analytical skills necessary to perform the required analysis and interpret the results from these analyses. Analytical capability was said to start with the ability to know which questions to ask in order to be able to solve the problem at hand. It also includes skills in the use of analytical, typically statistical techniques, to be able to formulate a problem in a way that can be addressed using the available BI tools. This embodies two different concepts. One is an ability to be able to look at problems and develop a definition that lends itself to solving using available techniques. This would be considered a non-cognitive skill in that it is not purely reasoning based, but is related to cognitive ability. The other is the skill and knowledge to be able to apply the appropriate statistical techniques. This ability has been referred to as statistical thinking, reasoning, or literacy (delMas 2002). Both the knowledge of techniques and the ability to apply them can be trained (Garfield 2002; Schafer et al. 2003). A director of business analysis specifically referred to these abilities when he said:

> *...our screening when we hire folks in is literally looking for critical problem solving skills. So they can view this problem, structure it and come up with an approach to solve it. There are things like specifically design of experiments. So if I'm going to run a test I need to know how to set it up I need to know how to get the data to support it, I need to get a project set up to be able to implement the test and to monitor and track the results, I need to know it's relevant. I may not have all the answers but I need to support it.*

And a human resource analyst observed; *"we screen in for intelligence, but it's really more screening out for people who really aren't good problem solvers."* He went on to comment;

> *That's another issue, problem identification. In business settings people spend a lot of time chasing the symptoms or just burning a lot of time or energy, but not really understanding what they're trying to solve for. Even if they sort of know I need to solve for these three things then they go back to the customer to make sure and maybe the customer only needs one of those three things. So the people end up in analysis paralysis where they're over working themselves to provide too much information. You could kind of wrap it up into formal problem identification and solving, systems thinking…*

Still other non-cognitive abilities have to do with an individual's work style. Business intelligence tools impose change on an organization. They are used support changes to business strategy, product, operations, or other aspects of the business (Davenport et al. 2005; Howson 2008). Individuals must be comfortable with change in order for BI to have impact. If you have too many individuals who are resistant to change, the likelihood of BI tools' recommendations being adopted is reduced. The impact of individuals change orientation has been noted in the literature on strategic adaptation (Brabazon et al. 2005; Brown et al. 1997; Hannan et al. 1984). Others have noted that in order for organizations to adapt there must be a willingness and ability to adopt change recommendations (Belasco 1991; Davis et al. 1998; Hammer et al. 1993). As a data warehousing director said; *"the ability to adapt to change is critical to surviving here, the ability to change roles, the ability to change approach."*

Related to this is the tolerance for ambiguity. Business problems to be addressed by BI are not usually neatly structured, and many of the underlying constructs or data sets are often missing. Individuals need to be comfortable working with a level of ambiguity both in goals and in the underlying data to be able to develop recommendations from BI (Alvesson 1993; Belasco 1991). As a data analyst observed:

> *There's another thing that we look for … which is critical and probably very much ties into what you're looking at and that is; are they change oriented or do they have a high tolerance for ambiguity. Because any time you have a lot of business systems and data that means that you're also going to have a lot of changes and training and you need people who just don't moan and groan every time you have a new system update or every time you have to switch to a new system. …There's this sort of openness to use of technology and there's also just the tolerance for ambiguity, the ability of users to handle those changes over time.*

Knowledge:

Up to now we have been discussing ability or skill. Another way to describe this would be know-how. Know-how represents an individual's ability to perform a certain task or operate in their environment. There are both innate and learned abilities that are important for effective use of BI. In addition to know-how, individuals must have knowledge, or know-that, to be able to effectively use BI. Knowledge consists of information about certain topics. A significant volume of research has looked at systems specifically designed to manage knowledge in organizations (Alavi et al. 2001; Arnold et al. 2006; Coakes 2004; Davenport et al. 1998; Schultze et al. 2004). Having knowledge by itself does not insure that someone can effectively use it (Schultze et al. 2004), but it is necessary to have the appropriate knowledge to be able to use BI effectively. In our research we identified a number of specific types of knowledge that are necessary for BI success.

Business Knowledge:

One type of knowledge that is consistently identified by our respondents is business knowledge. This includes both general business concepts and knowledge of information specific to the industry of company in which an individual works. It seems almost tautological that someone must understand the business in which they work to be able to develop strategy for it, but knowledge tends to be compartmentalized in an organization. Individuals make sure to acquire the knowledge necessary for their job function, whether that is operations, finance, human resources, or any other function (Noll et al. 2002; Sumner 2000). However, not all employees take the time or are given the training to understand the industry and their organization's position in that industry. In order to effectively use BI, individuals must have an understanding of not only how their business operates, but the context of these operations relative to the marketplace (Cody et al. 2002).

Another aspect of business knowledge has to do with information systems professionals. The information systems organization is often viewed as a service organization whose role is to implement technology based solutions based on the needs of the business departments. Respondents in this study clearly noted that it is important for IT personnel to understand not only the technology with which they are working, but the data being loaded into and used by their systems and the underlying business processes and business environment in which they operate (Noll et al. 2002; Trauth et al. 1993). A vice president of data management observed:

> *I think the need is business understanding on the technical side because as technology advances the need for understanding of technology by the business people is getting less and less in my opinion. ... as a business decision maker you don't really need to understand the difference between a gigabyte and a terabyte. ... On the technical side there is a real lack of ... what am I keeping all these boxes humming for, it's not really because this is the latest cool stuff, it's so the people across the street… so their numbers add up. What are those numbers telling us and that really kind of… moving from heads down technical guy working with the stuff and kind of taking a look up and getting a broader perspective; that seems to be the biggest area that's lacking.*

Data Knowledge:

Another type of knowledge that was mentioned was data knowledge. This refers to an understanding of the data that is stored in analytical systems and ultimately to be used in business intelligence analytical processes. There are many different aspects of understanding data that were found to be important. Some of these are generic to the access and manipulation of data, and others are specific to an individual organization. Generic data management skills referenced included the ability to access data, understanding of how data is stored, understanding of relationships between types of data, and understanding and ability to use metadata (Miller et al. 2006). Most data used for business intelligence is stored in some form of a relational database. Even those systems that use specialized database management systems (DBMS) or product specific storage methods acquire their data from systems that use a standard relational DBMS. Most tools require some or of Structured Query Language (SQL) for access (Loshin 2003). An organization needs individuals who have skills in using SQL to extract the appropriate data for analysis.

It's not just enough to be able to access this data. Individuals must understand the meaning of the data being accessed. Certain fields may seem obvious, like name or address, but there are many fields, especially in analytical applications, that are summarized or derived from relationships between multiple data elements. An organization must have individuals who understand what these data elements represent and can relate those meanings to the analysis for which the data is being used (Davenport et al. 2007; Loshin 2003; Miller et al. 2006). A good metadata repository can help maintain information about the underlying data, but even metadata repository can have ambiguities that must be dealt with. For this reason it is important for individuals to understand the context of the data being used for analysis and the specific characteristics of the data to avoid ambiguity in analytical results. A data management VP noted this need when she said:

> *…people in different areas, even in IT, look at data differently. An ability to look at the way our applications work with a different eye and it's always good to have everyone looking at those things so that we don't miss anything. With those who are working with the BI tools… they need to have the ability to identify either actual or potential issues with the data before we would provide a product out to one of our business departments or to any of our membership.*
>
> *I think you have to have a really good understanding of how the data's collected, how it's stored, and the relationships between the data.*
>
> *I think a BI team would need to have a broader… or an understanding of all the data where the business units, particularly the group we were working with was a small group within a business unit that looked at specific data. My expectation would be that they would know that data at that same level, know how we collect it, why we collect it and the relationships between the data.*

In reviewing the findings above it becomes clear that the key elements that contribute to the comprehension dimension in the model we are using are cognitive style, the level of individual ability or skill, and the level of individual knowledge. These specific elements of individual skills and knowledge identified are summarized in the table below:

Cognitive Skills	Numerical Reasoning Verbal Reasoning Problem solving ability
Non-Cognitive Skills	Verbal Communications Written communications Effective listening skills Data manipulation skills Tolerance for change and ambiguity Team orientation
Knowledge	Understanding of organization's business Understanding of competitive market Knowledge of data meanings Knowledge of statistical/analytical techniques

Table 4.1 – Individual competence characteristics.

In the next section we will discuss the relationship that emerges between these elements.

4.2.3 Emergent model:

One of the important findings regarding individual characteristics impacting effective BI was regarding cognitive style. Cognitive style has been observed to impact information system usage in general (Chakraborty et al. 2008; Keen et al. 1981), and decision support systems specifically (Green et al. 1986; Huysmans 1970). While some have suggested that cognitive style is not a reliable criteria to use when evaluating MIS designs (Huber

1983), our research indicates that cognitive style does impact the ability of an organization to derive benefits from BI.

As mentioned earlier, there are quite a number of different measures of cognitive style (Benbasat et al. 1978; Doktor et al. 1973; Keen et al. 1981; Kozhevnikov 2007). In our research the respondents consistently referred to one style as being fact or data based and the other being more intuitive. These cognitive style dimensions are consistent with the analytic reasoning vs. heuristic reasoning dichotomy proposed by Huymans (1970) as described earlier. The underlying concepts in cognitive style have been recognized in the popular press in a recent article in which the author recounted recent research by Accenture in which they found that 40% of business leaders surveyed used factors other than quantitative analysis for making their decisions (Wailgum 2009). The fact that business people use both qualitative and quantitative factors to make decisions is not new or surprising (Fox 2003; Nutt 1993). In fact it is not clear that one style would result in better decisions than another (Churchman 1964; Leonard et al. 1999). The question here however is whether or not a BI implementation can have a positive impact on business results, not whether cognitive style impacts the quality of decision making (Lusk 1979). In order for BI to have an impact the recommendations resulting from its analysis would have to be used in some way (Davenport et al. 2005; Howson 2008) and our research indicates that cognitive style does have an impact on the likelihood of decision makers to take action based on BI system outputs (Doktor et al. 1973). Therefore any model of individual elements supporting competence for BI should include the construct of cognitive style.

A number of skills and certain types of knowledge were identified by the respondents as being important for BI success. The way individuals acquire those skills and knowledge is through learning (Argyris et al. 1978). Argyris (1991) identified two different levels by which learning takes place. Single loop learning represents development of knowledge of how to do something. With this type of learning one gains a superficial understanding. Double loop learning on the other hand represents learning not only about the phenomena, but understanding the underlying mechanisms of the phenomena and the cognitive processes by which an individual learns (Argyris 1991).

These concepts of single and double loop learning both explain how skills and knowledge are related to competence and are determined by the level of skills and knowledge in an organization (Drejer 2000; Leonard-Barton 1995). Those organizations that predominantly exercise single loop learning only are unlikely to develop high levels of skills and knowledge. Although individuals in those organizations may develop complex skills and knowledge, because their learning takes place at a superficial level they are unlikely to be able to adapt to changing situations and their skills and knowledge become obsolete (Argyris et al. 1978). At the same time there is an interaction between organizational learning and cognitive style. Individuals with a more heuristic cognitive style are less likely to develop the level of understanding of their learning processes that would support double loop learning (Argyris 1992; Leonard-Barton 1995).

Organizational learning has been identified as one of the mechanisms by which decision support systems can provide benefits to an organization (Bhatt et al. 2002; Chou 2003), and learning organizations have been shown to have superior business performance (Carayannis et al. 2002; Skerlavaj et al. 2007; Steensma 1996). Huber (1991) identified four constructs associated with organizational learning. Those constructs are knowledge acquisition, information distribution, information interpretation, and organizational memory (Huber 1991). One can directly relate those constructs to the technological components of business intelligence. Knowledge acquisition can be considered analogous to the data extraction, transformation, and loading processes that are typically associated with BI databases. Information distribution is represented in the data access tools that typically comprise the front end of BI systems. Information interpretation is what data visualization and analysis tools perform, and a BI data warehouse represents a form of organizational memory. This relationship is represented in the table below:

Components of Organizational Learning	**Analogous Business Intelligence Components**	**Competence Component**
Knowledge Acquisition	Extraction Transformation and Load (ETL) tools and processes, data entry processes, external data sources	Data quality, database management, data content skills and knowledge
Information Distribution	Data Access tools, metadata repositories, corporate	Data access, data meaning, skills and

	network, corporate dashboards	knowledge
Information Interpretation	Online Analytical Processing (OLAP), Statistical analysis tools	Analytical skills, data interpretation skills, problem identification skills
Organizational Memory	Data Warehouses, Data Marts, Operational Databases	Database management skills

Table 4.2 – Huber (1991) organizational learning model related to BI.

From the discussion above it becomes clear that a model that explains individual level constructs to support BI benefits must include cognitive style and organizational learning constructs related to the levels of skills and knowledge in the organization. Combining these constructs into a single model gives us the framework illustrated below:

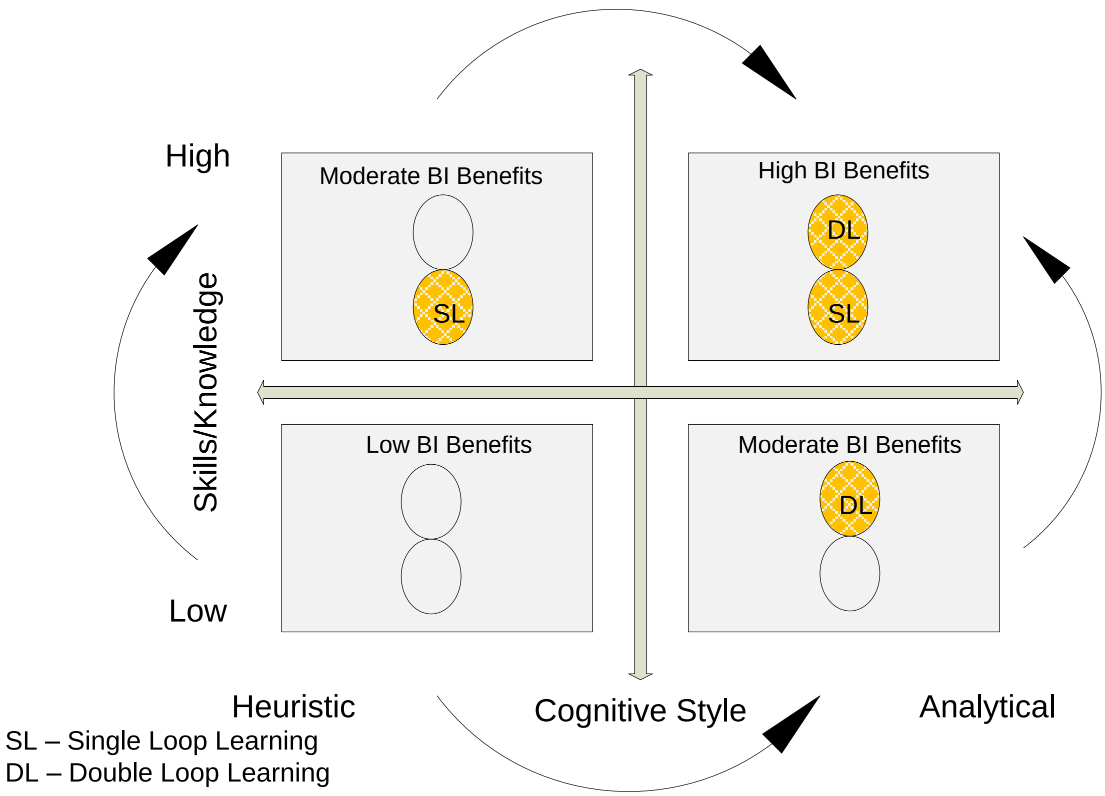

Figure 4.2 – Individual level model of competence for BI

The horizontal axis in this diagram represents cognitive style as described above. The vertical axis represents the level of skill/ability and knowledge of individuals in the organization. The double circles in each quadrant represent learning style. The top circle represents "double loop learning," while the bottom represents "single loop learning" (Argyris 1991; 1997). A shaded circle indicates the presence of the requisite learning style.

This model represents the individual skills and knowledge component of the Dhillon model illustrated above that leads to emerging competences (Dhillon 2008). Moving from the bottom left, where individuals have low skill and a more heuristic cognitive style, to the top right, where there is an analytical style and high skills, improves the benefits derived from BI. The lower left box represents the lowest potential benefit situation. In this quadrant individuals don't have the skills or abilities identified for successful BI so they are unable to effectively perform the operations required to use the BI tools. In addition, the heuristic cognitive style indicates a tendency of individuals to be less likely to have a tendency to use analytical tools in making their decisions (Fox 2003; Leonard et al. 1999). The lack of skills and knowledge would indicate that learning, either single or double loop is not taking place (Argyris 1991). In addition, due to the limited learning taking place in this scenario, it is unlikely that the requisite skills and knowledge will be acquired. This would lead to limited benefits being derived from the organization's BI implementations.

As one moves up to the top left quadrant, you have individuals who have the appropriate skills to be able to exercise BI tools. The existence of these skills is an indication that single loop learning is taking place. In order for individuals to have acquired these skills, they must have realized at least this type of learning (Argyris et al. 1978). The heuristic cognitive style will tend to limit the detailed introspection that is required for double loop learning to be taking place (Argyris et al. 1996). The heuristic cognitive style also means that these tools are less likely to be used in making business decisions (Fox 2003). Although they have skills and knowledge that will help them to build and use BI, an organization with individuals in this quadrant is likely to attain only a moderate level of benefits from their BI investments due to their predominant cognitive style and lack of double loop learning.

In the bottom right you have individuals of low skill with an analytic cognitive style. In this case you have individuals who prefer to make decisions using tools such as would be embodied in BI systems, but they don't have the skills to effectively use those tools. The fact that there is a low level of skills and knowledge would indicate a low level of single loop learning, but their cognitive style would indicate more developed tendency towards double loop learning (Argyris et al. 1996; Leonard-Barton 1995; Leonard et al. 1999). The result would be as in the top left that moderate BI benefits would be realized.

The top right box represents the high skill, analytic style combination. In this case you have individuals with the skills and abilities, technical, cognitive, and non-cognitive, which would allow for effective use of BI tools. Further these individuals tend to have a cognitive style that would create a tendency to rely on the outputs of BI tools in making their decisions (Argyris et al. 1996; Fox 2003; Leonard et al. 1999). This quadrant also represents a situation where both single and double loop learning is occurring. This combination of learning styles, cognitive style, and skills and abilities would lead to a high level of benefit from BI systems.

This diagram also has arrows representing how an organization can move towards increased BI benefit. In order to move to the top right an organization must have individuals working with their BI systems that have the requisite skills and knowledge and cognitive style. Acquiring certain skills and knowledge can be done through training (Argyris 1992). This training may consist of technical training to focus on the specific technologies used; analytical training to improve the level of skills in tools and techniques; or business training to improve the level of understanding of industry specific characteristics (Andreu et al. 1996; Blau et al. 2008; delMas 2002).

By ensuring that the personnel in key BI roles have a more analytic cognitive style an organization can also improve the likelihood that both single and double loop learning, necessary for maximum benefits, is taking place (Berson et al. 2006; Drejer et al. 1999; Dunphy et al. 1997). However, cognitive style is difficult to change in individuals (Hunt et al. 1989). As such, for an organization to move from left to right in this model they would have to ensure that the personnel who will be working with BI have a more analytic style (Blais et al. 2005; Chandrasekaran et al. 1986).

However, some of the abilities identified are difficult to change. One of these is general cognitive ability, labeled "g." The only way to reliably assure that this ability exists in the individuals upon whom they rely to use these systems is to screen for it (Gottfredson 1997; Hunter 1986). This is a somewhat controversial subject. There are many who have argued against a direct relationship between g and job performance (Bowman et al. 2002; McClelland 1973; Sternberg 1997; Young et al. 2000). When examined objectively the evidence still supports a direct relationship between general cognitive ability and job performance (Barrett et al. 1991; Gottfredson 1986; Gottfredson 1997; Hunter 1986; Kranzler 2001; Sternberg et al. 2002). This would indicate that one key to assuring the high level of cognitive ability necessary to gain benefits from BI would be to screen BI users and analysts for cognitive ability as a prerequisite for the job.

However, BI benefits take more than just g. Other skills and knowledge, such as understanding and capabilities to use statistical tools and techniques, and knowledge of the underlying business for which the analysis is being performed were identified in our study as having an impact. An organization can move from the bottom quadrants to the top by providing training in these areas (Argyris 1992).

Changing cognitive style is more difficult. Research on cognitive style seems to indicate that it changes slowly and with difficulty for individuals (Chakraborty et al. 2008; Green et al. 1986; Huysmans 1970; Keen et al. 1981). Still, a more analytic cognitive style can be attained through cognitive style awareness and through training (Argyris et al. 1996). It is easier however to screen for cognitive style in hiring for those individuals who are likely users of BI in their every day work.

4.3 Purposeful, Heedful Interactions:

The previous section reviewed competences at the level of individuals in an organization. In the next section we will discuss our findings relative to organizational level constructs.

4.3.1 Definitions:

While individual level antecedents to emergent competences are necessary to build competence to attain benefits from information systems, they're not sufficient. Those individuals must be able to work together in a coordinated fashion. The Dhillon model which we are using describes those organizational level antecedents to emerging competences for harnessing IT as "purposeful heedful interactions" (Dhillon 2008). Heedful purposeful interactions take place when individuals work as if they were of the same mind. Even though they may operate at an individual level, their actions when looked at in combination represent a level of coordination beyond the sum of their individual actions. As Weick and Roberts described it:

> When these conditions are given we have a social system or a process of a definite form that embraces the actions of a number of individuals. Such a system does not reside in the individuals taken separately, though each individual contributes to it; nor does it reside outside them; it is present in the interrelations between the activities of individuals (Weick et al. 1993, pg 362).

From this description it becomes clear that purposeful heedful interactions involve organizational level concepts that impact how people work together. This raises the question of what differentiates an organization from a group of individuals. One of the most prevalent theories of a firm in use today is resource based theory or the resource based view (RBV) (Barney 1991; Chmielewski et al. 2007; Fernandez et al. 2000; Grant 1991; Wernerfelt 1984). The RBV has been used extensively in IS research (Caldeira et al. 2003; Clemons 1991; Kearns et al. 2000; Kearns et al. 2003; Rivard et al. 2006; Wade 2001; Wade et al. 2004).

The basic premise of the RBV is that an organization is made up of an idiosyncratic combination of resources that provide unique capabilities that allow a firm to compete (Barney 1991; Grant 1991). These resources can be described as consisting of technological/financial, human, and organization/culture (Drejer 2000; Drejer 2001;

Drejer et al. 1999). The technological and financial resources represent the physical assets that an organization uses to perform their regular operations. This would include information technology and the associated data. Human resources include the people, who we discussed in the prior section. Finally there are the organizational/cultural aspects of an enterprise. By organizational we are referring to the formal organizational structure and mechanisms by which an organization is governed (Drejer 2001). Complementing the formal structures are the informal structures that embody corporate culture. "The corporate culture influences the human beings via shared values and norms which guide activities" (Drejer 2001, pg 137). Culture can be hard to capture and it can change over time, but at any point in time there are aspects of corporate culture that can be observed and that impact an organization's operations (Schein 2004).

4.3.2 Evidence of organizational impacts:

Leadership Style:

One of the first organizational aspects to emerge from the respondents was leadership style. One of the prevalent leadership style taxonomies comes from the work of Kurt Lewin (Burnes 2007; Lewin et al. 1938). His original model consisted of two types of leadership style, autocratic and democratic. The autocratic style (also called authoritarian (Wissema et al. 1980)) is characterized by centralized decision making and authority usually embodied in a single strong leader or a small number of dominant members of the organization, without active participation or input from other members of the organization (Lewin et al. 1938; Wissema et al. 1980). The democratic style on the other hand is characterized by more group participation in management decisions, although with leadership taking a key role. Under this leadership style there is an opportunity for a larger number of members of the organization to influence direction with the leadership still setting the overall tone (Lewin et al. 1938; Wissema et al. 1980).

More recently a third leadership style has been added to the model called Laissez Faire (Deluga 1990; Eagly et al. 2003; Skogstad et al. 2007). The Laissez Faire style is similar to democratic, but with the distinction that the leader is generally not involved in the day to day decision making or operations (Skogstad et al. 2007). Under this style members of the organization are given a general set of goals and left to manage themselves. It is characterized by the lack of direction of active participation by a leader in the tasks for which that leader has been appointed (Skogstad et al. 2007). This is distinguished from what have become to be known as "self-managed" or "self-directed" work teams (Elmuti 1996; Tata et al. 2004). Self-managed team receive direction from their leadership and regularly report on results (Singer et al. 2000; Yeatts et al. 1996). Laissez-faire leadership is essentially lack of any value added by the leader, making it less effective and even destructive in nature (Deluga 1990; Eagly et al. 2001; Eagly et al. 2003; Skogstad et al. 2007).

The respondents in our study may not have used the same terms to describe the most effective leadership style for successful BI, but they generally agreed that a democratic style was the most effective. As a data management VP commented:

> *...it definitely has to be a collaboration. Ultimately we want to have the collaborative relationship. Because of our recent history we are actually in the process of reorganizing the IT department and we're going to build in more customer service for our internal customers, which would be the business units and for our external customers, which would be our membership.*

In following up with this VP, she agreed that in her experience a non-authoritarian approach was important to the potential for BI success. She then added; "o*ur prior CIO was very directive and it didn't always work well with the business units in the organization. So there was some reluctance from the business units in accepting the direction from the IT department in this is how you should do your work."*

A data stewardship director noted issues associated with a Laissez Faire style when he said, *"instead of a centralized command and control kind of function we had organized chaos it's almost like a holding company instead of a corporation."* He noted that there needed to be more of a balance between total lack of control (Laissez-Faire) and total centralized control (authoritarian) and added "*if you have a command and control industrial model where it's like the upper levels have more information, then you can't work that way."*

The general consensus among the respondents was that a democratic style, sometimes referred to as participative or collaborative, was the most effective style versus autocratic or authoritarian, which many referred to as "command and control," or Laissez Faire.

Leadership style was further observed to be something that is an element of organizational culture as opposed to strictly an individual characteristic. A Business Analytics Director summed it up best when he said:

> *…a CEO may hire all these smart people, but unless there is that complete willingness to trust your very low level in the organization staff to tell you, this is what the data says, I don't care what your strategy was or what you expected the outcome to be this is the correct answer and trust and empower those folks to do it. You can go through a whole laundry list of these are the types of competences you need your teams to have to be successful at BI, but at the end of the day you need to have complete trust in that system to do what it says no matter what it says.*

Change Orientation:

Another organizational aspect that was observed was the orientation and acceptance of change (Schein 1989). While this was also noted as an individual characteristic, the respondents observed that there needed to be a consistent organizational culture that supported this change orientation for it to be effective in supporting benefits of BI (Brabazon et al. 2005; Brown et al. 1997; Davis et al. 1998; Hammer et al. 1993; Hannan et al. 1984). As a business analysis manager observed; "*They expect change, they expect you to question, if you're not…you're not going to be successful here."* He then added; *", the ability to adapt to change, the ability to question things as well, not to just accept things, those are the things that we are finding that make ideal analysts…"*

A BI consultant supported this perspective when he said:

> *I think culturally there needs to be a willingness to reinvent to change things to change the way you're doing things thoughtfully and that comes about with… OK we're doing everything we need to do but we need to take a half an hour at the end of the week and say how could we do this differently how can we do this better and there needs to be an ongoing discussion of how to do things better, there needs to be a willingness to say, you know what we're not doing it right here. We need to think about this, figure it out and then start doing it right.*

Another consultant commented on situations where BI wasn't found to be effective as resulting partially from lack of a culture supporting change when he observed; "*… senior executive staff don't mandate change. They're not willing to rework, they aren't willing to engage their technology providers and reap those benefits of having organization efficiencies as a result of technology insertion. The leadership of the organization needs to walk people through change."*

Related to a culture of change is an organization's orientation towards testing new concepts for products, services, or other aspects of their business (Schein 1999; 2004). The respondents consistently noted that a culture supporting testing new ideas before implementing was integral to their likelihood of benefiting from BI. The perspective was that one of BI tools' main uses was to help analyze possible strategies, and a company needs to have a culture that supports doing that kind of analysis for these tools to have an impact. A number of people mentioned what they called a "test and learn environment" (Davenport et al. 2007). They explained that by this they meant that any new concept being proposed is tested both through the use of analytical tools, and then a live test is run using real customers or products. As one of the analysts mentioned: "*the culture is accepting allowing us to test realizing that out of 10 tests 9 will fail, but the tenth will pay for all the others and connect everything else tenfold. … Testing gives us the empirical grounding of that we are making the right answers."*

Financial Resources:

Another organizational aspect mentioned has to do with the availability of financial resources to support the collection and maintenance of the data associated with BI tools. BI relies on extensive data, both internal and external to the organization (Davenport et al. 2007; Howson 2008; Williams 2004). While some companies implement BI tools, they can't benefit from the tools unless they have the right data at the right time to perform the analysis appropriate to the questions being asked (Loshin 2003; Miller et al. 2006). Yet many companies don't plan for the financial resources to make sure that the data is available when needed (Miller et al. 2006; Watson et al. 2007; Williams et al. 2007). A data warehouse manager noted the importance of collecting as much data as possible up front when she said; "w*ith the industry traditional warehouse, you go after a business problem you'd use 10 attributes, you wait for the business to come up with some use for those attributes, then you go do a business case to get the rest of the data. What we do is as long as we're going after the 10 we might as well go after the next 300."*

Data Management:

In addition to a financial commitment to capturing, storing and maintaining a large volume of data to support BI analysis, an organization must be organized in a way that allows this data to be supported and have the appropriate technology in place (Loshin 2003; Miller et al. 2006). These represent the human and physical resources associated with data management. If the resources are not in place to manage the data, it's perceived value could be diminished as in this example: "*What we had is that the departments here are used to getting data from our research department, that's our main SAS user group, and there was a level of mistrust of the data coming through another toolset. Well how do we know that this data is as good as what we get through our SAS queries and the reports that we get that way.*"

A data management VP talked about the importance of dedicating resources to managing their data for BI:

> *We have a group of staff who are dedicated to monitoring the quality of the data and working with our members to make any necessary corrections. ... we look at completeness and the validity of the data and because we track patients over time we look for consistency and validity of the data between reporting periods…. The way we monitor the quality… we have reports that we use to look for missing or invalid data; there's certain data that we want to confirm.*

A BI consultant addressed the fact that part of the technical resources for data support includes processes to manage data integrity. His statement summarizes a number of the aspects that were considered important for managing BI data by the majority of the respondents:

> *The data integrity is particularly important. You have to have data owners. To take that a step further, that information is added into your data stores, whether that's a data mart or however it becomes available to the greater user-ship. There has to be a defined, concise method for entering that data and sustaining that data so that those conclusions that are reached through the rule sets are consistent and are more or less representative of the organization and how it conducts business.*

Information Culture:

From this it becomes clear that effective data management takes more than individual skills and knowledge. An organization must make a commitment to providing the financial resources to build a data management technological environment; they must put procedures in place that govern the collection and management of the data on an ongoing basis; and they must have an organizational structure that supports maintaining this data management discipline. These characteristics are part of what has been described as an "information culture" (Choo et al. 2008; Curry et al. 2003; Davenport et al. 1994; Davenport et al. 1998; Oliver 2008). One definition of information culture is as

> A culture in which the value and utility of information in achieving operational and strategic success is recognized, where information forms the basis of organizational decision making and Information Technology is readily exploited as an enabler for effective Information Systems (Curry et al. 2003, pg 94).

The research into information culture supports the concept that financial, technological, and human resources required to support the information environment are necessary for the development of such a culture and the resultant ability to use the underlying information for organizational benefit (Choo et al. 2008; Curry et al. 2003; Oliver 2008).

Business Goal Clarity:

For information systems to provide benefits to an organization they must be developed to meet a specific business need (Henderson et al. 1993). When data warehouses were first being proposed organizations would sometimes build them with the expectation that they would eventually find a use for the data in them (Inmon 1992). Companies found that they were not realizing benefits from those original data warehouses. They only began to realize benefits when the warehouses were built for specific business purposes (Davenport et al. 2007; Inmon 1992; Kimball et al. 1998).

Similarly, the respondents consistently noted that an organizational culture in which business goals were clearly defined, especially when considering systems requirements, was an important factor in the ultimate success of the BI systems. As one BI director noted:

> *Having a champion for the organization in the adoption of BI tools [is important]. Clearly defined requirements, not just from a systems standpoint but from a business standpoint, from an engineering standpoint is always of value. Often it's not a failure in functionality it's a failure in the presentation layer ... the utility of the system and human factors interface have to be considered.*

This should not come as a surprise because many researchers have noted the need for alignment of business goals and system goals, in fact it's one of the most common areas mentioned regarding information systems strategy (Beise 1994; Chan et al. 2006; Henderson et al. 1993; Hirschheim et al. 2001; Luftman et al. 1993; Mirani et al. 1998; Sabherwal et al. 2001; Van Der Zee et al. 1999). Yet companies continue to plan to build analytic systems with a perspective that they should build it first and then figure out how they will use it to support their business (Howson 2008; Miller et al. 2006). The evidence collected in this study indicates that to build an analytic capability without having specific goals in mind up front is a recipe for failure.

To summarize, at an organizational level those factors that contribute to successful BI include leadership style; where a participative style is preferred vs. either autocratic or Laissez-Faire; and the level of resources available to support BI. Technological resources are critical for the support of the data storage and management environment. Financial resources must be available to be able to instantiate the data environment, to support training for the users and developers, and to maintain an ongoing robust data quality process. Human resources must be available with the skills and knowledge referenced in the previous section and the must be a culture that encourages and supports change and continuous learning.

The organizational competences identified are summarized in the table below:

Learning organization	Well organized availability of training, both technical and business. Management support for ongoing education. Expectation of continuous learning. Understanding of value of institutional memory
Participative leadership style	Management by consensus, but with bias towards making decisions quickly. Balance of data based and intuitive decision makers Balance between action orientation and introspective, methodical decision makers
Clearly defined business goals	Business goals are available to all members of organization. Goals for BI systems are defined before building system.
Technological resource availability	Commitment to integrating data into operational projects. Well defined data environment including stewardship and metadata. Universal data access. General understanding of data structures. Data quality tools. Metadata tools.
Financial Resource availability	Funding for acquiring BI tools and building related systems Funding for building and maintaining an

	analytical data environment.
Human Resource availability	People are available to manage the BI data People are available to analyze data in the BI systems

Figure 4.3 Organizational competence characteristics.

4.3.3 Emergent Model:

This data focused on heedful purposeful interactions, which represent the way that individuals work together to develop competence that allows the group to accomplish tasks that would not be attainable by individuals either acting alone or working together in an uncoordinated fashion (Weick et al. 1993). The way that the coordination associated with heedful purposeful interactions is attained is through deftness (McGrath et al. 1995). While both of these concepts have been described in prior research, that research did not specify what elements constituted heedful purposeful interactions (McGrath et al. 1995). In this section we will discuss the components of heedful purposeful interactions that emerged from the data we've collected and the relationships between those elements.

One of the key organizational level concepts to emerge from the evidence is that of leadership style. As described above, leadership style is typically described along a spectrum from autocratic through democratic, to laissez-faire (Deluga 1990; Wissema et al. 1980). The respondents consistently noted that a democratic style was important to the realization of BI benefits. They suggested that other styles impacted the tendency of the organization to follow the advice or use the analytical outputs of BI systems, consistent with extant research on leadership style and decision making (Cotton et al. 1988; Hannah et al. 2008; Müller et al. 2007). Any model of organizational level antecedents to competence for BI must therefore include some element of leadership style.

Another concept that emerged from the data at an organizational level was that of resource availability. Organizational resources identified as necessary for BI success in the data were human, physical, and financial. Physical resources in this case are primarily technical including the hardware and software for data acquisition, management, analysis, and reporting. Financial resources refer to the availability of the funding to acquire and support the physical and human resources required for these solutions and human resources represent the people building, maintaining and using BI. All of these have been found to impact an organization's ability to build competence (Drejer 2001; Miller et al. 2006; White 2008).

The two key concepts that have emerged so far are leadership style and resource availability. The question to answer is what is the relationship between these concepts and the realization of benefits from BI? The overall finding is that BI benefits are optimized when there is a participative leadership style and a high level of resources. One way to illustrate this relationship would be through the model illustrated below as figure 4.4. This diagram shows the interaction between the level of resources available to the organization and the predominant leadership style.

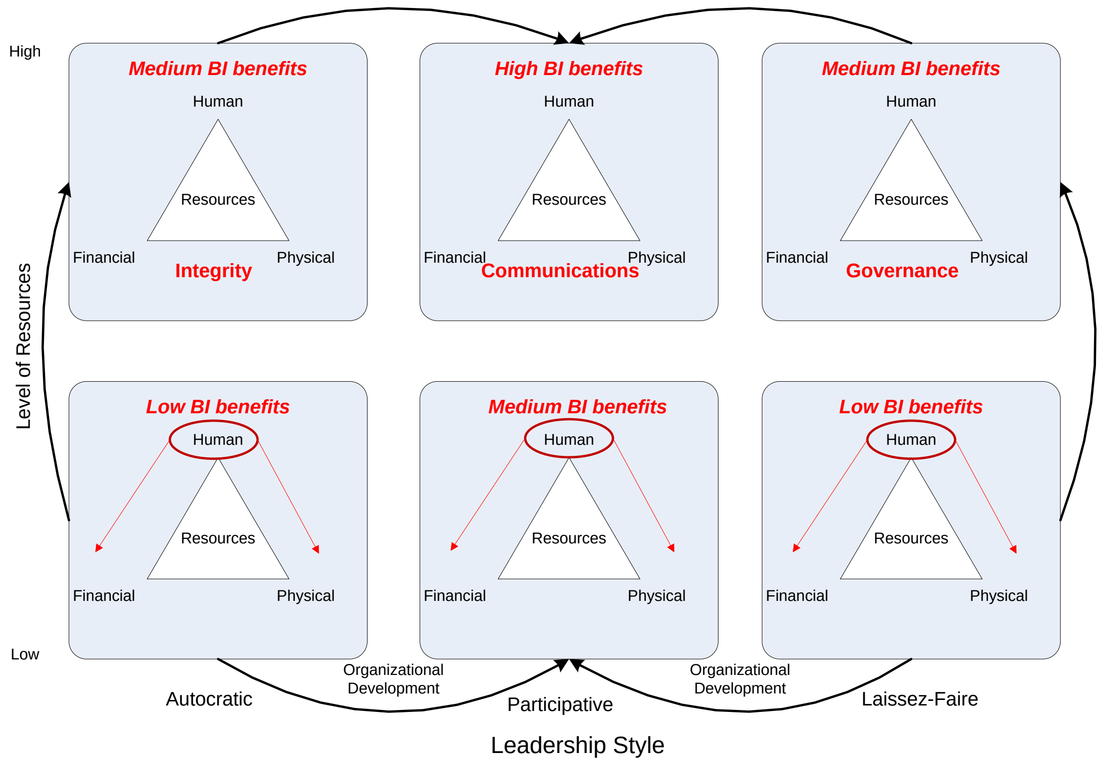

Figure 4.4 Organizational model of competence for BI.

The left side column represents the autocratic leadership style (Eagly et al. 2003; Wissema et al. 1980). In this case an organization's leadership will tend to dictate solutions, which has the effect of minimizing the impact of the recommendations that emerge from BI systems (Skogstad et al. 2007; Van Vugt et al. 2004). This tendency to impose solutions acts as an impediment to implementing the solutions that may emerge from analysis performed by BI systems (Peterson 1997).

The middle section of this diagram represents the participative leadership style. The respondents in this study referred to this as collaborative or democratic, but in each case it meant the same thing; a leadership style in which the members of the organization participate in the decision making process, but with a clear leader who directs the process and makes the final decision. Under this leadership style challenges to the status quo are encouraged and considered (Deluga 1990; Skogstad et al. 2007). This style supports change and analysis even if that analysis may be counter to the intuitive view of the correct answer before any analysis (Tripsas et al. 2000). This style was therefore found to be the most effective for benefiting from BI.

On the right is the laissez-faire style. If an organization tends to be managed with this style, the members of the organization are left to set their own direction and make their own decisions (Skogstad et al. 2007). The lack of clearly defined goals and limited management oversight in this section of the model can result in lowering the potential benefits to be realized from BI (Deluga 1990; Skogstad et al. 2007).

The rows represent the levels of resources available to an organization. Resources can be categorized as human, physical, or financial. Human resources are the people in an organization and their associated skills and knowledge as described in the prior section. Financial resources represent the amount of money available for a particular function, which can be not only the capital available to an organization, but whether it is allocated to the function under study. Physical resources in this case refer to the systems assets to be made available to support BI (Powell et al. 1997). The bottom row represents the situation where there are low resources levels. The impact of an organization having low resource levels is that it will limit their ability to support the physical resources necessary to ensure timely and accurate data, to support their human resources to provide training and maintain the necessary number of personnel to develop the analysis from these tools, and to provide the funding to develop enhance and use the systems that they do have (de Stricker 2004). The top row by way of contrast represents high levels of these resources, which will support developing the environment that allows a higher level of benefits to be realized from BI (Powell et al. 1997).

An organization's combination of resources available to BI and leadership style impacts their likelihood of realizing benefits from BI. An organization in the top left may be able to gain a moderate level of benefits from BI. This is because while their autocratic style reduces likelihood of BI results being adopted in a way that has positive impact (Van Vugt et al. 2004), they have the resources that provide for a strong foundation for developing and using BI in the underlying data and people.

In the middle column an organization has the greatest likelihood of benefiting from BI. If they have low resources their participative leadership style can still allow them to achieve moderate benefits because the outputs are likely to be applied in a way that introduces positive change (Scott-Ladd et al. 2006). However, if they have a high level of resources they would achieve the highest level of BI benefits because not only do they have leadership that is likely to adopt BI recommendations, they have the resources to make sure that their BI implementations are complete and well managed and to be able to implement the systems recommendations.

A laissez-faire organization with low resources is likely to achieve a low level of BI benefits. This is because they lack the leadership direction required to make the best use of BI results, or to even ask the right questions and they don't have the resources to develop BI effective models (Schwartz 1964). If they have a high level of resources with this leadership style they can achieve moderate levels of BI benefits. Their resources in this situation will allow them to overcome some of the lack of clear direction that typifies the laissez-faire leadership style. The fact that it is up to the individuals in the organization using the system to identify the problems to be addressed increases the likelihood that the wrong questions will be asked, mitigating the potential benefit from BI.

The question then becomes what can organizations do to increase the benefits realized from BI based on where they fall in this model? If an organization has a low level or resources supporting BI, as represented by the bottom row, they would need to focus on their "human capital" to try to realize BI benefits. This becomes necessary because even if they have low levels of financial and physical resources, they must have some people. Because other resources are limited all they have to rely on are their people. Human capital refers to not only the people within an organization, but their underlying capabilities and attitudes (Lawler III 2009). This focus on human capital therefore means that these organizations must focus on the development of the appropriate skills and in reinforcing the sense of worth understood by their employees (Melody 1999).

The term typically used for this approach to business improvement is organizational development (Sharma 2008; Wirtenberg et al. 2007). Organizational Development (OD) has been defined as "a planned and collaborative process for understanding, developing, and changing organizations to improve their health, effectiveness, and self-renewing capabilities" (Warrick 2006) pg 93. OD programs focus on participative training that encourages employees to plan for change, to understand business processes and to be aware of the human aspects of working in an organization (Kulper 2007; Lawler III 2009; McDonagh et al. 2006). These programs are designed to allow organizations to benefit from their existing employees to be able to gain effectiveness in their business operations, as would be required in the situation where there are limited resources available (Argyris 1985). In addition, due to their focus on an empowering, yet participative leadership approach, they would have the tendency to help an organization move from autocratic or laissez-faire leadership styles to a participative style. For example, one goal of OD is to "seek clarity regarding task expectations and goals/objectives" (Burke 1997, pg 18). For this reason O.D. would enable organizations in both rows to move towards the middle of this model, or towards a situation where they are more likely to realize benefits from their BI implementations.

For organizations in the top row but with autocratic leadership the focus needs to be on integrity of the organizational resources. The tendency of an autocratic leader to limit the autonomy of individual human resources can lead to less focus on maintaining the appropriate physical and financial resources (Van Vugt et al. 2004). Focusing on the integrity of all resources necessary to support BI by an organization with this profile would allow them to maintain the level of BI benefit they are already realizing. Focus on OD and training could however move the organization to the middle of the model, increasing the benefits realized from BI (Burnes 2007; French 1944; Scott-Ladd et al. 2006).

If an organization has a high level of resources and a participative style they should already be realizing a high level of benefits from BI. In order to maintain this they need to focus on those things that got them to this point. The key in this case would be communications (Häkkinen et al. 2008). Communications in project teams has been shown to increase participant satisfaction, to ensure appropriate coordination and to enable effective maintenance of the appropriate levels of resources (Dennis et al. 2003).

Organizations on the top right, with a high level of resources and a laissez-faire leadership style, would need to focus on governance (Hinkin et al. 2008; Marques 2008). Governance refers to the way that an organization controls its processes and assures accountability (Garud et al. 2006). With a laissez-faire leadership style it is even more important that organizational level policies and processes are in place to ensure continuing smooth operations (Marques 2008). While this can't take the place of enlightened and present leadership (Skogstad et al. 2007), having well defined governance processes would provide a mechanism to monitor and adapt operations.

4.4 Emergent competences:

In the competence model on which this research is based individual skills and knowledge and heedful purposeful interaction are antecedents to organizational competence (Dhillon 2008; McGrath et al. 1995). While this model represents the relationship between these antecedents, it doesn't provide guidance as to what the resultant competences might look like. Weick and Roberts (1993) discuss the need for "heedful" interactions between individuals in order to achieve results that could not be attained by individuals operating independently. McGrath et. al. (1995) discuss the concept that the people operating in a heedful manner must also have individual skills and knowledge necessary to make their interactions meaningful. Yet these models shed no light as to what the individual skills and knowledge or the nature of the heedful interactions that lead to emergent competences might be. This research has identified models that provide some insight into these individual characteristics and their relationships. The combined view of these models is illustrated in figure 4.5 below. The question to be answered now is; what are the interactions between the individual and organizational level constructs represented in this model?

If an organization has low levels of resources we have indicated that they must rely on human capital to support their BI programs. Those individuals who comprise the major element of human capital must have the right skills, knowledge and decision making approach for those interactions to be purposeful. Therefore the human capital component of the heedful purposeful sub-model is impacted by the levels of skills and knowledge and by the organizational commitment to strategic human resource systems. If organizations have low resources and also have low levels of skills and knowledge among the members of their organization relying on human capital will not provide as much benefit. This will make it more difficult to improve the benefits realized from BI. Therefore there is a direct relationship between the elements of comprehension that impact an organization's deftness. Organizations must focus on developing the skills and knowledge of their individuals, increasing their comprehension before they can improve deftness.

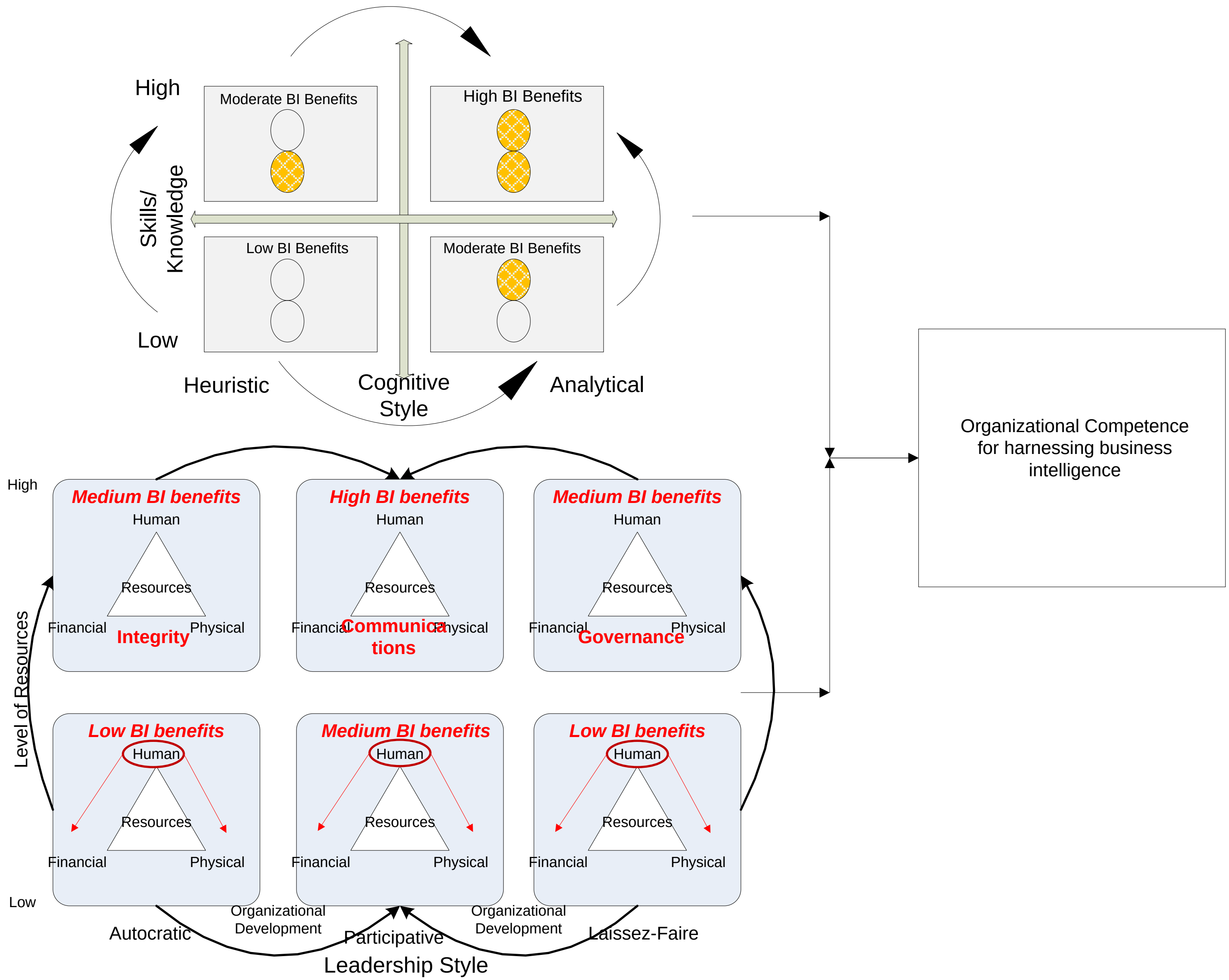

Figure 4.5 – Integrated model of competence for BI.

If organizations have a high level of resources the availability of financial and physical resources may limit the impact of the comprehension of the human resources. If those individuals don't have the appropriate level of skills and knowledge their ability to support the delivery of benefits from BI systems may be reduced. Therefore in the situation where an organization has high resources but low skills and knowledge the potential for BI success is reduced.

Cognitive style also interacts with leadership style to impact potential BI success. An organization with an autocratic style has already been observed to have reduced likelihood of successful BI. A heuristic cognitive style would reduce this likelihood further. Individuals with an autocratic style are already more likely to impose solutions rather than listening to recommendations coming from subordinates, even if those recommendations are the result of analysis from BI. If they have a heuristic cognitive style it will tend to reinforce this tendency by lessening their perspective on the value of analytical systems outputs. On the other hand if they have an analytic cognitive style it may mitigate the impact of an autocratic style to some extent. In this case their preference to use data to make decisions will cause them to have a tendency to be more receptive to recommendations that are derived from data based analysis.

4.5 Summary:

In this chapter we have developed examined evidence collected from BI practitioners and developed models that represent detailed mechanisms by which individual know-how and skill, and purposeful heedful interactions for BI lead to emergent competence for BI. The evidence suggests that cognitive ability, non-cognitive ability, individual knowledge, and cognitive style interact to impact individual level antecedents to BI competence. We have further found that resources levels and leadership style impact the organizational level antecedents to BI competence. These models can provide guidance for organizations to enable them to increase the likelihood of realizing benefits from their investments in BI.

5. Assessing BI competence in organizations

5.1 Introduction:

In the previous chapter we developed a model relating organizational competences to BI success. While this model can help an organization determine individual and organizational characteristics to increase the likelihood of benefitting from BI, it does not help them understand where their individual organization stands relative to these characteristics. In this section we will propose a measurement scale that would allow an organization to perform such an evaluation.

5.2 Development of a measurement scale:

Development of measurement scales can provide a useful tool for performing and evaluating IS research (Moore et al. 1991; Petter et al. 2007; Straub 1989; Wixom et al. 2001). These scales can be used to describe the constructs emerging from the research and to provide a consistent measure to use in confirmatory research (Boudreau et al. 2001). Constructs in such scales can be either reflective or formative in nature. A reflective construct is one that is used to measure aspects of phenomena where the "underlying construct is unobservable" (Petter et al. 2007). These constructs are designed to measure the "effect" of an underlying concept rather than the nature of the concept itself.

A formative measure consists of individual items that are directly measureable. The elements of a formative construct combine to represent the overall construct being evaluated (Petter et al. 2007). The constructs identified as the emerging competence characteristics in this research are formative in nature because each of them combine to determine the overall concept. For example, cognitive ability is made up of numerical reasoning, verbal reasoning, and problem solving ability. These three elements are distinct and measureable, but combine to represent the construct of cognitive ability.

Petter, Straub, and Rai (2007) proposed the following four step process for the development of formative measures:

1. Identify the constructs, and apply rules to determine if they are indeed formative.
2. Assess content validity using expert evaluation.
3. Assess construct validity and reliability of the measures.
4. Evaluate/Assess the model (using the appropriate statistical technique).

The first of these steps is to identify the elements of the construct. This can be done using either a qualitative or quantitative approach (Boudreau et al. 2001). In our case the constructs were developed through the case study interviews. Those characteristics identified as the competence characteristics at the individual and organizational levels would comprise the constructs in our measurement scale. The development of the scale will be described in more detail below.

The next step would be to review the constructs for content validity. Content validity refers to whether the elements in the construct represent the underlying concept to be measured (Pedhazur et al. 1992). Content validity can be established by reviewing relevant literature and by expert review of the elements of the constructs (Petter et al.

2007). In our case we used both methods, the results of which are discussed subsequently.

The next step in the development of this type of measure would be to test for construct validity and reliability. Construct validity is generally considered to consist of two concepts, convergent validity and discriminant validity (Jarvis et al. 2003). Convergent validity represents the extent to which different methods of measuring a construct would yield the same results, while discriminant validity is the extent to which the items in the measurement scale represent distinct elements (Pedhazur et al. 1992). While there are many statistical tests that can be performed to evaluate both forms of validity (Pedhazur et al. 1992), they are beyond the scope of this research.

The other aspect of the measurement scale to be evaluated in this step is reliability. This concept refers to the extent to which repeated use of the measurement scale would give the same results (Straub 1989). The evaluation of measurement scale reliability and a full statistical evaluation of the model are beyond the scope of this dissertation. What we have done is to perform a pilot test of the constructs in the model. A pilot test allows one to begin to evaluate construct validity by determining if the individual measures represent the underlying constructs and to examine each item for ambiguity (Boudreau et al. 2001). A BI competence instrument consisting of an initial set of formative constructs were developed in this research and a pilot test was performed to provide initial evidence as to the usefulness of this tool. We will now discuss the elements of the instrument and the pilot test results.

5.3 Development of the constructs:

The competence model presented earlier was built of elements that comprise individual know-how and skill and purposeful heedful interactions for BI. These elements emerged from analysis of the interview data collected from individuals with direct experience with BI. Examining an organization's level of attainment of each of these elements can help them determine where they fit into the proposed model, which can help them determine their likelihood of benefitting from BI and what actions they can take to improve their chance of BI success. A framework was built that incorporated these individual elements to be used for this examination. Members of one of the organizations that participated in this study were asked to evaluate their organization's level of attainment for each of these elements and their perspective on the importance of each element to help determine the utility of this tool. We will now discuss each of the components in the tool individually.

The first area to be addressed in the tool is that of cognitive ability. Cognitive ability refers to the general capability of individuals to think and reason. At the individual level one common measure used by organizations is the Wonderlic Personnel Test (WPT) (Gottfredson 1997). Organizations commonly use this to evaluate prospective employees for the appropriate level of cognitive ability for a job (Holzer 1996). Organizational records of employee entrance test scores could provide an objective measure of cognitive ability to be used to determine an organization's readiness for BI. In lieu of such scores, an organization needs to be able to evaluate the cognitive ability of the personnel who will be building and using BI. Our assessment tool contains three items that represent the elements of cognitive ability; numerical reasoning, verbal reasoning and problem solving ability.

A number of non-cognitive abilities were identified as contributing to BI success in addition to cognitive abilities. These abilities are those that represent capabilities of individuals that allow them to formulate problems to be addressed with BI, analyze data to generate potential solutions to those problems, or present the results of their analysis (Young et al. 2000). These represent know-how, or ability to do something, as opposed to know-that or personality attributes of individuals that contribute to their effectiveness in working with BI. The non-cognitive abilities identified in this research are; verbal communications, written communications, effective listening skills, data manipulation skills, tolerance for change and ambiguity.

In addition to skills or abilities, individuals working with BI must have certain knowledge to be effective. One key type of knowledge identified was business knowledge. By business knowledge the respondents were referring to knowledge of the products and services of the organization in which they work and knowledge of the business processes by which that organization operates (Hunter 1986). This knowledge allows those working with BI to understand the context within which their solutions will be used, which helps in both formulating problem statements and analyzing data.

Another type of knowledge that was mentioned by the respondents was that of the competitive market. A way to think of this knowledge would be as understanding of Porter's five competitive forces of current competitors, possible new entrants, potential replacement products, customers, and suppliers (Porter 1980). The specific knowledge required may depend on the types of problems to which BI is being applied, but if one is to assume that BI analysts may address a variety of different problems at any time, it is important to have knowledge of all of these factors to some extent.

Finally a key knowledge identified was that of the meanings of the data with which BI analysts would be working. This knowledge is necessary to be able to make sure that the data being used for analysis represents the concepts related to the problems being addressed. Fortunately there are tools readily available to provide these meanings to these analysts. This type of information is what metadata management systems are designed to provide (Sen 2004). While a metadata repository can help analysts find data meanings for those elements with which they are not familiar, the more understanding of this type of information that they have the more productive they can be because they will not have to constantly be referring to another system to look up this information.

This research found that cognitive style also impacted the success of BI. We found that users of BI should have a more analytic cognitive style to be more likely to adopt BI recommendations. As such, any tool that assesses an organization's potential for BI benefit should include a measure of cognitive style. This tool includes one question regarding cognitive style of those working with BI.

A number of categories of organizational antecedents to competence for BI were identified in this research. They were related to the whether the organization had a learning proclivity, the predominant leadership style, the existence of and clarity of business goals and the availability of technological, financial, and human resources to support BI. Questions regarding these aspects of the organization must therefore be included in any assessment tool.

5.4 Evaluating the Measures:

The complete instrument used to assess BI readiness is presented in Appendix C. A pilot test of this instrument was run with a subset of the original respondents who were members of a financial services organization. They were asked to evaluate their organization based on their perspective of the level of each element on a five point Likert scale. They were then asked to use the same five point scale to rate their perspective on the importance of each element. Nine individuals provided responses to this instrument. While the respondents did provide responses for each of the elements in the tool, our primary purpose in performing this review is to evaluate the potential benefit of the tool, not necessarily in the value of the specific responses. While the sample is not large enough to perform and tests for statistical validity, the responses can provide insight into how this tool might be used to help an organization understand their BI readiness. The responses to the items in the tool are shown in figure 5.1 below.

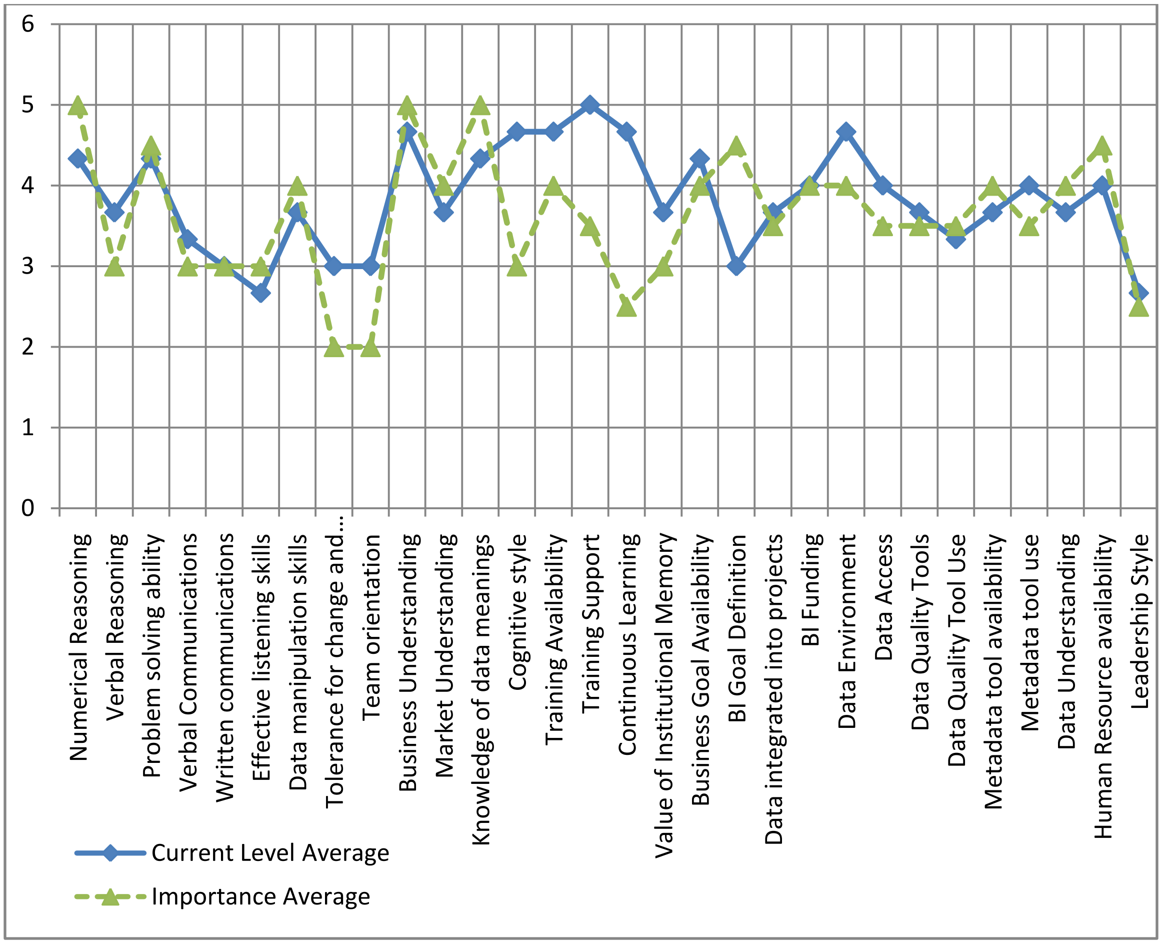

Figure 5.1 Summary of responses to BI evaluation tool.

The solid line in this graph represents where their organization stands on each of the individual elements represented in this tool, while the dotted line represents their evaluation of the importance of each.

The first step in evaluating content validity was to review the extant literature relating to each of the elements in each construct. As mentioned earlier, the elements of each construct come from the interview data collected and discussed in chapter 4 of this dissertation. As each item was identified the relevant research literature was reviewed to determine how similar items had been included in prior work. A review of how each characteristic defined had been included in the literature is provided in chapter 4. Prior work has supported each of the elements included in this measurement scale. In addition to using prior research to determine content validity, the elements of the scale were reviewed by each of the respondents to the pilot test for content validity. They indicated that they understood the meaning of each of the items and all were able to answer every question. This demonstrates that the constructs have content validity; that is that the individual items were meaningful and represent the concepts underlying the constructs (Straub 1989).

Construct validity exists if the items accurately represent the underlying concepts that are being measured (Boudreau et al. 2001). One way to evaluate this is to use the respondents' evaluation of the importance of each item. If the respondents determine that certain items are unimportant, it may be because those items do not accurately represent the underlying construct or may be ambiguous to the point that it wasn't clear to respondents how the item contributes. Only three of the items had importance ratings of less than medium, although none of them were rated as totally unimportant. This would seem to indicate construct validity, but a more extensive test of the instrument is warranted to allow statistical evaluation of instrument validity.

Although the number of pilot test responses were not sufficient to draw any generalized conclusions, the responses can provide indications as to how this tool may be used in an organization. We will examine the responses and indicate some ways that meanings could be derived from them. One way this scale could be used would be to determine an organization's level on each of the attributes included. In this case there is only one item, effective listening skills, for which there was an evaluation less than average. The organization could deal with this by providing communications skills training and by working with HR to ensure that listening skill was one of the attributes for which they screen when hiring. If there were other items that were low on this scale the organization would need to determine where they fit in the models from the previous chapter and take the appropriate action. For example low cognitive ability items would mean that they would need to evaluate the effectiveness of their hiring program for people working with BI. Low access to data quality tools may mean they need to address their technology availability, while a low score on data quality tool use may be mitigated by additional training.

The relationship between the solid and dotted line also has meaning. Where the solid line is below the dotted line it means that the rating of the level of a particular attribute is lower than their perception of the importance of that attribute. If this were the case it would indicate an area where the organization does not have a high level of competence in an area that is deemed to be of particular importance. In this case the organization would need to go back to the model and determine where this particular item fits and what the model suggests is the appropriate way to improve BI performance based on the rating.

For example, in figure 5.1 BI goal definition is an item for which the current level in the organization is below the level of importance. When asked if BI goals were well understood before starting BI projects the respondents' average response was 3, which is exactly in the middle of the range from low to high. However, the average level of importance of this attribute was 4.5, which is nearly at the highest point of the scale. Goal clarity is an item that was associated with leadership style. A lack of goal clarity indicates that the organization's leadership does not have the characteristics associated with a participative style. They would therefore need to focus on organizational development to improve their level of BI benefits.

The other thing that this tool can do is help an organization determine the perception of the importance of each of the elements in the model. If any points on the dotted line are low it would indicate that there are elements in our model that members of their organization find unimportant. Our study indicated that all of these items are important for benefiting from BI. Items for which the average score is below three would indicate areas in which additional training may be required. If the organization does not perceive these to be important, then changing that perception can lead to improved focus on them supporting increased BI benefits.

5.5 Conclusions:

This measurement scale can provide a useful way for organizations to understand the attributes of individuals or their organization that may contribute to or detract from their ability to benefit from BI. Evaluating the perceived level and the perceived importance on each of these items can provide a roadmap to help an organization take steps to improve their BI performance.

More study is required to determine whether there is a direct correlation between each of the items in this survey and the likelihood of BI success. This sample use of the tool does provide some interesting insight into its value. Since their organization was found to be below average on only one item on the scale, they have an above average level of each of the items in the survey. Since they are known for being successful in gaining benefits from their BI usage, this may indicate a connection between these items and that success. A quantitative analysis of this tool against a larger population would allow the evaluation of this hypothesis.

6. Synthesis

6.1 Introduction:

Now that the evidence has been analyzed and a model of the elements impacting successful BI has been proposed, it is important to reflect on the critical concepts that have been proposed and attempt to bring them together into a coherent view. Doing this can provide a perspective for future researchers to build on these concepts, and provide guidance for practitioners as to how to use the findings to support their organizations. In this section the key concepts that have been identified will be reviewed and their impact on successful BI discussed.

6.2 Strategic Human Resource Management:

One of the aspects that impacted the organizational level of the model was human capital management. What we mean by human capital management is the acquisition, training and retention of people with the necessary "motivation, skills, knowledge, competencies, and personality to perform well given the strategy, goals and practices the organization has" (Lawler 2005, pg 13). As noted in the discussion above, in order for BI systems to have beneficial impact on the organization, the individuals developing and using those systems must have the necessary cognitive ability, technological skills, and a cognitive style that supports learning from BI results. General cognitive ability and cognitive style were identified as being tacit capabilities in individuals and therefore very difficult, if not impossible to train (Sternberg 2004). An organization must therefore have HR systems that allow them to hire those with the appropriate abilities to ensure that they have the right people to work with BI.

Once they have hired the appropriate people organizations must assure that they have the appropriate skills and knowledge. The hiring process can screen for certain key skills (Becker et al. 1996), but there are certain types of knowledge, such as knowledge of company specific goals and systems, that must be learned. Even with employees who are hired with a high level of skills and knowledge, changes to markets, tools, and technology require them to participate in ongoing training (Miller et al. 2001). For this reason an organization must have the appropriate training programs available to their employees to build and maintain individual competencies (Barney et al. 1998).

Both the skills and knowledge of individuals were suggested as having potential impact. The evidence identified skills at both the cognitive and non-cognitive levels. Cognitive skills are developed by individuals over time, but by the time individuals have reached an age of maturity their levels of general cognitive ability have been substantially established (Hunt 1995). The items that are used for measuring cognitive skill evaluate abilities to understand concepts and answer associated questions using mathematical and analytic reasoning (Anderson 1995). While cognitive ability is different from basic intelligence, its measures are an attempt to evaluate some level of underlying intelligence (Gottfredson 1997).

The evidence collected suggests that users of BI must have relatively high levels of cognitive ability to be effective in formulating the questions to be addressed, in using the associated tools, and in presenting the results in a way that makes it clear what the appropriate actions to take would be. Since cognitive ability is difficult to impact once established, the best way to assure that the individuals who will use an organization's BI capabilities have the appropriate level of cognitive ability is through the hiring process (Gottfredson 1986).

This research also identified a number of non-cognitive abilities that contribute to successful BI. Non-cognitive abilities generally refer to abilities that individuals develop that are not directly related to thinking and reasoning. They include ability to communicate clearly, both verbally and in writing, the ability to listen for comprehension, and tolerance for change. These abilities have a tacit component and a learned component (Te'eni et al. 2001). If recommendations resulting from BI driven analysis cannot be effectively communicated they are not likely to be adopted (Howson 2008). Those developing or using BI systems need the capacity to effectively listen to business goals and understand them in a way that supports building the appropriate tools or using them to effectively address business goals. These are just some of the examples identified in this research that reinforce the importance of these non-cognitive skills to BI success. Individuals may have inherent strength or weakness in some of these areas, but their levels of non-cognitive ability can be impacted by appropriate training and development (Miller et al. 2001). This suggests that availability of appropriate training is important to BI success.

The other aspect of human cognition that the evidence indicates impacts successful BI is cognitive style. The impact of cognitive style on IS development has been debated over the years (Chakraborty et al. 2008; Huber 1983). Whether it is appropriate to use in designing information systems or not, research supports the conclusion that it does have an impact on individuals' use of decision aids (Doktor et al. 1973; Fox 2003; Hunt et al. 1989; Huysmans 1970; Premkumar 1989). One of the reasons given by practitioners for the failure of BI initiatives has been the tendency of managers to use "gut feel" or intuition when making decisions (Todd 2009; Wailgum 2009). If individuals rely on intuition or heuristics to make decisions or to analyze situations BI recommendations are unlikely to be adopted, or the organizational resources might not even be applied to developing those recommendations. Cognitive style can be influenced through training, but it is also a characteristic that is well developed in most individuals before they ever join an organization (Keen et al. 1981; Kozhevnikov 2007). It is important for an organization to be aware of cognitive style when hiring or when assigning employees to BI related roles to match style to job function.

The part of an organization that deals with hiring and supporting people is typically referred to as human resources (HR). Historically HR has been seen as a necessary function for an organization to be able to operate, but has not been seen as having the potential for strategic impact (Becker et al. 1996). In spite of this attitude many companies have described their people as their greatest assets (Rees 2007). Organizations have long recognized effective asset management as a key to business success (Weill et al. 2004). If this is the case it is incumbent on an organization to manage their human resources with as much rigor as would be applied to other types of resources. Another way to describe this would be strategic human resource management (Becton et al. 2009).

For an organization to have the right resources to be effective in building BI solutions and analyzing business information using those solutions they must view HR as a strategic part of their business. HR plans and programs must be developed with a perspective of how they can add strategic value to the organization. A strategic HR management program to support BI would include recruiting processes that recognized the levels of cognitive and non-cognitive skills required for people who will be part of their BI environment. Once the right people have been hired it is necessary to have programs in place to ensure that these assets are retained. A SHRM program would recognize the strategic nature of human capital in supporting critical BI functions and develop salary, promotion, and recognition programs to ensure retention of key resources (Stavrou et al. 2005).

Access to the appropriate training resources is necessary to ensure the right levels of knowledge are acquired by those who don't yet have it (Miller et al. 2001). In addition training must continue to be available to ensure that employees' knowledge is refreshed as the business, technology, and external environment change. This training can be developed and delivered through internal resources or can be delivered by external entities, but the SHRM program needs to be in place to identify the necessary training and arrange for its availability. For BI to be successful an organization must have people with the right skills and knowledge to be able to develop and make beneficial use of BI. The way that an organization can do this is through an effective program of strategic HR management.

6.3 Learning Organization

BI can be viewed as a form of organizational learning, as described in Chapter 4. BI systems include data that represents organizational memory and tools that allow the analysis, representation, acquisition, and distribution of information. For an organization to benefit from these capabilities they must have a culture that supports these underlying processes. An organization might have the best, most comprehensive data warehouse and the most sophisticated models of their business problems, but if they don't have a culture that supports learning from the lessons that come out of these capabilities they are unlikely to realize their benefits.

Organizational learning is not the same as individual learning (Argyris et al. 1978). While we talk about organizational learning using the same terms as for individual learning, it is different. An organization is made up of individuals, yet the specific individuals in that organization change over time. If one or even a few individuals learn processes or tasks, the organization has not really learned until those processes are institutionalized (Levitt et al. 1988). BI can help support this institutionalization process. BI makes data and analytical processes available across an organization. The reporting and visualization capabilities are typically deployed in a way that provides broad access across an organization (Rosenberger et al. 2009). In this way BI can support learning taking place across an organization instead of only taking place at an individual level.

Argyris (1991) talks about two levels of learning, single loop and double loop. BI can support and is supported by both types of learning. Single loop learning has also been described as "problem solving" (Bhatt et al. 2002). BI supports single loop learning by providing institutional memory capability that ensures consistent information used for addressing problems, and by providing tools to analyze these problems. Double loop learning is supported by BI through the transparency that it allows to understand the detailed approaches taken to solve classes of problems. By providing a clear record of problem solving approaches, BI supports the analysis of those approaches to allow reflection on what was effective and adjustment to processes to improve the approaches taken. In addition, organizations with a learning culture are more likely to use BI address business issues because they are more likely to have institutionalized the use of analysis to solve the business problems (Argyris et al. 1996).

Organizational learning has consistently been associated with improved company performance (Argyris et al. 1978; Ellinger et al. 2002). This research has indicated that BI is one mechanism by which organizational learning benefits can be realized. In addition, a learning organization improves the likelihood of realizing benefits from BI by providing an environment in which the use of BI is more likely to be supported and encouraged.

6.4 Information Culture

Organization culture has been defined as "the learned, shared, tacit assumptions on which people base their daily behavior" (Schein 1999, pg 24). Organization culture is something that has an impact on how people make decisions, perform their work processes, and interact both within and outside an organization. An information culture is one in which there is a shared expectation that information will be used in most aspects of organizational processes and decision making, that such information is viewed as a strategic asset, as an asset information is expected to be effectively managed including clearly defined ownership and maintenance processes (Curry et al. 2003; Oliver 2008).

An organization may have a comprehensive data warehouse, and well planned processes for loading and maintaining the associated data, but if they don't have a culture that reinforces the use of the information that results from the data as part of their regular operations they are unlikely to realize benefits from their investments. BI success requires that an organization be receptive to the use of information to provide direction for their business decisions. An information culture can be considered the analogous organizational level construct to cognitive style at the individual level. Just as individuals who have a tendency to make decisions based on "gut feel" are unlikely to make beneficial use of BI, an organization that doesn't have a culture that supports using data to make decisions and set directions is unlikely to benefit from BI.

An information culture however does more than just reinforce the use of BI for formulating business strategy of directing operations. Organizations with information cultures are more likely to recognize the value of investments in an infrastructure that supports BI. In an organization with an information culture there is more likely to be an expectation that data extraction for analytic purposes will be a regular part of the development of operational systems. In organizations without an information culture it may be more difficult to gain support for acquiring and maintaining the physical and financial resources to build and expand the necessary data and analytic infrastructure.

Systems that support operational functions, such as customer billing, have different data needs than analytic systems. Operational processes typically require access to data on a single customer at a time and one or a few products. An analytic system must be designed in such a way as to allow access to potentially millions of customers' data at the same time. This is why companies started separating their analytical data from their operational data by putting it in data warehouses. The design of data for analytical purposes is different than for operational. Adding data to analytical data stores can be done at any time, even long after the operational system is built. However, the longer a company waits to build these processes, the more likely it is that they will not be built, or that when they are built that the expertise to understand the data being extracted will not be current. Companies with an information culture will recognize the value of this data for more than processing transactions and will plan for the resources to capture and store the data as part of their operational projects.

A data warehouse represents "a subject oriented, integrated, nonvolatile, time variant collection of data in support of management's decisions" (Inmon 1992, pg 29). Non-volatile means that once the data is stored it is not changed. Data for analytic purposes represents a snapshot in time to provide a single version of the truth. But that doesn't mean that there isn't a need to maintain this data. While data elements in the warehouse may not change values, there is a constant need to evaluate whether to add or remove data from the warehouse. These decisions are typically made by data stewards. Data stewards are also responsible for maintaining the metadata that allows users to understand the meanings of any of the data to ensure that when it is used for decision making that they are using the right interpretation of the information that is derived from the data. The value placed on information in an information culture will support a more structured information maintenance environment.

The concept of an information culture has been discussed primarily in the context of knowledge management systems (Davenport et al. 1998). Yet, the elements of an information culture comprise many of the organizational level elements of competence that support successful BI. Information culture is therefore one of the key concepts to be identified as an organizational characteristic associated with BI success.

6.5 Governance

Governance refers to the process, policies, procedures and responsibilities that determine how an organization operates and the process of "monitoring performance to ensure that objectives are attained" (Weill et al. 2004, pg 4). Governance can make the difference between a company that thrives and one that just survives. One way of looking at governance is that it is responsible for controlling the way a company manages assets in six categories "human, financial, physical, intellectual property, information and information technology, and relationships" (Weill et al. 2004, pg 6).

IT governance refers to the way companies plan IT projects, monitor system performance and evaluate system development project effectiveness (DeHaes et al. 2004). It is one way that organizations try to ensure that they are realizing value from their IT investments. This research has found that to benefit from BI an organization needs to have effective corporate governance of all their asset classes, not just information and technology.

Another way to think of governance is as the formalized processes through which the objectives of an information culture are realized. Having an information culture supports a common goal of an organization using information as a key part of their operations. Yet just having a goal does not assure that the goal will be realized. Governance provides a framework supporting the attainment of the goals of an information culture.

Governance achieves this through a number of mechanisms. Good governance processes provide clearly defined responsibilities for project and process leadership and associated decision making responsibilities. Having clear decision responsibility is an element of heedful purposeful interactions identified in our research. Another aspect of governance is goal setting and communications. We have identified the existence and communications of business goals to be an important element contributing to BI success. If goals are not well understood then BI tools are likely to be applied to the wrong problems, or at least not developed consistently with overall corporate goals. Alignment of IT goals and business goals has consistently been shown to be a source of information systems failure. Well defined governance processes can assure that this alignment exists.

Good governance defines mechanisms for measuring the impact of organizational programs. This means that programs to manage any of the types of corporate resources identified above will have tangible means to determine if they are effective. Measurements may take the form of financial indicators, such as profit increase or cost reduction, or more qualitative measures such as employee or customer satisfaction. Whatever the measures, having a governance process in place to identify how the value of programs is to be evaluated provides support for the use of resources for those programs. This can assure that the appropriate level of financial, physical, and human resources are dedicated to BI initiatives. Measurement programs also need ways to collect and report on the underlying metrics used. BI is one class of systems that is typically used for performing these evaluations. Therefore, not only does governance support effective BI, but the existence of formal governance processes reinforces the need for BI. BI can also serve in these cases to enhance the effectiveness of corporate governance.

6.6 Leadership Style

The concept of leadership style has been considered a factor impacting effective management for many years (Allport 1945; French 1944; Lewin et al. 1938). The evidence collected in this research supports the value of a participative, or democratic, leadership style in supporting BI success. Democratic leaders set clear goals and group directions while supporting participation by all members of a team in making decisions (Somech 2006). This is important to BI success because of the nature of the function that BI performs in an organization. The objective of BI is to help identify solutions to business problems based on analysis of data. In order for these recommendations to be adopted it is important to have leadership that is receptive to hearing them. A democratic leader is more likely to listen to and ultimately adopt BI recommendations than an autocratic one.

Autocratic leaders tend to have strongly held predetermined beliefs (French 1944; Van Vugt et al. 2004). Their leadership style is such that recommendations coming from below them in an organizational hierarchy as given less importance than their own ideas. This mindset would make it less likely that recommendations derived from BI analysis would be adopted.

On the other end of the spectrum is the laissez-faire leadership style. Laissez-faire leadership has also been called "non-leadership" (Hinkin et al. 2008). In other words, with this leadership style members of an organization are not given clear directions as to what they should be doing, goals in the organization are not commonly shared or understood, and there is limited feedback regarding decisions and operations that do take place (Skogstad et al. 2007). While it is possible that BI can provide benefits, the lack of leadership direction to synchronize the use of BI with organizational goals limits the likelihood that this will happen.

The organizational level model indicates that leadership style and organizational resources are the keys to achieving benefits from BI. The method by which an organization can maintain and enhance these characteristics is organization development (Burke 1997). In order for BI to have the greatest benefit an organization needs to be able to accept the changes embodied in BI outputs. OD helps create an environment where change is accepted and supported (Brabazon et al. 2005). OD helps build an environment where leadership is active and engaged, yet accessible and flexible (Wirtenberg et al. 2007). A competence in OD would therefore support an organization's maintaining heedful purposeful interactions or building a more effective environment if one doesn't exist.

6.7 Technology Environment

This research did not focus on the technology environment associated with BI. There are a number of technologies that are typically considered key elements of BI systems. They include data warehouse database management systems such as Teradata or Netezza, ETL tools such as Ab Initio or Informatica, OLAP tools such as Cognos or Business Objects, and analysis tools such as SPSS or SAS. Yet this research has found that it is possible to have successful BI implementations without elaborate hardware and software solutions.

Several respondents discussed the fact that their company's early analytic solutions were done using flat files stored and analyzed using spreadsheet software. The outputs of these systems helped them define their initial products and market strategy in a way that created exponential growth in the first few years of their usage. Their ability to use business intelligence systems concepts without advanced technology reinforced the concept that the critical factors associated with BI success were the competencies of individuals and the organization in which they work.

This isn't to say that technology doesn't matter. Once they moved to more advanced data storage and analysis solutions they were able to perform more complex analysis than before. They also had more reliable data that helped improve the likelihood that the output of their analysis was correct. In an ideal BI implementation an organization will have a well managed data environment using advanced data storage, retrieval, analysis, and presentation tools in addition to having competences that support the beneficial use of these technologies (Howson 2008). This research however highlights the fact that having the appropriate organizational resources and structures in place can have as big an impact on the ability to gain organizational benefits from analytical capabilities as the technology itself.

6.8 Discussion:

Each of the areas described above contribute to competences for successful BI in various ways. Their contributions can be viewed by considering a model of problem solving that represents how BI contributes to an organization, such as the one shown in Figure 6.1 below:

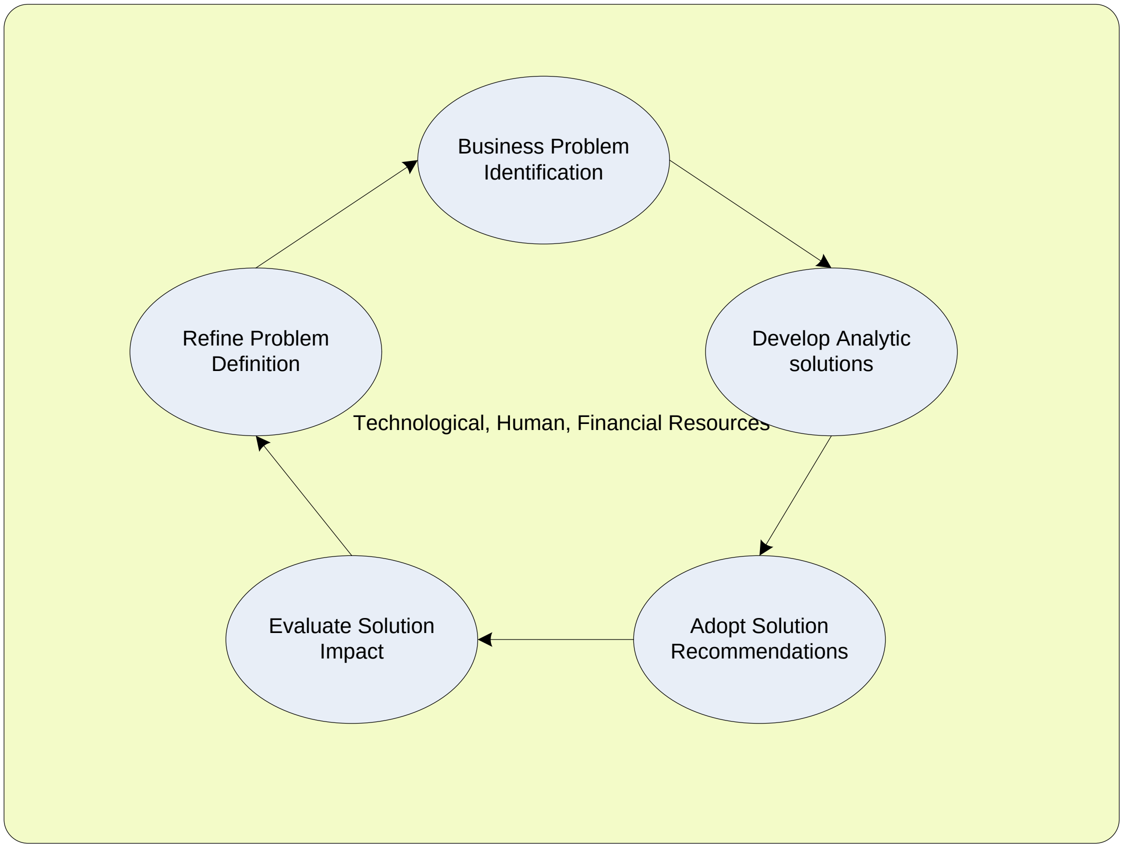

Figure 6.1 BI process model.

Problem identification consists of not only recognizing the business issues that need to be addressed for business success, but also ensuring that the problems are communicated to the organization once identified. Individuals in the organization need to have the necessary cognitive skills to be able to effectively identify the right problems to solve. They must have appropriate non-cognitive skills to ensure that the problem is articulated in a way that is clearly understood by all who will be addressing it. These rely on having the competence to hire and retain the right human capital.

An organization needs to have appropriate governance to support seeking to address business problems. Governance processes encourage the investigation of issues impacting the business and seeking solutions. In addition a leadership style conducive to seeking to solve problems is required. Autocratic leaders may believe that they already know the problems to be addressed and the answers, leading them to not ask the questions. Laissez-faire leaders can be disconnected from daily issues leading them to not seek to identify problems and not encourage the members of their organizations to do so.

Developing analytic solutions to business problems requires the appropriate level of analytical skill and knowledge among those performing this task. Organizations must have the appropriate processes in place to assure that these skills and knowledge exist among the personnel performing these tasks. They must also have learning capabilities and proclivities to ensure that those serving in these roles have the breadth of knowledge to perform effectively and that such knowledge remains current. Both a strategic HR management approach and a learning organization culture support the acquisition and development of these resources.

In order for BI solutions to have impact it’s not sufficient for them to be developed with the right goals in mind and by people with the appropriate skills and knowledge. Those solutions must be adopted by an organization once they are recommended if they are to contribute to organizational success. A number of the factors identified in this research contribute to the potential for BI solution adoption. A learning organization is one in which there is an expectation of continuous learning and as a result change. A learning organization has the culture that contributes to acceptance of BI recommendations even if they may be counter to individuals' preconceived ideas.

Leadership must also be receptive to adopting programs that incorporate concepts that they did not originate. Autocratic leaders are less likely to have this attitude and laissez-faire leaders may not have the engagement to provide the support necessary to see them implemented. This supports the need for a democratic leadership style to support BI recommendation adoption. In addition it has been shown that managers with a heuristic cognitive style are less likely to adopt analytically generated recommendations (Chandrasekaran et al. 1986; Huysmans 1970). If an organization is to benefit from their investments in BI they must have managers with a cognitive style that supports BI outputs.

An information culture can also support the adoption of BI recommendations. In organizations with this culture there is an expectation that information will be used as the basis of many aspects of their operations. This culture will help reinforce the value of using the outputs of BI systems.

Finally the solution is evaluated and the problem statement refined as a result of this evaluation. Good governance programs require the development and use of programs to evaluate performance. Governance therefore supports the continuous improvement that results from BI and reinforces the need to continue to use BI to develop approaches to improve their business.

6.9 Conclusions:

Without commitment to acquiring and using the right level of resources to support BI, an organization is unlikely to be able to realize value. Governance provides the mechanism by which the appropriate resources are allocated, SHRM insures a focus on acquiring, retaining, and developing the right human resources, and a learning organization with an information culture supports the recognition of the value of these resources. The diagram below summarizes the key mechanisms discussed above by which the elements of competence contribute to successful BI.

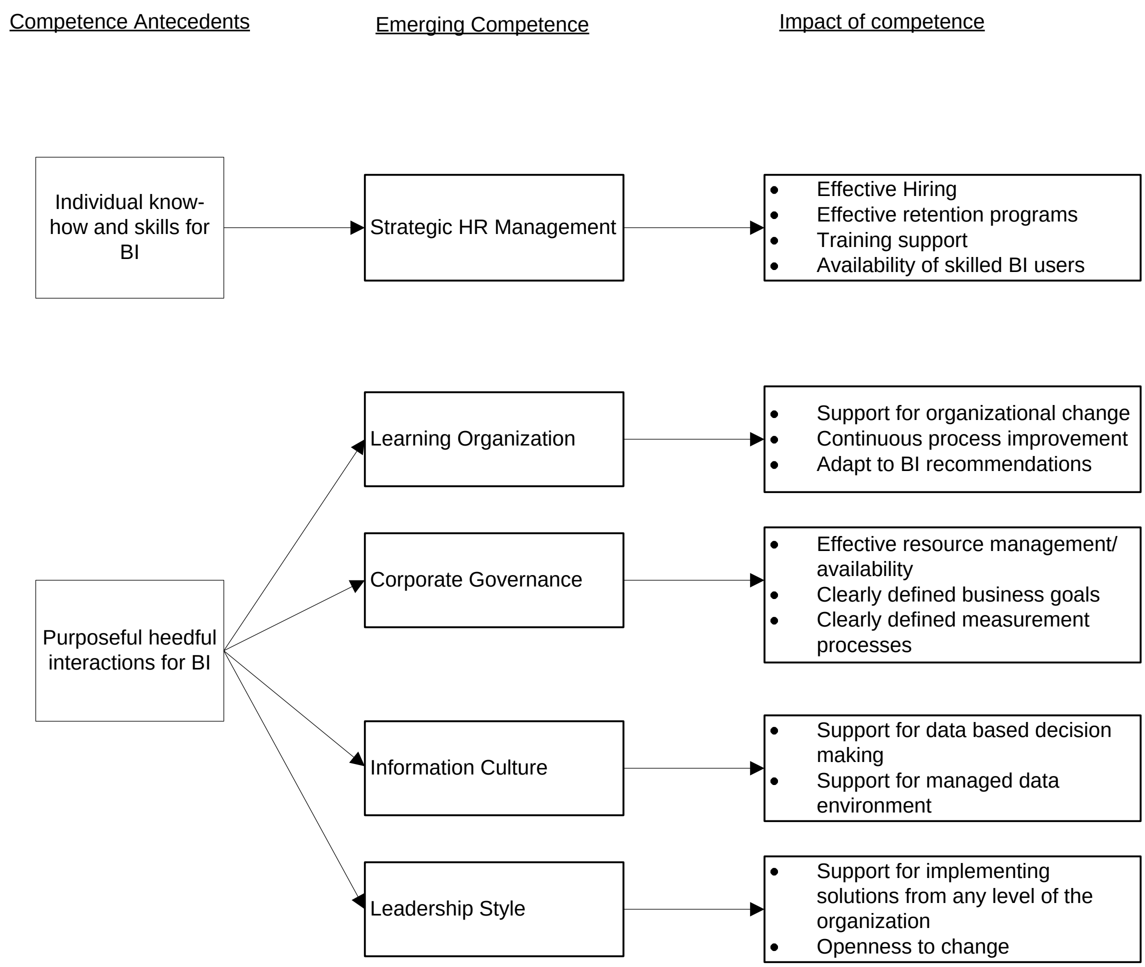

Figure 6.2 Integrated model of BI competence impact.

Competence for BI success is manifest throughout an organization's entire structure. Characteristics of individuals, organizational processes, leadership, and culture all contribute to the potential for BI success. This research has illustrated that for BI to be effective it takes more than advanced data management technology or complex decision algorithms; it takes an organization wide set of competences encompassing people, technology, organization, and culture.

7. Conclusions

7.1 Introduction:

This research began with the question of how organizations can be successful in gaining benefits from their investments in business intelligence. This is an area in which practitioners have provided a number of recommendations, but academic research is sparse. Early research on information systems recognized that "people problems" have a potential impact on the value attained from decision support systems (Alter 1975). Yet very little research has looked at how the characteristics of users and the organizations in which they work can impact value attained from information systems. This study seeks to begin to fill that gap.

This research was approached using a multiple case study approach. Representatives from 5 different organizations with experience building and using BI were interviewed using semi-structured interviews. Using a competence model from Dhillon as a theoretical framework, the data was analyzed to identify themes that emerged regarding competences for BI. The results of that analysis provided answers to the questions posed at the beginning of this investigation:

What are the characteristics of individual know-how and skill for BI?

What are the characteristics of purposeful and heedful interactions for BI?

What is the relationship between individual know-how and skills and BI success?

What is the relationship between purposeful heedful interactions and BI success?

Individual know-how and skill for BI were found to fall into three main categories, cognitive ability, non-cognitive ability, and knowledge. The evidence collected indicated that the levels of these skills and knowledge can impact effective problem definition, development, and adoption of BI solutions leading to organizational benefits. We have proposed a model that emerged from the data that describes how skills and knowledge, cognitive style and learning style relate to benefits realized from BI. We found that analytical cognitive style and high skills and knowledge resulted in the highest level of benefits from BI.

Purposeful heedful interactions represent how individuals in an organization work together to achieve results. We found that leadership style and the level of resources represent mechanisms by through which organizational level constructs can impact the attainment of BI success. A model of the interaction between physical, human, and financial resources and leadership style and the impact of these items on BI success was derived that indicated that democratic leadership coupled with a high level of resources resulted in the highest level of benefits from BI.

Combining the individual level and organizational level antecedents to organizational competence for BI leads us to develop a perspective on emergent competences for BI. The key competences that emerge are those of strategic human resource management and organizational development.

7.2 Theoretical contributions:

This work uses the theoretical model of organizational competence proposed by McGrath et. al. (1995) and modified by Dhillon (2008). While this model has been used to investigate information systems competence, specific competence for IS antecedents associated with the model have not been previously developed. This works adds to the theoretical record by supporting and expanding on the relationships proposed by this model.

This research is one of few that specifically investigates the detailed relationship between characteristics of users and the organizations in which they work and BI success. While others have suggested that how information systems are used can impact their value to an organization, limited work has investigated the mechanisms by which this happens. The proposed model can provide a theoretical starting point for investigating the relationship between user characteristics and other types of information systems.

Finally, this work adds to the research record regarding a specific class of information systems, business intelligence systems. To date there is very limited work that examines BI in an organizational setting in a holistic manner. This work provides a theoretical model that can begin a research stream investigating the relationship between BI and organizations.

7.3 Methodological Contributions:

This work was undertaken from a critical realist perspective. Realism has only been used in a limited way in information systems research. The nature of IS as a field is such that the outcomes of research provide value through their ability to be applied in an organizational setting. Realism provides a perspective that facilitates this application while still recognizing the transient nature of the underlying reality. By using a realist perspective this work illustrates the value of such an approach in IS research, and can provide guidance to others as to how it can add value.

7.4 Practical Contributions:

One of the primary motivations behind this research was to begin to define the organizational characteristics necessary for BI to be applied successfully. This has been achieved in a number of different ways. A large number of BI projects are considered to be failures either because they are not used or organizations do not see tangible business value from them (Todd 2009). The emergent competences identified can help organizations understand the capabilities that they need to build in order to benefit from their BI investments.

Besides providing prescriptive recommendations for improving the chances of BI success, a tool was developed that can be used to assess an organization's likelihood of achieving BI success. This would allow organizations to understand whether they have the people or organizational structure that would make a BI initiative likely to be beneficial. It can also help those organizations understand the areas in which they would have to focus their efforts to increase the likelihood of BI success.

7.5 Limitations:

This research was conducted via a case study using semi-structured interviews of individuals representing 6 different organizations. It is possible based on the nature of the respondents that this sample is not representative of the full range of organizations that make use of business intelligence. For example, the majority of these individuals came from the financial services industry, while the remainder came from other service industries. These results may therefore not be representative of the relationships that may exist in other types of industries.

Further, the data used in this research did not allow any conclusions to be drawn relative to the impact of industry on BI benefits. Management literature supports the finding that industry can have an impact on firm profitability and competitive position (Mauri et al. 1998; Sea-Jin et al. 2000). While our research is not directly examining firm profitability, the same factors by which industry impacts firms' profitability may impact a firm's likelihood of realizing BI benefits. This may impact the relationships that emerged in the models presented. Further study to examine how industry might impact these models would be warranted.

In addition to industry type, the size of a firm may have an impact on the models presented. All of the firms studied had more than 1000 employees, making them medium to larger firms. Firm size has been shown to have an impact on the most appropriate leadership approach (Grinnell 2003; O'Regan et al. 2004). While our research indicated that a participative leadership style provided the highest likelihood of realizing BI benefits, it is possible that a different leadership style might be more effective in smaller firms.

Related to firm size is the age of a firm. Newer firms, especially those considered entrepreneurial, have different priorities and different ways of leading than more established firms (Lumpkin et al. 2006). Our study did not include any firms that were new or entrepreneurial in nature. As such we cannot draw any conclusions relative to the efficacy of our proposed models in these environments. It is possible that in a newer firm different individual skills and organizational characteristics are necessary to benefit from BI capabilities.

This research was focused on organizations that already had BI systems in place. As noted earlier, the impact of the nature of these systems has been studied elsewhere and was not the focus of this research (Corbitt 2003; Nelson et al. 2005). Still it is possible that there is an interaction effect whereby the characteristics identified in the models that emerged from this research may have different impact depending on the specific tools or technologies being used. In addition, each organization that implements BI goes through a process of selecting the appropriate tool for their situation. The processes used for this tool selection and the characteristics of the organizations and individuals involved in tool selection may have an impact on the ultimate value attained from BI. It is possible that the individual and organizational characteristics in the models that emerged from this research may be applied to help organizations make more effective choices of BI tools. This relationship was not however examined as part of this research.

BI is used to address many different classes of business problems. This research did not focus on the nature of the business problem being addressed. The data collected addressed benefits from a holistic organization perspective. It is possible that different skills and knowledge may be appropriate for different areas being addressed by BI.

Many of the practices identified as necessary for BI success have been studied relative to general business success. While the respondents were specifically asked to discuss practices that relate to their BI efforts, it is possible that some of the practices identified are generally good business practice that are necessary for organizational success independent of whether or not they are implementing or using BI. This does not mean that these practices do not contribute to BI success, but it does raise the question as to whether an organization can be successful in gaining benefits from BI without following these practices, but not achieve overall business success.

7.6 Areas of Future Study:

This is one of few studies that look exclusively at organizational factors' impact on BI success. As such, the models that emerged are still in a formative stage. Future work needs to be done to validate the relationships and impacts embodied in these models.

There are a number of different elements that were identified as contributing to BI success in this research. The specific mechanisms by which these elements contribute to BI success were not explored in detail. Additional work into the details of how these mechanisms work could provide deeper understanding to allow refinement of the models and more detailed prescriptions for practitioners.

This research was begun partially based on the premise that BI systems are different from other systems due to the complex relationship between the problems to be addressed and the use of these systems to develop recommendations. While this work specifically looked at BI, the impact of the models that emerged is not necessarily limited to BI. It is possible that similar relationships impact organizational likelihood for realizing benefits from investments in other forms of information technology. Additional work to look at how the individual and organizational factors identified may impact the success of other information technologies may provide useful insights.

References

Ahituv, N. "A Systematic Approach Toward Assessing the Value of an Information System," *MIS Quarterly* (4:4) 1980, pp 61-75.

Ahn, H., and Kim, K.-j. "Using genetic algorithms to optimize nearest neighbors for data mining," *Annals of Operations Research* (163:1) 2008, pp 5-18.

Alavi, M., and Joachimsthaler, E.A. "REVISITING DSS IMPLEMENTATION RESEARCH - A METAANALYSIS OF THE LITERATURE AND SUGGESTIONS FOR RESEARCHERS," *MIS Quarterly* (16:1), Mar 1992, pp 95-116.

Alavi, M., and Leidner, D.E. "*Review:* Knowledge Management and Knowledge Management Systems: Conceptual Foundations ans Research Issues," *MIS Quarterly* (25:1), March 2001 2001, pp 107-136.

Allport, G.W. "The psychology of participation," *Psychological Review* (52:3) 1945, pp 117-132.

Alter, S.L. "A Study of Computer Aided Decision Making in Organizations," MIT, Cambridge, MA, 1975.

Alvesson, M. "ORGANIZATIONS AS RHETORIC: KNOWLEDGE-INTENSIVE FIRMS AND THE STRUGGLE WITH AMBIGUITY," *Journal of Management Studies* (30:6) 1993, pp 997-1015.

Amidon, S.R. "WRITING THE LEARNING ORGANIZATION," *Business Communication Quarterly* (68:4) 2005, pp 406-428.

Anderson, B. "G explained," *Medical Hypotheses* (45:6) 1995, pp 602-604.

Andreu, R., and Ciborra, C. "Organisational learning and core capabilities development: the role of IT," *The Journal of Strategic Information Systems* (5:2) 1996, pp 111-127.

Apte, C., Bing, L., Pednault, E.P.D., and Smyth, P. "BUSINESS APPLICATIONS OF DATA MINING," in: *Communications of the ACM*, Association for Computing Machinery, 2002, p. 49.

Argyris, C. *Strategy, Change and Defensive Routines* Pitman Publishing Limited, Marshfield, MA, 1985.

Argyris, C. "Teaching Smart People How to Learn," *Harvard Business Review Reflections* (4:2) 1991, pp 4-15.

Argyris, C. *On Organizational Learning* Blackwell Business, Cambridge, MA, 1992.

Argyris, C. "Learning and Teaching: A theory of Action Perspective," *Journal of Management Education* (21:1) 1997, pp 9-26.

Argyris, C., and Schon, D. *Organizational Learning: A Theory of Action Perspective* Addison-Wesley Publishing Company, Reading, MA, 1978.

Argyris, C., and Schon, D. *Organizational Learning II: Theory, Method, and Practice* Addison-Wesley Publishing Company, Reading, MA, 1996.

Arnold, V., Clark, N., Collier, P.A., Leech, S.A., and Sutton, S.G. "THE DIFFERENTIAL USE AND EFFECT OF KNOWLEDGE-BASED SYSTEM EXPLANATIONS IN NOVICE AND EXPERT JUDGMENT DECISIONS," *MIS Quarterly* (30:1) 2006, pp 79-97.

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

Arnott, D., and Pervan, G. "Eight key issues for the decision support systems discipline," *Decision Support Systems* (44:3) 2008, pp 657-672.

Azvine, B., Cui, Z., and Nauck, D.D. "Towards real-time business intelligence," *BT Technology Journal • Vol 23 No 3 • July 2005* (23:3) 2005, pp 214-225.

Bajema, C.J. "A Note on the Interrelations among Intellectual Ability, Educational Attainment, and Occupational Achievement: A Follow-up Study of a Male Kalamazoo Public School Population," *Sociology of Education* (41:3), Summer68 1968, pp 317-319.

Ballou, D.P., and Tayi, G.K. "Enhancing data quality in data warehouse environments," *Communications of the ACM* (42:1), January 1999 1999, pp 73-78.

Barki, H., and Huff, S.L. "Change, attitude to change, and decision support system success," *Information & Management* (9:5) 1985, pp 261-268.

Barney, J. "Firm resources and sustained competitive advantage. (The Resource-Based Model of the Firm: Origins, Implications, and Prospects)," *Journal Of Management* (v17:n1) 1991, p p99(22).

Barney, J.B. "Organizational Culture: Can It Be a Source of Sustained Competitive Advantage?," *The Academy of Management Review* (11:3) 1986, pp 656-665.

Barney, J.B. *Gaining and Sustaining Competitive Advantage* Addison-Wesley, Reading, MA, 1999.

Barney, J.B., and Wright, P.M. "On becoming a strategic partner: The role of human resources in gaining competitive advantage," *Human Resource Management* (37:1), Spring98 1998, p 31.

Barrett, G.V., and Depinet, R.L. "A reconsideration of testing for competence rather than for intelligence," *American Psychologist* (46:10) 1991, pp 1012-1024.

Bassellier, G., Benbasat, I., and Reich, B.H. "The Influence of Business Managers' IT Competence on Championing IT," *Information Systems Research* (14:4) 2003, pp 317-336.

Becker, B., and Gerhart, B. "THE IMPACT OF HUMAN RESOURCE MANAGEMENT ON ORGANIZATIONAL PERFORMANCE: PROGRESS AND PROSPECTS," *Academy of Management Journal* (39:4) 1996, pp 779-801.

Becton, B.J., and Schraeder, M. "Strategic Human Resources Management," *Journal for Quality & Participation* (31:4) 2009, pp 11-18.

Beise, C.M. "A Model of the IS/Organizational Interface And Users' Perceptions of IS Effectiveness," *ACM SIG Computer Personnel*) 1994, pp 10-24.

Belasco, J.A. *Taching the Elephant to Dance: The Manager's Guide to Empowering Change* Plume, New York, 1991.

Benbasat, I., Goldstein, D., and Mead, M. "The Case Research Strategy in Studies of Information Systems," *MIS Quarterly* (11:3), Sept 1987 1987, pp 369-386.

Benbasat, I., and Taylor, R.N. "The Impact of Cognitive Styles on Information System Design," *MIS Quarterly* (2:1) 1978, p 12.

Berson, Y., Nemanich, L.A., Waldman, D.A., Galvin, B.M., and Keller, R.T. "Leadership and organizational learning: A multiple levels perspective," *The Leadership Quarterly* (17:6) 2006, pp 577-594.

Bhaskar, R. "Philosophy and Scientific Realism," in: *Critical Realism: Essential Readings,* M. Archer, R. Bhaskar, A. Collier, T. Lawson and A. Norrie (eds.), Routledge, London, 1998, pp. 16-47.

Bhatt, G.D., and Zaveri, J. "The enabling role of decision support systems in organizational learning," *Decision Support Systems* (32:3), Jan 2002, pp 297-309.

Blaikie, N. *Approaches to Social Enquiry (2nd Edition)* Polity Press, Cambridge, England, 2007.

Blais, A.-R., Thompson, M.M., and Baranski, J.V. "Individual differences in decision processing and confidence judgments in comparative judgment tasks: The role of cognitive styles," *Personality and Individual Differences* (38:7) 2005, pp 1701-1713.

Blau, G., Andersson, L., Davis, K., Daymont, T., Hochner, A., Koziara, K., Portwood, J., and Holladay, B. "The relation between employee organizational and professional development activities," *Journal of Vocational Behavior* (72:1) 2008, pp 123-142.

Bontempo, C., and Zagelow, G. "The IBM data warehouse architecture," *Communications of the ACM* (41:9), September 1998 1998, pp 38 - 48.

Boudreau, M.-C., Gefen, D., and Straub, D.W. "VALIDATION IN INFORMATION SYSTEMS RESEARCH: A STATE-OF-THE-ART ASSESSMENT," *MIS Quarterly* (25:1) 2001, pp 1-16.

Bowman, D.B., Markham, P.M., and Roberts, R.D. "Expanding the frontier of human cognitive abilities: so much more than (plain) g!," *Learning and Individual Differences* (13:2) 2001, pp 127-158.

Bowman, D.B., Markham, P.M., and Roberts, R.D. "Expanding the frontier of human cognitive abilities: so much more than (plain) g!," *Learning and Individual Differences* (13:2) 2002, pp 127-158.

Brabazon, A., Silva, A., De Sousa, T.F., O'Neill, M., Matthews, R., and Costa, E. "ORGANIZATIONAL STRATEGIC ADAPTATION IN THE PRESENCE OF INERTIA," *Advances in Complex Systems* (8:4) 2005, pp 497-519.

Brown, S.L., and Eisenhardt, K.M. "The Art of Continuous Change: Linking Complexity Theory and Time-paced Evolution in Relentlessly Shifting Organizations," *Administrative Science Quarterly* (42:1) 1997, pp 1-34.

Burke, W.W. "The New Agenda for Organization Development," *Organizational Dynamics* (26:1), Summer97 1997, pp 6-20.

Burnes, B. "Kurt Lewin and the Harwood Studies: The Foundations of OD," *The Journal of Applied Behavioral Science* (43:2) 2007, pp 213-231.

Burrell, G., and Morgan, G. *Sociological Paradigms and Organizational Analysis* Ashgate Publishing Company, Burlington, VT, 1979.

Busygin, S., Prokopyev, O., and Pardalos, P.M. "Biclustering in data mining," *Computers & Operations Research* (35:9) 2008, pp 2964-2987.

Caldeira, M.M., and Ward, J.M. "Using resource-based theory to interpret the successful adoption and use of information systems and technology in manufacturing small and medium-sized enterprises," *European Journal of Information Systems* (12:2), June 2003 2003, pp 127-141.

Carayannis, E.G., and Alexander, J. "Is technological learning a firm core competence, when, how and why? A longitudinal, multi-industry study of firm technological learning and market performance," *Technovation* (22:10) 2002, pp 625-643.

Carr, N.G. *Does IT Matter* Harvard Business School Press, Boston, MA, 2004.

Chakraborty, I., Hu, P.J.-H., and Cui, D. "Examining the effects of cognitive style in individuals' technology use decision making," *Decision Support Systems* (45:2) 2008, pp 228-241.

Chan, Y.E., Sabherwal, R., and Thatcher, J.B. "Antecedents and Outcomes of Strategic IS Alignment: An Empirical Investigation," *IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT* (53:1), Feb 2006 2006, pp 27-47.

Chandrasekaran, G., and Kirs, P.J. "Acceptance of management science recommendations: The role of cognitive styles and dogmatism," *Information & Management* (10:3) 1986, pp 141-147.

Chen-Fu, C., Yi-Chao, H., and Chih-Han, H. "A hybrid approach of data mining and genetic algorithms for rehabilitation scheduling," *International Journal of Manufacturing Technology & Management* (16:1/2) 2009, pp 76-100.

Chen, L.-d., Soliman, K.S., Maoc, E., and Frolick, M.N. "Measuring user satisfaction with data warehouses: an exploratory study," *Information & Management* (37:3) 2000, pp 103-110.

Chen, M.-C., Chen, L.-S., Hsu, C.-C., and Zeng, W.-R. "An information granulation based data mining approach for classifying imbalanced data," *Information Sciences* (178:16) 2008, pp 3214-3227.

Cheng, B.-W., Chang, C.-L., and Liu, I.S. "Enhancing care services quality of nursing homes using data mining," *Total Quality Management & Business Excellence* (16:5) 2005, pp 575-596.

Chmielewski, D.A., and Paladino, A. "Driving a resource orientation: reviewing the role of resource and capability characteristics," *Management Decision* (45:3) 2007, pp 462-483.

Choo, C.W., Bergeron, P., Detlor, B., and Heaton, L. "Information culture and information use: An exploratory study of three organizations," *Journal of the American Society for Information Science & Technology* (59:5) 2008, pp 792-804.

Chou, S.-W. "Computer systems to facilitating organizational learning: IT and organizational context," *Expert Systems with Applications* (24:3) 2003, pp 273-280.

Chung, W., Chen, H., and Nunamaker Jr, J.F. "A Visual Framework for Knowledge Discovery on the Web: An Empirical Study of Business Intelligence Exploration," *Journal of Management Information Systems* (21:4), Spring2005 2005, pp 57-84.

Churchman, C.W. "Managerial Acceptance of Scientific Recommendations," *California Management Review* (7:1), Fall64 1964, pp 31-38.

Clemons, E.K. "Corporate strategies for information technology: a resource-based approach," *Computer* (24:11) 1991, p 23.

Coakes, E. "KNOWLEDGE MANAGEMENT: A PRIMER," *Communications of the Association for Information Systems* (14), 2004 2004, pp 406-489.

Cody, W.F., Kreulen, J.T., Krishna, V., and Spangler, W.S. "The integration of business intelligence and knowledge management," *IBM Systems Journal* (41:4) 2002, pp 697-714.

Corbitt, T. "Business Intelligence and Data Mining," *Management Services* (47:11) 2003, pp 18-19.

Cotton, J.L., Vollrath, D.A., Froggatt, K.L., Lengnick-Hall, M.L., and Jennings, K.R. "Employee Participation: Diverse Forms and Different Outcomes," *Academy of Management Review* (13:1) 1988, pp 8-22.

Curry, A., and Moore, C. "Assessing information culture--an exploratory model," *International Journal of Information Management* (23:2) 2003, pp 91-110.

Datta, R.P. "Data Mining Applications and Infrastructural Issues: An Indian Perspective," *ICFAI Journal of Infrastructure* (6:3) 2008, pp 42-50.

Davenport, T., and Linder, J. "Information Management Infrastructure: The New Competitive Weapon?," The Twenty Seventh Annual Hawaii International Conference on System Sciences, Honolulu Hawaii, 1994, pp. 885-896.

Davenport, T.H., De Long, D.W., and Beers, M.C. "Successful Knowledge Management Projects," *Sloan Management Review* (39:2), Winter98 1998, pp 43-57.

Davenport, T.H., and Harris, J.G. "Automated decision making comes of age: after decades of anticipation, the promise of automated decision-making systems is finally becoming a reality in a variety of industries," *MIT SLOAN MANAGEMENT REVIEW* (46:4) 2005, p 83(87).

Davenport, T.H., and Harris, J.G. "Competing on analytics.(Decision Making)," *Harvard Business Review* (84:1) 2006, p 98(10).

Davenport, T.H., and Harris, J.G. *Competing on Analytics: The New Science of Winning* Harvard Business School Press, Boston, MA, 2007.

Davis, G.B. "A Research Perspective for Information Systems and Example of Emerging Area of Research," *Information Systems Frontiers* (1:3), 1999 1999, pp 195-203.

Davis, S., and Meyer, C. *Blur: the speed of change in the connected economy* Perseus Books, New York, 1998.

de Stricker, U. "Hunches and Lunches," *Searcher* (12:4) 2004, pp 57-61.

Dedrick, J., Gurbaxani, V., and Kraemer, K.L. "Information technology and economic performance: A critical review of the empirical evidence," *ACM Computing Surveys* (35:1), March 2003 2003, pp 1-28.

DeHaes, S., and VanGrembergen, W. "IT Governance and Its Mechanisms," *Information Systems Control Journal* (1) 2004.

delMas, R.C. "Statistical Literacy, Reasoning, and Learning," *Journal of Statistics Education* (10:3) 2002.

DeLone, W.H. "Determinants of Success for Computer Usage in Small Business," *MIS Quarterly* (12:1) 1988, pp 51-61.

DeLone, W.H., and Ephraim, R.M. "Information Systems Success: The Quest for the Dependent Variable," *Information Systems Research* (3:1) 1992, pp 60-95.

DeLone, W.H., and McLean, E.R. "The DeLone and McLean Model of Information Systems Success: A Ten-Year Update," *Journal of Management Information Systems* (19:4) 2003, pp 9-30.

Deluga, R.J. "The Effects of Transformational, Transactional, and Laissez Faire Leadership Characteristics on Subordinate Influencing Behavior," *Basic and Applied Social Psychology* (11:2) 1990, pp 191 - 203.

Dennis, A.R., and Garfield, M.J. "The adoption and use of GSS in project teams: Toward more participative processes and outcomes," *MIS Quarterly* (27:2) 2003, pp 289-323.

Dhaliwal, J.S., and Benbasat, I. "The Use and Effects of Knowledge-based System Explanations: Theoretical Foundations and a Framework for Empirical Evaluation," *Information Systems Research* (7:3) 1996, pp 342-362.

Dhillon, G. "Gaining benefits from IS/IT implementation: Interpretations from case studies," *International Journal of Information Management* (25:6) 2005, pp 502-515.

Dhillon, G. "Organizational competence for harnessing IT: A case study," *Information & Management* (45:5) 2008, pp 297-303.

Doktor, R.H., and Hamilton, W.F. "COGNITIVE STYLE AND THE ACCEPTANCE OF THE MANAGEMENT SCIENCE RECOMMENDATIONS," *Management Science* (19:8) 1973, pp 884-894.

Drejer, A. "Organisational learning and competence development," *The Learning Organization* (7:4) 2000, p 206.

Drejer, A. "How can we define and understand competencies and their development?," *Technovation* (21:3) 2001, pp 135-146.

Drejer, A., and Riis, J.O. "Competence development and technology: How learning and technology can be meaningfully integrated," *Technovation* (19:10) 1999, pp 631-644.

Dunphy, D., Turner, D., and Crawford, M. "Organizational learning as the creation of corporate competencies.(The use of reshaping competencies)," *Journal of Management Development* (v16:n4) 1997, p p232(213).

Eagly, A.H., and Johannesen-Schmidt, M.C. "The Leadership Styles of Women and Men," *Journal of Social Issues* (57:4) 2001, p 781.

Eagly, A.H., Johannesen-Schmidt, M.C., and van Engen, M.L. "Transformational, transactional, and laissez-faire leadership styles: A meta-analysis comparing women and men," *Psychological Bulletin* (129:4) 2003, pp 569-591.

Ein-Dor, P., and Segev, E. "Organizational Context and the Success of Management Information Systems," *Management Science* (24:10) 1978, pp 1064-1077.

Ein-Dor, P., and Segev, E. "Organizational Context and MIS Structure: Some Empirical Evidence," *MIS Quarterly* (6:3) 1982, pp 55-68.

Ein-Dor, P., Segev, E., and Steinfeld, A. "Use of Management Information Systems: An Empirical Study," International Conference on Information Systems, Cambridge, MA, USA, 1981.

Elbashir, M.Z., Collier, P.A., and Davern, M.J. "Measuring the effects of business intelligence systems: The relationship between business process and organizational performance," *International Journal of Accounting Information Systems* (9:3) 2008, pp 135-153.

Ellinger, A.D., Ellinger, A.E., Yang, B., and Howton, S.W. "The Relationship Between the Learning Organization Concept and Firms' Financial Performance: An Empirical Assessment," *Human Resource Development Quarterly* (13:1), Spring2002 2002, pp 5-21.

Elmuti, D. "Sustaining high performance through self-managed work teams," *Industrial Management* (38:2) 1996, p 4.

Er, M.C. "Decision Support Systems: A summary, problems, and future trends," *Decision Support Systems* (4:3) 1988, pp 355-363.

Evelson, B. "It's Time to Reinvent Your BI Strategy," in: *Intelligent Enterprise*, 2007.

Feeny, D.F., and Willcocks, L.P. "Core IS Capabilities for Exploiting Information Technology," *Sloan Management Review* (39:3), Spring 1998 1998, pp 9-22.

Fernandez, E., Montes, J.M., and Vazquez, C.J. "Typology and strategic analysis of intangible resources: A resource-based approach," *Technovation* (20:2) 2000, pp 81-92.

Foster, S., Hawking, P., and Stein, A. "Business Intelligence Solution Evolution: Adoption and Use," *Business Intelligence Journal* (10:4) 2005, pp 44-54.

Fox, T.L. "EXAMINING THE INFLUENCE OF COGNITIVE STYLE ON THE USE OF A DECISION SUPPORT TOOL FOR STRUCTURED AND UNSTRUCTURED TASKS," Americas Conference on Information Systems, 2003, pp. 2131-2141.

French, J.R.P., Jr. "Retraining an autocratic leader," *The Journal of Abnormal and Social Psychology* (39:2) 1944, pp 224-237.

Friedman, T., and Hostmann, B. "The Cornerstones of Business Intelligence Excellence," The Gartner Group.

Gable, G.G., Sedera, D., and Chan, T. "Enterprise Systems Success: A Measurement Model," International Conference on Information Systems, Seattle, WA, 2003.

Gallagher, C.A. "Perceptions of the Value of a Management Information System," *The Academy of Management Journal* (17:1) 1974, pp 46-55.

Gantz, J., Morris, H., Vesset, D., and Manfrediz, A. "Taming Information Chaos," IDC.

Garfield, J. "The Challenge of Developing Statistical Reasoning," *The Journal of Statistics Education* (10:3) 2002.

Garud, R., Kumaraswamy, A., and Sambamurthy, V. "Emergent by Design: Performance and Transformation at Infosys Technologies," *Organization Science* (17:2) 2006, pp 277-286.

Ghoshal, S., and Kim, S.K. "Building Effective Intelligence Systems for Competitive Advantage; The Problems with Business Intelligence Systems " *Sloan Management Review* (28:1) 1986, pp 49-58.

Gibson, M., and Arnott, D. "The Evaluation of Business Intelligence: A Case Study in a Major Financial Institution,"!6th Australian Conference on Information Systems, Sydney, Australia, 2005.

Ginzberg, M.J. "Redesign of Managerial Tasks: A Requisite for Successful Decision Support Systems," *MIS Quarterly* (2:1) 1978, pp 39-52.

Gnatovich, R. "Making a case for business analytics," *Strategic Finance* (88:8) 2007, pp 46-51.

Golfarelli, M., Rizzi, S., and Cella, I. "Beyond data warehousing: what's next in business intelligence?," 7th ACM international workshop on Data warehousing and OLAP, ACM, Washington, DC, USA, 2004 pp. 1 - 6.

Gorla, N. "FEATURES TO CONSIDER IN A DATA WAREHOUSING SYSTEM," *Communications of the ACM* (46:11) 2003, pp 111-115.

Goslar, M.D. "Capability Criteria for Marketing Decision Support Systems," *Journal of Management Information Systems* (3:1), Summer 1986, pp 81-95.

Gottfredson, L.S. "Societal consequences of the g factor in employment," *Journal of Vocational Behavior* (29:3) 1986, pp 379-410.

Gottfredson, L.S. "Why g matters: The complexity of everyday life," *Intelligence* (24:1) 1997, pp 79-132.

Gottschalk, P., and Solli-Sæther, H. "Critical success factors from IT outsourcing theories: an empirical study " *Industrial Management + Data Systems* (105:5/6) 2005, pp 685-702.

Grant, R. "The Resource-Based Theory of Competitive Advantage: Implications for Strategy Formulation," *California Management Review* (33:3) 1991, pp 114-135.

Green, G.I., and Hughes, C.T. "Effects of Decision Support Systems Training and Cognitive Style on Decision Process Attributes," *Journal of Management Information Systems* (3:2), Fall 1986, pp 83-93.

Gregor, S., and Benbasat, I. "EXPLANATIONS FROM INTELLIGENT SYSTEMS: THEORETICAL FOUNDATIONS AND IMPLICATIONS FOR PRACTICE," *MIS Quarterly* (23:4) 1999, pp 497-530.

Grinnell, J.P. "An Empirical Investigation of CEO Leadership in Two Types of Small Firms," *SAM Advanced Management Journal (07497075)* (68:4), Fall2003 2003, pp 36-41.

Grover, V., Seung Ryul, J., and Segars, A.H. "Information systems effectiveness: The construct space and patterns of application," *Information & Management* (31:4) 1996, pp 177-191.

Guimaraes, T., Igbaria, M., and Lu, M.-T. "The Determinants of DSS Success: An Integrated Model," *Decision Sciences* (23:2) 1992, pp 409-430.

Häkkinen, L., and Hilmola, O.-P. "ERP evaluation during the shakedown phase: lessons from an after-sales division," *Information Systems Journal* (18:1) 2008, pp 73-100.

Hammer, M., and Champy, J. *Reengineering the Corporation: A Manifesto for Business Revolution* HarperBusiness, New York, 1993.

Hannah, S.T., Avolio, B.J., Luthans, F., and Harms, P.D. "Leadership efficacy: Review and future directions," *The Leadership Quarterly* (19:6) 2008, pp 669-692.

Hannan, M.T., and Freeman, J. "Structural Inertia and Organizational Change," *American Sociological Review* (49:2) 1984, pp 149-164.

Henderson, J.C., and Venkatraman, H. "Strategic alignment: Leveraging information technology for transforming organizations," *IBM Systems Journal* (32:1) 1993, p 13.

Hertzberg, R. "TOP 10 Projects in '07," in: *Innovations*, Ziff-Davis, 2007, pp. 18-22.

Hevner, A.R., March, S.T., Jinsoo, P., and Ram, S. "DESIGN SCIENCE IN INFORMATION SYSTEMS RESEARCH," *MIS Quarterly* (28:1) 2004, pp 75-105.

Hinkin, T.R., and Schriesheim, C.A. "An Examination of "Nonleadership": From Laissez-Faire Leadership to Leader Reward Omission and Punishment Omission," *Journal of Applied Psychology* (93:6) 2008, pp 1234-1248.

Hirji, K.K. "Exploring Data Mining IMPLEMENTATION," *Communications of the ACM* (44:7) 2001, pp 87-93.

Hirschheim, R., and Sabherwal, R. "Detours in the Path toward Strategic Information Systems Alignment," *California Management Review* (44:1), Fall 2001 2001, pp 87-108.

Hitt, M.A., and Ireland, R.D. "Corporate Distinctive Competence, Strategy, Industry and Performance; Summary," *Strategic Management Journal* (6:3) 1985, pp 273-293.

Hitt, M.A., and Ireland, R.D. "RELATIONSHIPS AMONG CORPORATE LEVEL DISTINCTIVE COMPETENCIES, DIVERSIFICATION STRATEGY, CORPORATE STRUCTURE AND PERFORMANCE," *Journal of Management Studies* (23:4) 1986, pp 401-416.

Holzer, H.J. *What Employers Want* The Russell Sage Foundation, New York, NY, 1996.

Hong, K.K., and Kim, Y.G. "The critical success factors for ERP implementation: an organizational fit perspective," *Information & Management* (40:1), Oct 2002, pp 25-40.

Howson, C. "The Seven Pillars of BI Success," in: *Intelligent Enterprise*, 2006

Howson, C. *Successful Business Intelligence: Secrets to Making BI a Killer App* McGraw-Hill, New York, NY, 2008.

Huber, G.P. "COGNITIVE STYLE AS A BASIS FOR MIS AND DSS DESIGNS: MUCH ADO ABOUT NOTHING?," *Management Science* (29:5) 1983, pp 567-579.

Huber, G.P. "Organizational Learning: The Contributing Processes and the Literatures," *Organization Science* (2:1) 1991, pp 88-115.

Hunt, E. *Will We Be Smart Enough? A Cognitive Analysis of the Coming Workforce* The Russell Sage Foundation, New York, 1995.

Hunt, R.G., Krzystofiak, F.J., Meindl, J.R., and Yousry, A.M. "Cognitive style and decision making," *Organizational Behavior and Human Decision Processes* (44:3) 1989, pp 436-453.

Hunter, J.E. "Cognitive ability, cognitive aptitudes, job knowledge, and job performance," *Journal of Vocational Behavior* (29:3) 1986, pp 340-362.

Huysmans, J.H.B.M. "THE EFFECTIVENESS OF THE COGNITIVE-STYLE CONSTRAINT IN IMPLEMENTING OPERATIONS RESEARCH PROPOSALS," *Management Science* (17:1) 1970, pp 92-104.

Inmon, W.H. *Building the Data Warehouse* John Wiley & Sons, Inc., New York, New York, 1992.

Ives, B., Olson, M.H., and Baroudi, J.J. "The measurement of user information satisfaction " *Communications of the ACM* (26:10) 1983, pp 785 - 793.

Jarvis, C.B., Mackenzie, S.B., Podsakoff, P.M., Mick, D.G., and Bearden, W.O. "A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research," *Journal of Consumer Research* (30:2) 2003, pp 199-218.

Javidan, M. "Core competence: What does it mean in practice?," *Long Range Planning* (31:1) 1998, pp 60-71.

Jourdan, Z., Rainer, R.K., and Marshall, T.E. "Business Intelligence: An Analysis of the Literature," *Information Systems Management* (25:2), Spring 2008, pp 121-131.

Jukic, N. "MODELING STRATEGIES AND ALTERNATIVES FOR DATA WAREHOUSING PROJECTS," *Communications of the ACM* (49:4) 2006, pp 83-88.

Kasper, G.M. "The Effect of User-Developed DSS Applications of Forecasting Decision-Making Performance in an Experimental Setting," *Journal of Management Information Systems* (2:2), Fall 1985, pp 26-39.

Kaye, G.R. "Information systems successes and failures: research findings from the compounding industry," *Journal of Information Technology (Routledge, Ltd.)* (5:2) 1990, p 73.

Kearns, G.S., and Lederer, A.L. "The effect of strategic alignment on the use of IS-based resources for competitive advantage," *The Journal of Strategic Information Systems* (9:4) 2000, pp 265-293.

Kearns, G.S., and Lederer, A.L. "A Resource-Based View of Strategic IT Alignment: How Knowledge Sharing Creates Competitive Advantage," *Decision Sciences* (34:1) 2003, pp 1-29.

Keen, P.G.W., and Bronsema, G.S. "Cognitive Style Research- A Perspective for Integration," International Conference on Information Systems, Cambridge, MA, 1981.

Kimball, R., Reeves, L., Ross, M., and Thornthwaite, W. *The Data Warehouse Lifecycle Toolkit: Expert Methods for Designing, Developing, and Deploying Data Warehouses* John Wiley & Sons, Inc., New York, NY, 1998.

Kogut, B., and Zander, U. "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology," *Organization Science* (3:3) 1992, pp 383-397.

Kohavi, R., Rothleder, N.J., and Simoudis, E. "EMERGING TRENDS IN BUSINESS ANALYTICS," *Communications of the ACM* (45:8) 2002, pp 45-48.

Kozhevnikov, M. "Cognitive Styles in the Context of Modern Psychology: Toward an Integrated Framework of Cognitive Style," *Psychological Bulletin* (133:3) 2007, pp 464-481.

Kranzler, J.H. "Commentary on "Is g a viable construct for school psychology?"," *Learning and Individual Differences* (13:2) 2001, pp 189-195.

Kulper, T. "Beyond Management Consultation: Partnering with Human Resources for Organizational Effectiveness," *Journal of Workplace Behavioral Health* (22:2) 2007, pp 75-90.

Kwon, D., and Watts, S. "IT valuation in turbulent times," *Journal Of Strategic Information Systems* (15:4), Dec 2006, pp 327-354.

Lawler, E.E., III "Creating high performance organizations," *Asia Pacific Journal of Human Resources* (43:1), April 1, 2005 2005, pp 10-17.

Lawler III, E.E. "Make Human Capital a Source of Competitive Advantage," *Organizational Dynamics* (38:1) 2009, pp 1-7.

Leonard-Barton, D. *Wellsprings of knowledge : building and sustaining the sources of innovation* Harvard Business School Press, Boston, Mass, 1995.

Leonard, N.H., Scholl, R.W., and Kowalski, K.B. "Information processing style and decision making," *Journal of Organizational Behavior* (20:3) 1999, p 407.

Levitt, B., and March, J.G. "Organizational Learning," *Annual Review of Sociology* (14) 1988, pp 319-340.

Lewin, K., and Lippitt, R. "An Experimental Approach to the Study of Autocracy and Democracy: A Preliminary Note," *Sociometry* (1:3/4) 1938, pp 292-300.

Liebowitz, J. *Strategic Intelligence* Auerbach Publications, Taylor & Francis Group, Boca Raton, FL, 2006.

Little, R.G., Jr., and Gibson, M.L. "Perceived influences on implementing data warehousing," *Software Engineering, IEEE Transactions on* (29:4) 2003, pp 290-296.

Loshin, D. *Business Intelligence: The Savvy Manager's Guide* Morgan Kaufmann, San Francisco, 2003.

Luftman, J.N., Lewis, P.R., and Oldach, S.H. "Transforming the enterprise: The alignment of business and information technology strategies," *IBM Systems Journal* (32:1) 1993, pp 198-221.

Lumpkin, G.T., Wales, W.J., and Ensley, M.D. "ENTREPRENEURIAL ORIENTATION EFFECTS ON NEW VENTURE PERFORMANCE: THE MODERATING ROLE OF VENTURE AGE," Academy of Management Proceedings, Academy of Management, 2006, pp. N1-N6.

Lusk, E.J. "A Test of Differential Performance Peaking for a Disembedding Task," *Journal of Accounting Research* (17:1), Spring79 1979, pp 286-294.

Mackay, J.M., and Elam, J.J. "A Comparative Study of How Experts and Novices Use a Decision Aid to Solve Problems in Complex Knowledge Domains," *Information Systems Research* (3:2) 1992, pp 150-172.

Marques, J. "LEAD -- or get out of the way!," *Management Services* (52:2), Summer2008 2008, pp 42-43.

Marshall, C., and Rossman, G.B. *Designing Qualitative Research*, (Fourth ed.) Sage Publications, Thousand Oaks, CA, 2006.

Mason, R.O., and Mitroff, I.I. "A Program for Research on Management Information Systems," *Management Science* (19:5) 1973, pp 475-487.

Mauri, A.J., and Michaels, M.P. "Firm and industry effects within strategic management: An empirical examination," *Strategic Management Journal* (19:3) 1998, p 211.

McCarthy, J. "Phenomenal DATA MINING," *Communications of the ACM* (43:8) 2000, pp 75-79.

McClelland, D.C. "Testing for competence rather than for 'intelligence.'," *American Psychologist* (28:1) 1973, pp 1-14.

McDonagh, J., and Coghlan, D. "INFORMATION TECHNOLOGY AND THE LURE OF INTEGRATED CHANGE: A NEGLECTED ROLE FOR ORGANIZATION DEVELOPMENT?," *Public Administration Quarterly* (30:1/2), Spring2006 2006, pp 22-55.

McGrath, R.G., MacMillan, I.C., and Venkatraman, S. "Defining and Developing Competence: A Strategic Process Paradigm," *Strategic Management Journal* (16:4) 1995, pp 251-276.

Meier, J. "The importance of relationship management in establishing successful interorganizational systems," *The Journal of Strategic Information Systems* (4:2) 1995, pp 135-148.

Melody, W.H. "Human Capital in Information Economies," *New Media Society* (1:1), April 1, 1999 1999, pp 39-46.

Melone, N.P. "A Theoretical Assessment of the User-Satisfaction Construct in Information Systems Research," *Management Science* (36:1) 1990, pp 76-91.

Melville, N., Kraemer, K., and Gurbaxani, V. "*Review:* Information Technology and Organizational Performance: An Integrative Model of IT Business Value," *MIS Quarterly* (28:2) 2004, pp 283-322.

Miller, D. "A Preliminary Typology of Organizational Learning: Synthesizing the Literature," *Journal Of Management* (22:3), June 1, 1996 1996, pp 485-505.

Miller, D., and Lee, J. "The people make the process: commitment to employees, decision making, and performance," *Journal of Management* (27:2) 2001, p 163.

Miller, G.J., Brautigam, D., and Gerlach, S.V. *Business Intelligence Competency Centers: A Team Approach to Maximizing Competitive Advantage* John Wiley & Sons, Hoboken, NJ, 2006.

Miner, A.S., and Mezias, S.J. "Ugly Duckling No More: Pasts and Futures of Organizational Learning Research," *Organization Science* (7:1) 1996, pp 88-99.

Mirani, R., and Lederer, A.L. "An instrument for assessing the organizational benefits of IS projects," *Decision Sciences* (29:4) 1998, pp 803-838.

Montazemi, A.R. "Factors Affecting Information Satisfaction in the Context of the Small Business Environment," *MIS Quarterly* (12:2) 1988, pp 239-256.

Moore, G.C., and Benbasat, I. "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation," *Information Systems Research* (2:3) 1991, pp 192-222.

Müller, R., and Turner, J.R. "Matching the project manager's leadership style to project type," *International Journal of Project Management* (25:1) 2007, pp 21-32.

Nash, K.S. "What It Takes to Succeed Now as a CIO," in: *CIO*, International Data Group, 2008.

Negash, S., and Gray, P. "Business Intelligence," Americas Conference on Information Systems, Tampa, FL, 2003, pp. 3190-3199.

Nelson, R.R., Todd, P.A., and Wixom, B.H. "Antecedents of Information and System Quality: An Empirical Examination Within the Context of Data Warehousing," *Journal of Management Information Systems* (21:4), Spring 2005, pp 199-235.

Noll, C.L., and Wilkins, M. "Critical Skills of IS Professionals: A Model for Curriculum Development," *Journal of Information Technology Education* (1:3) 2002.

Nutt, P.C. "FLEXIBLE DECISION STYLES AND THE CHOICES OF TOP EXECUTIVES," *Journal of Management Studies* (30:5) 1993, pp 695-721.

O'Regan, N., and Ghobadian, A. "Drivers of performance in small- and medium-sized firms â€“ an empirical study," *International Journal of Business Performance Management* (6:2) 2004, pp 1-1.

Oh, W., and Pinsonneault, A. "On the assessment of the strategic value of information technologies: Conceptual and analytical approaches," *MIS Quarterly* (31:2), Jun 2007, pp 239-265.

Oliver, G. "Information culture: exploration of differing values and attitudes to information in organisations," *Journal of Documentation* (64:3) 2008, p 21.

Outhwaite, W. "Realism and Social Science," in: *Critical Realism: Essential Readings*, M. Archer, R. Bhaskar, A. Collier, T. Lawson and A. Norrie (eds.), Routledge, London, 1998, pp. 282-312.

Pedhazur, E.J., and Schmelkin, L.P. *Measurement, Design, and Analysis: An Integrated Approach* Lawrence Erlbaum Associates, Hillsdale, NJ, 1992.

Peppard, J., Lambert, R., and Edwards, C. "Whose job is it anyway?: organizational information competencies for value creation," *Information Systems Journal* (10:4) 2000, pp 291-322.

Peppard, J., and Ward, J. "Beyond strategic information systems: towards an IS capability," *Journal of Strategic Information Systems* (13) 2004, pp 167-194.

Peterson, R.S. "A directive leadership style in group decision making can be both virtue and vice: Evidence from elite and experimental groups," *Journal of Personality and Social Psychology* (72:5) 1997, pp 1107-1121.

Petter, S., Straub, D., and Rai, A. "SPECIFYING FORMATIVE CONSTRUCTS IN INFORMATION SYSTEMS RESEARCH," *MIS Quarterly* (31:4) 2007, pp 623-656.

Piccoli, G., and Ives, B. "Review: IT-Dependent Strategic Initiatives and Sustained Competitive Advantage: A review and Synthesis of the Literature," *MIS Quarterly* (29:4) 2005, pp 747-776.

Porter, M.E. *Competitive Strategy* The Pree Press, New York, NY, 1980.

Powell, J.H., and Bradford, L.P. "Targeting intelligence gathering in a dynamic competitive environment," *International Journal of Information Management* (20) 2000, pp 181-195.

Powell, T.C., and Dent-Micallef, A. " Information technology as competitive advantage: The role of human, business, and technology resources," *Strategic Management Journal* (18:5) 1997, pp 375-405.

Prahalad, C.K., and Hamel, G. "The core competence of the corporation. (also includes a related article on the corporate structure at Vickers Co.)," *Harvard Business Review* (68:3) 1990, pp 79-92.

Premkumar, G. "A cognitive study of the decision-making process in a business context: implications for design of expert systems," *International Journal of Man-Machine Studies* (31:5) 1989, pp 557-572.

Rainer, R.K., and Watson, H.J. "WHAT DOES IT TAKE FOR SUCCESSFUL EXECUTIVE INFORMATION-SYSTEMS," *Decision Support Systems* (14:2), Jun 1995, pp 147-156.

Rajesh, K.V.N. "Business Intelligence for Enterprises," *ICFAI Journal of Information Technology*) 2008, pp 45-54.

Ramaprasad, A. "COGNITIVE PROCESS AS A BASIS FOR MIS AND DSS DESIGN," *Management Science* (33:2) 1987, pp 139-148.

RandomHouse "Random House Dictionary," Random House, Inc, New York, NY, 2009.

Ravichandran, T., and Lertwongsatien, C. "Effect of Information Systems Resources and Capabilities on Firm Performance: A Resource-Based Perspective," *Journal of management Information Systems* (21:4) 2005, pp 237-276.

Raymond, L. "Organizational Characteristics and MIS Success in the Context of Small Business," *MIS Quarterly* (37-52:9) 1985, p 1.

Raymond, L. "Organizational Context and Information Systems Success: A Contingency Approach," *Journal of Management Information Systems* (6:4), Spring 1990, pp 5-20.

Rees, R.T. "The role of HR in organizational development and innovation," *Employment Relations Today (Wiley)* (33:4), Winter2007 2007, pp 29-35.

Rivard, S., Raymond, L., and Verreault, D. "Resource-based view and competitive strategy: An integrated model of the contribution of information technology to firm performance," *The Journal of Strategic Information Systems* (15:1) 2006, p 29.

Rosenberger, L., Nash, J., and Graham, A. *The Deciding Factor: The Power of Analytics to Make Every Decision a Winner* Jossey-Bass, San Francisco, CA, 2009.

Ross, J.W., Beath, C.M., and Goodhue, D.L. "Develop long-term competitiveness through IT assets. (information technology)," *Sloan Management Review* (v38:n1) 1996, p p31(12).

Rouach, D., and Santi, P. "Competitive Intelligence Adds Value: Five Intelligence Attitudes," *European Management Journal* (19:5) 2001, pp 552-559.

Rouibah, K., and Ould-ali, S. "PUZZLE: a concept and prototype for linking business intelligence to business strategy," *The Journal of Strategic Information Systems* (11:2) 2002, p 133.

Sabherwal, R., and Chan, Y.E. "Alignment between business and IS strategies: a study of prospectors, analyzers, and defenders.," *Information Systems Research* (12:1), March 2001 2001, pp 11-39.

Sabherwal, R., Jeyaraj, A., and Chowa, C. "Information system success: Individual and organizational determinants," *Management Science* (52:12), Dec 2006, pp 1849-1864.

Sanders, G.L., and Courtney, J.F. "A Field Study of Organizational Factors Influencing DSS Success," *MIS Quarterly* (9:1) 1985, pp 77-90.

Schafer, D.W., and Ramsey, F.L. "Teaching the Craft of Data Analysis," *Journal of Statistics Education* (11:1) 2003.

Schein, E.H. *The Corporate Culture Survival Guide: Sense and Nonsense About Corporate Culture* Jossey-Bass Publishers, San Francisco, CA, 1999.

Schein, E.H. *Organizational culture and leadership, 3rd ed.* Jossey-Bass, San Francisco, 2004.

Schein, L. "A Manager's Guide to Corporate Culture," The Conference Board, New York.

Scheps, S. *Business Intelligence for Dummies* Wiley Publishing, Inc., Hoboken, NJ, 2008.

Schultze, U., and Stabell, C. "Knowing What You Don't Know? Discourses and Contradictions in Knowledge Management Research," *Journal of Management Studies* (41:4) 2004, pp 549-572.

Schwartz, M. "The Reciprocities Multiplier: An Empirical Evaluation," *Administrative Science Quarterly* (9:3) 1964, pp 264-277.

Scott-Ladd, B., Travaglione, A., and Marshall, V. "Causal inferences between participation in decision making, task attributes, work effort, rewards, job satisfaction and commitment," *Leadership & Organization Development Journal* (27:5) 2006, pp 399-414.

Sea-Jin, C., and Singh, H. "CORPORATE AND INDUSTRY EFFECTS ON BUSINESS UNIT COMPETITIVE POSITION," *Strategic Management Journal* (21:7) 2000, p 739.

Seddon, P.B., Staples, S., Patnayakuni, R., and Bowtell, M. "Dimensions of Information Systems Success," *Communications of the Association for Information Systems* (2) 1999, pp 2-61.

Sen, A. "Metadata management: past, present and future," *Decision Support Systems* (37:1), April 2004 2004, pp 151-173.

Sharma, R. "Celebrating Change: The New Paradigm of Organizational Development," *ICFAI Journal of Soft Skills* (2:3) 2008, pp 23-28.

Shrivastava, P. "A TYPOLOGY OF ORGANIZATIONAL LEARNING SYSTEMS," *Journal of Management Studies* (20:1) 1983, pp 7-28.

Singer, J., and Duvall, S. "HIGH-PERFORMANCE PARTNERING BY SELF-MANAGED TEAMS IN MANUFACTURING," *Engineering Management Journal* (12:4) 2000, p 9.

Skerlavaj, M., Stemberger, M.I., Skrinjar, R., and Dimovski, V. "Organizational learning culture--the missing link between business process change and organizational performance," *International Journal of Production Economics* (106:2) 2007, pp 346-367.

Skogstad, A., Einarsen, S.l., Torsheim, T., Aasland, M.S., and Hetland, H. "The destructiveness of laissez-faire leadership behavior," *Journal of Occupational Health Psychology* (12:1) 2007, pp 80-92.

Soh, C., and Markus, M.L. "How IT Creates Business Value: A process Theory Synthesis," International Conference on Information Systems, Amsterdam, The Netherlands, 1995.

Somech, A. "The Effects of Leadership Style and Team Process on Performance and Innovation in Functionally Heterogeneous Teams," *Journal Of Management* (32:1), February 1, 2006 2006, pp 132-157.

Stavrou, E.T., and Brewster, C. "The Configurational Approach to Linking Strategic Human Resource Management Bundles with Business Performance: Myth or Reality?," *Management Revue* (16:2) 2005, pp 186-201.

Steensma, H.K. "Acquiring technological competencies through inter-organizational collaboration: An organizational learning perspective," *Journal of Engineering and Technology Management* (12:4) 1996, pp 267-286.

Sternberg, R.J. "Managerial intelligence: Why IQ isn't enough," *Journal Of Management* (23:3) 1997, pp 475-493.

Sternberg, R.J. "Successful intelligence as a basis for entrepreneurship," *Journal of Business Venturing* (19:2) 2004, pp 189-201.

Sternberg, R.J., and Hedlund, J. "Practical Intelligence, g, and Work Psychology," *Human Performance* (15:1/2) 2002, pp 143-160.

Stodder, D. "Special Report: BI Megatrends 2008," in: *Intelligent Enterprise*, 2008.

Straub, D.W. "Validating Instruments in MIS Research," *MIS Quarterly* (13:2) 1989, pp 147-169.

Strauss, A., and Corbin, J. *Basics of Qualitative Research: Techniques for Developing Grounded Theory*, (Second ed.) SAGE Publications, Thousand Oaks, CA, 1998.

Subramanyam, R.B.V., and Goswami, A. "A FUZZY DATA MINING ALGORITHM FOR INCREMENTAL MINING OF QUANTITATIVE SEQUENTIAL PATTERNS," *International Journal of Uncertainty, Fuzziness & Knowledge-Based Systems* (13:6) 2005, pp 633-652.

Sumner, M. "Risk factors in enterprise wide information management systems projects," The 2000 ACM SIGCPR conference on Computer personnel research, 2000, pp. 180 - 187.

Tata, J., and Prasad, S. "Team Self-management, Organizational Structure, and Judgments of Team Effectiveness," *Journal of Managerial Issues* (16:2) 2004.

Te'eni, D., Sagie, A., Schwartz, D.G., Zaidman, N., and Amichai-Hamburger, Y. "The process of organizational communication: a model and field study," *Professional Communication, IEEE Transactions on* (44:1) 2001, pp 6-20.

Todd, G. "The Imperative of Analytics," in: *Information Management*, 2009.

Trauth, E.M., Farwell, D.W., and Lee, D. "The IS Expectation Gap: Industry Expectations Versus Academic Preparation," *MIS Quarterly* (17:3) 1993, pp 293-307.

Tripsas, M., and Gavetti, G. "Capabilities, cognition, and inertia: evidence from digital imaging," *Strategic Management Journal* (21:10-11) 2000, pp 1147-1161.

Van Der Zee, J.T.M., and De Jong, B. "Alignment is not enough: Integrating business and information technology man.," *Journal of Management Information Systems* (16:2), Fall 1999 1999, pp 137-156.

Van Vugt, M., Jepson, S.F., Hart, C.M., and De Cremer, D. "Autocratic leadership in social dilemmas: A threat to group stability," *Journal of Experimental Social Psychology* (40:1) 2004, pp 1-13.

Vityaev, E., Rennolls, K., Kovalerchuk, B., and Vityaev, E. "Symbolic methodology for numeric data mining," *Intelligent Data Analysis* (12:2) 2008a, pp 165-188.

Vityaev, E., Rennolls, K., Pechenizkiy, M., Puuronen, S., and Tsymbal, A. "Towards more relevance-oriented data mining research," *Intelligent Data Analysis* (12:2) 2008b, pp 237-249.

Wade, M. "Exploring the Role of Information Systems Resources in Dynamic Environments," International Conference on Information Systems, 2001, pp. 491-496.

Wade, M., and Hulland, J. "Review: The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research," *MIS Quarterly* (28:1), March 2004 2004, pp 107-142.

Wailgum, T. "To Hell with Business Intelligence: 40 Percent of Execs Trust Gut," in: *CIO*, 2009.

Wang, E.T.G., Shih, S.-P., Jiang, J.J., and Klein, G. "The consistency among facilitating factors and ERP implementation success: A holistic view of fit," *Journal of Systems and Software* (In Press, Corrected Proof) 2008.

Warrick, D.D. "Teaching and Championing O.D.: Desigining an Introductory Course For Students and Managers," *Organization Development Journal* (24:3), Fall2006 2006, pp 92-97.

Watson, H.J., and Carr, H.H. "Organizing for Decision Support System Support: The End-User Services Alternative," *Journal of Management Information Systems* (4:1), Summer 1987, pp 83-95.

Watson, H.J., and Wixom, B.H. "The Current State of Business Intelligence," *Computer* (40:9) 2007, pp 96-99.

Watson, H.J., Wixom, B.H., Hoffer, J.A., Anderson-Lehman, R., and Reynolds, A.M. "REAL-TIME BUSINESS INTELLIGENCE: BEST PRACTICES AT CONTINENTAL AIRLINES," *Information Systems Management* (23:1), Winter2006 2006, pp 7-18.

Weick, K.E., and Roberts, K.H. "Collective mind in organizations: heedful interrelating on flight decks," *Administrative Science Quarterly* (v38:n3) 1993, p p357(325).

Weill, P., and Aral, S. "Generating Premium Returns on Your IT Investments," *MIT SLOAN MANAGEMENT REVIEW* (47:2) 2006, pp 39-48.

Weill, P., and Ross, J.W. *IT Governance* Harvard Business School Press, Boston, MA, 2004.

Wernerfelt, B. "A Resource-based View of the Firm," *Strategic Management Journal* (5:2) 1984, pp 171-180.

White, M. "Exploitation and Discovery," in: *EContent*, 2008, pp. 29-29.

Williams, S. "Assesing BI Readiness: A Key to BI ROI," *Business Intelligence Journal* (9:3) 2004, pp 15-23.

Williams, S., and Williams, N. *The Profit Impact of Business Intelligence* Morgan Kaufmann Publishers, San Francisco, CA, 2007.

Wirtenberg, J., Lipsky, D., Abrams, L., Conway, M., and Slepian, J. "The Future of Organization Development: Enabling Sustainable Business Performance Through People," *Organization Development Journal* (25:2), Summer2007 2007, pp P11-22.

Wissema, J.G., and Van der Pol, H.M. "Strategic Management Archetypes," *Strategic Management Journal* (1:1) 1980, pp 37-47.

Wixom, B.H., and Watson, H.J. "An Empirical Investigation Of The Factors Affecting Data Warehousing Success," *MIS Quarterly* (25:1), March 2001 2001, pp 17-41.

Wixom, B.H., Watson, H.J., Reynolds, A.M., and Hoffer, J.A. "Continental Airlines Continues to Soar with Business Intelligence," *Information Systems Management* (25:2), Spring 2008, pp 102-112.

Yeatts, D.E., and Barnes, D. "What are the key factors for self-managed team success?," *Journal for Quality & Participation* (19:3) 1996, p 68.

Yin, R.K. *Case Study Research Design and Methods* Sage Publications, Inc., Thousand Oaks, CA, 2003.

Young, B.S., Arthur Jr, W., and Finch, J. "PREDICTORS OF MANAGERIAL PERFORMANCE: MORE THAN COGNITIVE ABILITY," *Journal of Business & Psychology* (15:1), Fall2000 2000, pp 53-72.

Zeid, A. "Your BI Competency Center; A Blueprint for Successful Deployment," *Business Intelligence Journal* (11:3) 2006, pp 14-20.

Zmud, R.W. "INDIVIDUAL DIFFERENCES AND MIS SUCCESS: A REVIEW OF THE EMPIRICAL LITERATURE," *Management Science* (25:10) 1979, pp 966-979.

Zuboff, S. *In The Age of the Smart Machine: The Future of Work and Power* Basic Books, Inc., New York, NY, 1988.

Appendix A - Interview Record:

Initials	Title	Industry	Date of Interview
TF	Senior Director Data Management	Financial Services	July 21, 2008
ME	Senior Director enterprise data warehouse	Financial Services	August 8, 2008
KB	Director data stewardship	Financial Services	August 8, 2008
RC	Director business analytics	Financial Services	August 8, 2008
SH	Director Data Delivery	Financial Services	August 8, 2008
JD	Director collections analytics	Financial Services	August 8, 2008
RD	Business Analyst	Financial Services	September 18, 2008
MW	Engagement Manager	Defense contracting	October 16, 2008
AM	Security Compliance Manager	Petrochemical	October 20, 2008
PB	Director Database Management	Healthcare	October 20, 2008
SM	Database Administrator	Financial Services	October 22, 2008
RV	Business Analyst	Financial Services	October 27, 2008
KJ	Systems Analyst	Financial Services	October 30, 2008
HW	Customer Service manager	Financial Services	October 31, 2008
RG	Market Analyst	Financial Services	November 4, 2008
MR	Principal	BI Consulting	November 9, 2008
GH	Senior Consultant	IS Consulting	November 10, 2008
MC	Systems Analyst	Financial Services	November 10, 2008
TE	Systems Analyst	Financial Services	November 11, 2008
KW	Systems Analyst	Financial Services	November 13, 2008
DF	Operations Analyst	Financial Services	November 17, 2008
MH	Business Development Manager	Systems Integration	November 18, 2008

Appendix B - Interview Guide

The interview will be preceded by a discussion of informed consent. The investigator shall read the informed consent form and make sure the interviewee understands consent before continuing. The interviewee's signature on the consent form will signify their understanding and consent to continue. (This will be used a guideline for discussions and should not limit the questions or answers pursued)

Background Information:

1. How would you define the concept of business intelligence?
2. Do you use business intelligence systems regularly in your work?
    a. If so, why?
    b. If not, why not?

Comprehension:

3. How would you characterize your experience with business intelligence systems?
4. What is the nature of the types of problems for which you use business intelligence systems?
5. How have the BI systems available impacted the way you perform your job, if at all?
6. How well do the BI systems available to you meet your needs?
7. Did you use BI before you came to this company?
8. What skills or knowledge do you find most useful for being able to use BI capabilities?
9. How has BI contributed to:

a. Your sources of funding/revenue
b. Your key clients or users
c. Your client needs being satisfied
d. The competition you face
e. Sources of risk to your firm
f. Operations reliability/quality
g. Your costs

Deftness:

10. In what ways does the organization support your use of BI systems?

    a. What are the specific policies or procedures regarding the use of BI, if any?
    b. What are the expectations regarding using data for decision making?

11. How do you perceive your peers view the use of BI systems? Do they support your use of these systems, if so in what way?

12. How do you perceive your management views the use of BI systems?

13. Has working at your company changed your perception of using BI as part of your work? If so, in what way?

14. Discuss how effectively your teams work together either as a result of BI or to support your BI initiatives

Success Measures:

15. Has your use of BI contributed to any of the following aspects of your organization:

    a. Enhance competitiveness or create strategic advantage.
    b. Enable the organization to catch up with competitors.
    c. Align well with stated organizational goals.
    d. Help establish useful linkages with other organizations.
    e. Enable the organization to respond more quickly to change.
    f. Improve customer relations.
    g. Provide new products or services to customers.
    h. Provide better products or services to customers.

i. Enable faster retrieval or delivery of information or reports.
j. Enable easier access to information.
k. Improve management information for strategic planning.
l. Improve the accuracy or reliability of information.
m. Improve information for operational control
n. Present information in a more concise manner or better format.
o. Increase the flexibility of information requests.
p. Save money by reducing travel costs.
q. Save money by reducing communications costs.
r. Save money by reducing system modification or enhancement costs.
s. Allow other applications to be developed faster
t. Allow previously infeasible applications to be implemented.
u. Provide the ability to perform maintenance faster.
v. Save money by avoiding the need to increase the work force.
w. Speed up transactions or shorten product cycles.
x. Increase return on financial assets.
y. Enhance employee productivity or business efficiency.

16. What other characteristics, either of individuals or of the organization, are critical for successfully reaping the benefits available from the capabilities of your organizations business intelligence systems?

Appendix C – BI assessment tool

Some of the competencies for benefiting from business intelligence (BI) exist at the level of individuals within the organization. The list below represents those characteristics of individuals that have been identified in this research as being important for BI success. Of the people in your organization who use business intelligence as a regular part of their work, evaluate the average level of ability in each of the following categories by entering an X in the appropriate box:

		Low 1	2	3	4	High 5
CS_1	Numerical Reasoning					
CS_2	Verbal Reasoning					
CS_3	Problem solving ability					
NCS_1	Verbal Communications					
NCS_2	Written communications					
NCS_4	Effective listening skills					
NCS_5	Data manipulation skills					
NCS_6	Tolerance for change and ambiguity					
NCS_7	Team orientation					
K_1	Understanding of organization’s business					
K_2	Understanding of competitive market					
K_3	Knowledge of data meanings					

Cognitive style represents the way that individuals make decisions. One scale that has been used to define cognitive style ranges from heuristic to analytic. Someone with a heuristic cognitive style tends to make decision based on “gut feel” rather than relying on data or analysis. A person with an analytic style looks to use data, facts, and analysis of this information to come to a decision. Please rate the average cognitive style of the individuals in the organization who use business intelligence as a regular part of their work on the 5 point scale below:

	Heuristi c 1	2	3	4	Analyti c 5
Cognitive style					

There are a set of competencies for successful BI that represent characteristics of the overall organization. While these characteristics may exist at an individual level, when the individuals in an organization work together the impact is not the same as the impact of their individual capabilities. The statements below represent the organizational level constructs that have been identified as being necessary for BI success. Please put an X in the box that most represents the extent to which you disagree or agree that the statement represents your organization:

		Disagree		**Neither agree nor disagree**		**Agree**
		1	**2**	**3**	**4**	**5**
LO_1	There is a well organized availability of training, both technical and business.					
LO_2	Management supports ongoing education.					
LO_3	There is an organizational expectation of continuous learning.					
LO_4	Leadership understands the of value of institutional memory					
LO5	Business goals are available to all members of organization.					
LO_6	Goals for BI systems are defined before building a system.					
F_1	The organization has a commitment to integrating data into operational projects.					
F_2	Funding is available to support the building and maintenance of BI systems.					
P_1	There is a well defined data environment including stewardship and metadata.					
P_2	Universal data access exists					
P_3	Data quality tools are generally available					
P_4	Data quality tools are used regularly across the organization					
P_5	Metadata tools are generally available					
P_6	Metadata tools are used regularly across the organization					
HC_1	There is a general understanding of data structures across the organization					
HC_2	People are generally available as necessary to support building,					

	maintaining, and use of BI systems					

Leadership style has been described as existing on a spectrum from authoritarian to Laissez-Faire. Authoritarian leaders tend to give direction with limited interaction with the rest of the organization. Laissez-Faire leadership exists when teams are self managed with very little direction or input from their leadership. In the middle is the participative or democratic style. Under this style leaders actively seek input from various levels of the organization, but then provide clear direction based on this input. Please rate the prevalent leadership style relative to the dimensions below by putting an X in the appropriate box.

	Authoritarian		**Participative**		**Laissez-Faire**
	1		**3**		**5**
The leadership of my organization generally uses this leadership style.					

While all of the individual and organizational characteristics listed above have been identified as having an impact on BI success, each does not necessarily have the same impact. Please put an X in the box that represents the importance, or impact of each of the factors below to the success of BI where 1 means limited impact or unimportant while 5 represents extremely important:

	Unimportant 1	**2**	**3**	**4**	**Extremely Important 5**
Numerical Reasoning					
Verbal Reasoning					
Problem solving ability					
Verbal Communications					
Written communications					
Effective listening skills					
Data manipulation skills					
Tolerance for change and ambiguity					
Team orientation					
Understanding of organization's business					
Understanding of competitive market					
Knowledge of data meanings					
Cognitive Style					
There is a well organized availability of training, both technical and business.					
Management supports ongoing education.					
There is an organizational expectation of continuous learning.					
Leadership understands the of value of institutional memory					
Business goals are available to all members of organization.					
Goals for BI systems are defined before building a system.					
The organization has a commitment to integrating data into operational projects.					
Funding is available to support the building and maintenance of BI systems.					
There is a well defined data environment including stewardship and metadata.					
Universal data access exists					
Data quality tools are generally available					
Data quality tools are used regularly					

across the organization					
Metadata tools are generally available					
Metadata tools are used regularly across the organization					
There is a general understanding of data structures across the organization					
People are generally available as necessary to support building, maintaining, and use of BI systems					
Leadership style					

VITA

Lewis Chasalow was born in Washington, DC. He graduated from Lehigh University with a BS and MS in industrial engineering with emphasis on operations research and management information systems.

After graduation Lew worked for Western Electric Company in Reading, PA as a manufacturing engineer in integrated circuit manufacturing, as part of the AT&T Corporation. He worked for AT&T for nearly 20 years in various positions ending up as a director of information systems before moving to IBM. After working for IBM for a year he moved to a Wavebend consulting where he worked as a technology director managing software development consultants for a variety of clients. From there he was offered the position of Chief Operating Officer of Grafica.eCRM, building their initial business plan and getting the business started. He subsequently moved to Richmond, VA to take a position as a data management director with Capital One Corporation.

In 2004 he entered the Ph.D. program at VCU while working at Capital One. In 2006 he left Capital One to complete the Ph.D. and to prepare for a career in academia. He is a member of Tau Beta Pi, Phi Kappa Phi, and Beta Gamma Sigma.