FACTORS INFLUENCING BI DATA COLLECTION STRATEGIES:

AN EMPIRICAL INVESTIGATION

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The purpose of this dissertation is to examine the external factors that influence an organizations' business intelligence (BI) data collection strategy when mediated by BI attributes. In this dissertation, data warehousing strategies are used as the basis on which to frame the exploration of BI data collection strategies. The attributes include BI insightfulness, BI consistency, and the organizational transformation attribute of BI.

The research population consisted of IT professionals and top level managers involved in developing and managing BI. Data was collected from a range of industries and organizations within the United States. An online survey was used to collect the data to empirically test the proposed relationships. Data was analyzed using partial least square path modeling (PLS).

The results of this study suggest that there exists a positive relationship between institutional isomorphism and BI consistency. The results also indicate that there exists a positive relationship between BI consistency and BI comprehensive data collection strategy, and the organizational transformation attribute of BI and BI comprehensive data collection strategy. These findings provide a theoretical lens to better understand the motivators and the success factors related to collecting the huge amounts of data required for BI. This study also provides managers with a mental model on which to base decisions about the data required to accomplish their goals for BI.

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CHAPTER 1

INTRODUCTION

With the promise of increased return on investment (ROI) and improved customer satisfaction, Business Intelligence (BI) is being embraced by many organizations to support decision-making throughout the enterprise. For example, Continental Airlines realized an ROI of over 1000 percent by successfully using BI in the areas of demand forecasting and tracking, fraud detection, improved data center management, and marketing (Anderson-Lehman et al., 2004). Similarly, First American Corporation, a financial bank successfully implemented BI to improve its customer loyalty and increase its ROI (Cooper et al., 2000).

However, not all organizations have realized success with BI. Gessner and Volonino (2005) suggest that many companies fail to realize business value even after heavily investing in BI. A BearingPoint survey taken in 2003 indicates that out of 167 companies with annual revenue over $1 billion, only 37 percent achieved the performance they expected from BI investments (Gessner and Volonino, 2005). Thus, a good bit of research in the last few years has been conducted to determine the factors that contribute to the successful implementation of BI (Jourdan et al., 2008).

Much of the research about BI focuses on artificial intelligence (AI) (Baesens et al., 2003; Bose and Mahapatra, 2001), benefits (Cooper et al., 2000; Watson et al., 2002), decision making (Park, 2006), implementation (Hwang et al., 2004), and BI strategies (Allmendinger and Lombreglia, 2005; Andriole, 2006). The BI related research on AI within BI examines the applications and algorithms of AI for classification, machine learning, predicting, and web mining (Jourdan et al., 2008). The research about BI benefits largely focuses on the use of enterprise wide BI, data warehousing, and data mining to realize quantifiable economic benefits (Cooper et al., 2000; Jourdan et al., 2008; Watson et al., 2002). Research on decision making focuses on improving decisions made in an organization using BI (Jourdan et al., 2008; Park, 2006). Research on implementation examines the various project management issues involved in implementing BI (Hwang et al., 2004, Jourdan et al., 2008, Jukic, 2007), and research about BI strategies emphasizes the application of BI tools and technologies in the modern business environment (Ganapathy et al., 2004; Grover and Vasvani, 2000; Jourdan et al., 2008; Makadok and Barney, 2001).

There are few studies, however, that examine the factors that influence the data collection strategy for BI. BI is "the acquisition, interpretation, collation, assessment, and exploitation of business related information" (Marshall et al., 2004, p. 873). Therefore, data and information play an important role in BI applications. BI applications involve extensive use and analysis of data to support managerial activities and decision making (Burton et al., 2006). The amount of data gathered by companies is also rapidly growing (Dobbs et al., 2002). Therefore, the organizations data collection strategy may form a crucial foundation for BI success and differentiate between organizations that successfully implement BI to realize high benefits and organizations that are unable to gain high benefits through their BI.

In the current rapidly changing business environment, the success and the very survival of an organization often depends on timely and effective use of data and business information (Lonnqvist and Pirttimaki, 2006). One purpose of BI is to enable organizations to manage the huge stock and flow of this data and business information in an effective way (Lonnqvist and Pirttimaki, 2006). Therefore, an organization's approach to the collection of BI data may play an important role in an organization's ability to successfully utilize BI. However, a consistent picture of how to collect data for BI has not yet emerged. The purpose of this dissertation research is to examine the forces that influence an organization's BI data collection strategy. In this study I examine the different types of data collection strategies that can be used for BI. I draw on institutional theory (DiMaggio and Powell, 1983), research about competitive pressure (Porter, 1987), and research about the purpose of BI to build a theoretical model.

Institutional theory addresses the role of environmental pressures on the adoption of information technology by an organization (Salmeron and Bueno, 2005). Early adopters of technology adopt in order to improve performance. Once the technology becomes widespread, gaining legitimacy becomes the chief driving force behind the adoption of the technology (DiMaggio and Powell, 1983). DiMaggio and Powell (1983) argue that organizations are competing to achieve institutional legitimacy and political power for economic and social rewards in addition to competing for customers and resources. This leads to organizations within the same environment becoming more and more similar. DiMaggio and Powell use the term *isomorphism* to describe this phenomenon. They define isomorphism as "a constraining process that forces one unit in a population to resemble other units that face the same set of environmental conditions" (p. 149). The theory on institutional isomorphism, therefore, addresses how external environmental forces pressure organizations to act in a similar way.

Institutional theory has been applied in information systems research to explain assimilation and adoption of different systems in an organization (Liang et al., 2007; Teo et al., 2003). Teo et al.. (2003) suggest, for example, that isomorphic processes have been a strong driving force for the adoption of electronic data interchange (EDI). Lai et al.. (2006) investigates the influence of institutional isomorphism in the adoption of technology for supply chain management. Liang et al.. (2007) studies the role of institutional forces on the assimilation of

ERP systems in an organization. Others posit that institutional forces greatly influences enterprise information systems configuration (Gosain, 2004)

BI may very well be subject to isomorphism because BI technology has pervaded every large industry sector including retail, finance, banking, insurance and security, services, government, and manufacturing (Olszak and Zeimba, 2006). This ubiquitous nature of BI technology may force different organizations to adopt BI in order to gain legitimacy within their environment. I extend the concept of institutional isomorphism to the context of BI data collection strategies. I suggest that the data collection strategy for BI may be influenced by external environmental pressures. As organizations seek to adopt BI for legitimacy, they may also seek to establish their BI in a way as to be consistent with other organizations. Thus, in this dissertation I rely on the institutional theory lens to examine BI data collection strategies.

I also investigate how competitive pressure influences data collection strategy for BI. Competitive pressure is different from institutional pressures. Competitive pressure helps to explain why organizations function differently within the same environment as compared to institutional pressures that helps to explain why organizations are similar. Competitive pressure is "the degree of pressure that the company feels from competitors within the industry" (Zhu and Kramer, 2005, p. 70). Porter and Millar (1985) examine the strategic rationale behind competitive pressure as the driving force for innovation and diffusion. They suggest that companies can change the competitive landscape in which they operate by incorporating new innovations that help to alter the rules of competition and give these companies new ways to outperform their rivals. In information systems research, competitive pressure has been used to study the adoption of technologies such as EDI (Riggins and Mukhopadyay, 1994; Iacovou et al.,

1995) and data warehousing (Hwang et al., 2004). Robertson and Gatignon (1986) posit technology adoption is highly influenced by competitive pressure.

Porter (1987) further argues that competitive pressures within the environment in which a firm operates have a significant role in the firm's strategic decisions. Competitive pressure is a key driving force behind business strategies in an organization (Bradford and Florin, 2003). When an organization is operating in a highly competitive environment there is a constant need to continuously evaluate existing strategy and make changes in order to keep up with the competition (Premkumar et al., 1997). Under high competitive pressure, organizations may reevaluate their current strategy for managing data in their firm and adopt different strategies to leverage their data in order to stay ahead of competition. Extending this concept of competitive pressure to BI, I suggest that competitive pressures may influence an organizations BI data collection strategy.

In this dissertation, I further assign attributes to BI based on the purpose for which BI is implemented in the organization and also examine to what extent these BI attributes mediate the effect of institutional pressures and the competitive pressures on the BI data collection strategy. BI is primarily used to support decision making (Gould, 2001; Massa and Testa, 2004; Negash, 2003; On, 2006) and is considered by many researchers as an extension of decision support system (Negash, 2003; Thomsen, 2003). However, research about BI indicates that managers perceive the purpose of BI to be more than just to support decision making. For example, one purpose of BI is to help organizations manage the huge stock and flow of data and business information in an effective way to enhance enterprise performance (Lonnqvist and Pirttimaki, 2006; Clark et al., 2007). Another purpose of BI is to enable organizations to identify new business opportunities, cost-cutting ideas, and to react quickly to retail demand (Dragoon, 2003;

Gessner and Volonino, 2005). Furthermore, research indicates that the purpose for which data is collected influences the data warehousing strategies which form an underlying foundation for most BI (Sen and Sinha, 2005; Watson, 2006). Therefore, the BI attributes based on the purpose for which BI is implemented plays an important role in BI data collection strategy.

This dissertation primarily studies the relationship of institutional forces and competitive pressure on an organization's BI data collection strategy when being mediated by the attributes of BI.

Data is collected using a field survey method. The constructs used in this study are operationalized based on definitions from existing research. The research population consists of IT professionals and top level managers involved in developing and managing BI. The sampling frame consists of BI professionals maintained by a marketing research company, L.I.S.T. Inc.

This study has implications for both academicians and practitioners. One contribution is the development and testing of cogent framework from within which to study BI data collection. Findings will provide an empirical and theoretically grounded lens through which to better understand the motivators and success factors associated with collecting the vast quantities of data required for BI. These findings will also provide mangers with insight into how to develop strategies and plans for collecting data that match the purpose of the BI. This research also provides managers with a mental model on which to base decisions about the data required to accomplish their goals for BI.

The rest of the dissertation is organized as follows. In chapter 2, the theoretical framework is developed by presenting a review of the literature on institutional theory, competitive pressure concepts, purpose of BI concepts (BI attributes), and BI data collection strategies. Hypotheses based on the theoretical model are also proposed in this chapter. In chapter 3, a methodological description is provided. In this chapter a description of the operationalization of the constructs used is also given, and issues regarding reliability and validity of the measures used are described. In chapter 4, the results of the study are presented and, in chapter 5 discussion regarding findings and contributions are provided. Limitations of the study, its implications, and directions for further research are also provided in chapter 5.

CHAPTER 2

LITERATURE REVIEW

In this section I present the theoretical support for the study. I first discuss the importance of BI data collection strategies for the success of BI projects. I then review and present the extant literature associated with BI data collection strategies. From the literature review I investigate the theories that may explain the variance underlying the organization's decision choices for selecting different strategies with respect to BI implementation. Based on the relevant theories, I then propose several hypotheses.

In the last decade, BI has evolved as one of the critical applications in organizations to provide useful insight, support decision-making, and drive organizational performance (On, 2006). BI has permeated various industries including retail, insurance, banking, finance and securities, telecommunications, and manufacturing (Olszak and Zeimba, 2006). Companies such as Continental Airlines and First American Corporation (FAC) have successfully implemented BI to improve their customer loyalty and increase their ROI (Anderson-Lehman et al., 2004; Cooper et al., 2000). There are other organizations, however, that have not been as successful in utilizing BI to increase their profit and achieve their expected performance (Gessner and Volonino, 2005).

Such mixed results have motivated researchers and managers to examine the factors that contribute to the successful implementation of BI (Jourdan et al., 2008). BI researchers have focused on topics such as artificial intelligence, benefits, decision-making, implementation, strategies, and measurement of BI (Jourdan et al., 2008). Table 1 provides a summary of this research.

Table 1: Major Research Topics Addressed in BI Research

Topics in BI	Citations	Content
Artificial Intelligence	Cui et al.. (2006) Churilov et al.. (2005) Kim et al.. (2005) Baesens et al.. (2003) Bradley et al.. (2002) Bose and Mahapatra (2001) Jain and Vazirani (2001)	Research in this area examines the application and algorithms of Artificial Intelligence classification, machine learning, predicting, and web-mining
Benefits of BI	Fan et al.. (2006) Bose and Pal (2005) Anderson-Lehman et al.. (2004) Watson et al.. (2002) Apte (2002) Cooper et al.. (2000) Hui and Jha (2000) Glassey (1998)	Research in this area focuses on the use of enterprise wide BI, data warehousing, and data mining to realize quantifiable economic benefits
Decision-Making using BI	Bose (2006) Park (2006) Little (2004) Boonstra (2003) Speier and Morris (2003) Sauter (1999)	Research in this area focuses on improving decisions made in an organization using BI
Implementation of BI	Jukic (2006) Malhotra et al.. (2005) Hwang et al.. (2004) Gorla (2003) Shin (2002) Hasselbring (2000) Rundensteiner et al.. (2000)	Research in this area examines the various Project management issues involved in implementing BI
Strategies	Andriole (2006) Allmendinger and Lombreglia (2005) Chiasson and Davidson (2005) Ganapathy et al.. (2004) Earl (2001) Makadok and Barney (2001) Grover and Vasvani (2000)	Research in this area focuses on different strategies and the applications of tools and technologies in the modern business environment for BI implementation
Measuring BI	Lonnqvist and Pirttimaki (2006) Hoadley (2004) Davison (2001) Kilmetz and Bridge (1999) Kelly (1993)	Research in this area addresses different metrics to assess the value of BI in an organization

There are, however, a limited numbers of studies that examine the factors that affect data collection strategies for BI.

The effectiveness of BI lies in its ability to present business information in a timely manner (Clark et al., 2007; King, 2007; Lonnqvist and Prittimaki, 2006; Manglik, 2006; Marshall et al., 2004). Thus, the success of any BI project depends on the data available. Furthermore, research indicates that data consistency and data quality are a major cause of the success or failure of BI initiatives (Ballou and Tayi, 1999; Dubois, 2005; Marshall et al., 2004). Data collection does not refer just to the collection of data for BI applications, but it is also concerned with providing clean, consistent, high quality, and integrated data for BI applications (Moss and Atre, 2003). Therefore, data collection has an important role in the success of BI.

The data for BI is generally stored in a central repository known as the data warehouse (Eckerson, 2006; Sen and Sinha, 2005). Data warehousing strategies involve the collection and integration of data for BI purposes (Eckerson, 2006). Therefore examining the data warehousing architectures and strategies helps guide our understanding of BI data collection strategies. BI research provides considerable evidence about data warehousing strategies and architectures that can be used for BI for decision-making (Ariyachandra and Watson, 2005; Jukic, 2006). Commonly used data warehousing strategies include the collection and integration of data to design independent data marts, and the collection and integration of data to design enterprise wide data warehouses (Breslin, 2004; Sen and Sinha, 2005). The design of independent data marts is also referred to as the bottom-up approach for BI data collection (Breslin, 2004; Watson, 2006). This consists of collecting and integrating data to initially support either a single business process or a single business unit and then slowly expanding the structure to support more business units (Breslin, 2004; Jukic, 2006). This type of strategy is application centric.

Therefore, analytical and business requirements must be clearly defined prior to building a data mart (Watson and Haley, 1998; Sen and Sinha, 2005).

The second strategy consists of collecting, integrating, and placing all the data within an enterprise into a single repository called the enterprise wide data warehouse (Watson and Haley, 1998). The design of an enterprise wide data warehouse is also referred to as a top-down approach for BI data collection (Breslin, 2004). With this type of strategy it is not possible to define all the project requirements prior to building the warehouse (Sen and Sinha, 2005). The purpose of this strategy is to provide a single version of the truth that can help in enhancing decision performance within the organization (Watson, 2006).

Research has examined some factors that affect the selection of different data warehousing strategies. These factors include information interdependence between organizational units (Ariyachandra and Watson, 2005; Messa and Testa, 2005; Watson, 2006), upper management's information needs (Aryachandra and Watson, 2005), urgency of need for a data warehouse (Ariyachandra and Watson, 2005; Breslin, 2004), constraint on resources (Ariyachandra and Watson, 2005; Breslin, 2004), compatability with existing systems(Ariyachandra and Watson, 2005; Sen and Jacob, 1998), perceived ability of the in-house IT staff (Ariyachandra and Watson, 2005; Breslin, 2004), technical issues (Ariyachandra and Watson, 2005; Grover et al., 1999, Schick, 2006; Sen and Sinha, 2005), and expert influence (Ariyachandra and Watson, 2005; Jukic, 2006). Table 2 provides a summary of factors that affect data warehousing strategies.

Table 2: Factors Influencing Data Warehousing Strategies

Factors affecting data warehousing strategies	**Citations**	
Information Interdependence between Organizational Units	Ariyachandra and Watson (2005) Watson (2006)	All these studies are conceptual in nature and do not carry out any empirical investigation. Ariyachandra and Watson (2005) conducted a descriptive study and based on the factors given on the first column suggested centralized data warehouse architecture and independent data marts architecture to be the most popular data warehouse strategies.
Upper management's information needs	Ariyachandra and Watson (2005)	
Urgency of Need for a Data Warehouse	Ariyachandra and Watson (2005) Breslin (2004)	
Constraint on resources	Ariyachandra and Watson (2005) Breslin (2004)	
Compatibility with Existing Systems	Ariyachandra and Watson (2005) Sen and Jacob (1998)	
Perceived Ability of the In-House IT Staff	Ariyachandra and Watson (2005) Breslin (2004)	
Technical Issues	Ariyachandra and Watson (2005) Schick (2006) Sen and Sinha (2005)	
Expert Influence	Ariyachandra and Watson (2005) Jukic (2006)	

Although these studies provide a descriptive view of factors that influence data warehousing strategies, a consistent picture of how to collect data for the purpose of BI has not emerged. Furthermore, these studies investigate strategies from the perspective of factors that arise from within the organization. They are largely silent about factors in the organization's external environment that may affect BI data collection strategies. Research has, however, shown that external environmental factors such as institutional forces and competitive pressures play an important role in strategy and in the adoption of technology (Gosain, 2004; Robertson and Gatignon, 1986). The decision to implement BI is often a strategic decision that requires top management support (Moss and Atre, 2003). Therefore, in this dissertation I define BI data collection strategies based on the data warehousing strategies and examine the influence of external environmental factors on BI data collection strategies. Institutional theory and research about competitive pressure provides a powerful lens with which to examine the role of external factors that influence strategic decision making in an organization (Liang et al., 2007; Mizruchi and Fein, 1999; Porter, 1987).

Institutional theory helps examine organizational decision making from the perspective of the influence of external institutions (Powell and DiMaggio, 1991). This theory posits three different mechanisms – *coercive isomorphism, mimetic isomorphism,* and *normative isomorphism* through which external institutions influence an organization to incorporate changes and make decisions regardless of whether the decisions improve organizational efficiency (DiMaggio and Powell, 1983; Lai et al., 2006). Thus, institutional theory suggests that once technology becomes widespread, then organizations adopt that technology to gain legitimacy within the industry rather than improving efficiency (DiMaggio and Powell, 1983). BI technology has pervaded every industry sector including banking, finance, insurance and security, government, services, retail, and manufacturing (Olszak and Zeimba, 2006), and thus may be subject to institutional isomorphism.

The competitive pressure within which an organization operates also influences the decisions of an organization (Bradford and Florin, 2003). Firms implement BI to address competitive pressure within their environment and to stay ahead of the competition within their industry sector (Schiff, 2006). The competitive pressure within the environment in which a firm operates plays a significant role in the way top management make strategic decisions (Porter, 1987), and BI implementation is often a strategic decision that relies heavily on top executives

(Moss and Atre, 2003; Yeoh et al., 2005). Therefore, I rely on institutional theory (DiMaggio and Powell, 1983), and research about competitive pressure (Porter, 1987) to develop the theoretical model.

Strategies used for BI data collection vary, depending on the attributes of BI, i.e., the purpose for which BI is implemented. One purpose of implementing BI might be to have a single data source that supports few applications, whereas another might be to integrate different data sources that support and provide autonomy to different business units within the same organization (Watson and Haley, 1998; Messa and Testa, 2005). Still another purpose may be to integrate enterprise wide data sources that provide a single version of truth for transforming organizations to gain competitive advantage (Watson and Haley, 1998; Messa and Testa, 2005; Watson, 2006). Although research indicates the purpose of BI, and thereby BI attributes to be a driving force behind the selection of BI data collection strategy (Sen and Sinha, 2005; Watson, 2006), there are few, if any, empirical studies that examine at the relationship between the attributes of BI and BI data collection strategies. Therefore, this study examines the influence of institutional isomorphism and competitive pressure on BI data collection strategy mediated by the attributes of BI. Figure 1 provides the conceptual model of the study that serves to guide the reader through the remainder of the chapter. Each block in the conceptual model is discussed in the following sections. First, I discuss institutional isomorphism, then competitive pressure, BI attributes, and BI data collection strategies.

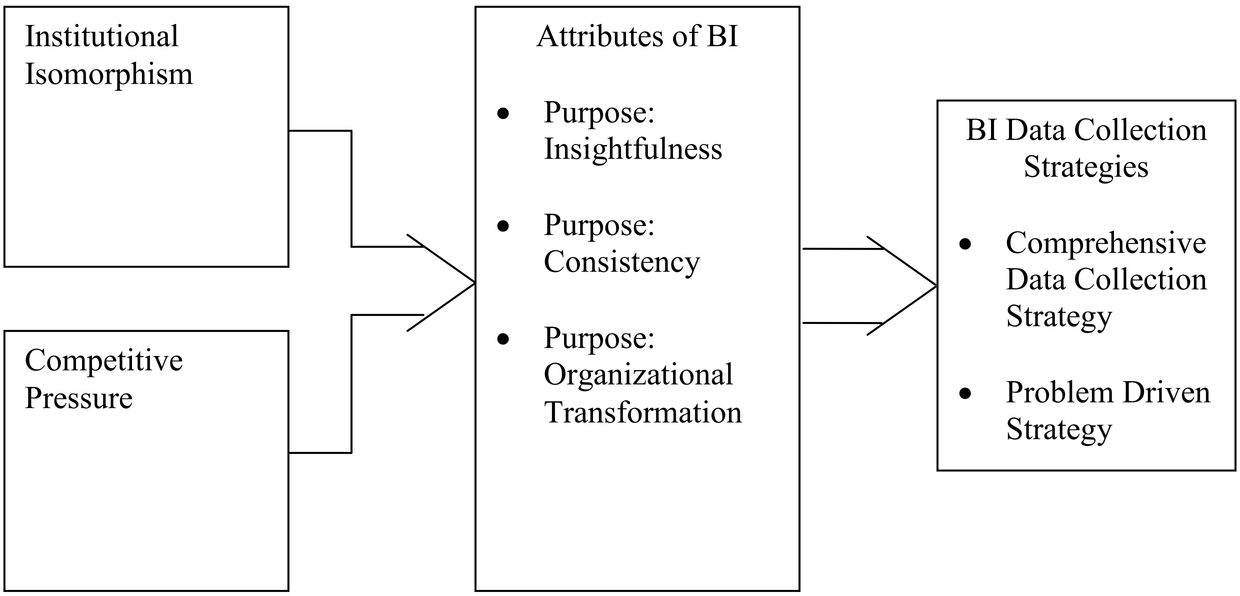

Figure 1: Conceptual Framework of BI Data Collection Strategy

Institutional Isomorphism

Institutional theory plays an important role in explaining the influence of external political, social, and technical environments on organizational behavior (Liang et al., 2007). It examines the processes through which structures such as norms, rules, and routines become authoritative guidelines for social behavior (Scott, 1995). Institutional theory suggests that organizational changes are driven more by the need to achieve legitimacy than the desire for efficiency (DiMaggio and Powell, 1983; Liang et al., 2007). This desire to achieve legitimacy gives rise to institutional isomorphism where organizations within the same environment become more similar without necessarily becoming more efficient (DiMaggio and Powell, 1983; Liang et al., 2007). Therefore, the theory on institutional isomorphism helps explain how external environmental forces pressure organizations to act in a similar way.

The three mechanisms through which institutional isomorphism are facilitated include coercive isomorphism, mimetic isomorphism, and normative isomorphism (DiMaggio and

Powell, 1983). Coercive isomorphism occurs when organizations submit to "both formal and informal pressures exerted on them by other organizations upon which they are dependent and by cultural expectations in the society within which the organization function" (Dimaggio and Powell, 1983, p. 150). Policies and regulations from government, industry, and professional networks and associations also results in coercive isomorphism (Gular et al., 2002; Mezias, 1990; Tolbert and Zucker, 1983).

Mimetic isomorphism arises from an organization's response to uncertainty (DiMaggio and Powell, 1983; Lai et al., 2006). Organizations try to cope with uncertainty by mimicking the actions of other organizations that they perceive to be successful within a similar environment (DiMaggio and Powell, 1983; Liang et al., 2007). Normative isomorphism results from "the collective struggle of members of an occupation to define the conditions and methods of their work, to control the production of producers and to establish a cognitive base and legitimization for their occupational autonomy" (DiMaggio and Powel, 1983, p. 152). Thus, normative isomorphism relates to the pressure exercised by professional associations by creating a cognitive base and legitimization for the autonomy of the industry (Lai et al., 2006).

Institutional theory has been widely used by researchers in the social sciences, accounting, financial, and management disciplines. For example, institutional theory is used to examine the social construction of organizational knowledge (Mizruchi and Fein, 1999) and to understand the diffusion of organizational practices across different countries (Guler et al., 2002). Haveman (1993) investigates the relationship between structure of markets and the rate of market entry through the institutional theoretical lens. Others have used institutional theory to examine the financial reporting practices at the Fortune 200 companies (Mezias, 1990), the decrease in the diversity of research topics within the accounting academic discipline (Tuttle and

Dillard, 2007), the changes in accounting and financial information systems in an organization (Tsamenyi et al.; 2006).

Researchers have also applied institutional theory to issues in information systems (IS). IS practitioners' share a grasp of the various problems faced within their discipline and develop a body of knowledge and establish norms of good practice that helps managers implement strategies and information systems efficiently within their organization (Swanson and Ramiller, 1997). Furthermore, adoption of established practices is observed due to the diffusion of different personnel from different background across different organizations sharing a common vision regarding the practice of IS (Gosain, 2004; Swanson and Ramiller, 1997). Thus, in information systems, institutional theory is mainly used to explain the role of external pressures in the adoption and assimilation of different systems in an organization, particularly systems for which the technology is so widespread as to be viewed as ubiquitous (Teo et al., 2003; Gosain, 2004; Lai et al., 2006). For example Liang et al. (2007) employs institutional theory to examine the assimilation of ERP. The results indicate that mimetic, coercive, and normative isomorphism indirectly affect the assimilation of ERP in an organization through top management behavior and top management planning. Institutional isomorphism is also a driving force behind the widespread adoption of EDI (Teo et al., 2003). Many companies have implemented EDI because of direct pressure from powerful supply chain partners while others implement EDI because it has become such a widespread technology that it is viewed as a necessity (Jones and Beatty, 1998). Institutional theory has also been used to explain the importance of extent of coordination, strategic investment rationale, and top management championship on the effective assimilation of web technologies within an organization (Chatterjee et al., 2003). Executive information systems (EIS) is another type of IS that is highly influenced by all the three mechanisms –

coercive, mimetic, and normative institutional isomorphism (Gosain, 2004). Table 3 gives a brief overview of the use of institutional theory in IS research.

Table 3: IS Related Institutional Isomorphism Research

Concept	**Studies**	**Content**
Internet based information systems, e-commerce, and web-technologies	Butler (2003) Chatterjee et al.. (2002) Damsgaard and Scheepers (1999) Gibbs and Kraemer (2004) Wu et al.. (2003)	These studies employ institutional theory lens to examine the factors that influence the innovation and adoption of web-based and e-commerce technologies
EIS and ERP systems adoption, assimilation, and implementation	Gosain (2004) Hedman and Borell (2004) Liang et al. (2007)	These studies examine the factors influencing the adoption and assimilation of ERP and EIS systems in an organization
EDI Adoption	Teo et al. (2003)	Findings suggest that isomorphic processes play an important role in the adoption of electronic data interchange by organizations
Software Development	Adler (2005) Laudon and King (1985) Nicolaou (1999)	These studies examine the influence of institutional isomorphism within the context of software development.
Adoption of IT for Supply Chain Management	Lai et al.. (2006)	This study examines the implications of institutional isomorphism on the adoption of IT for supply chain management

Little research has applied institutional theory in the context of BI. It seems, however, that this lens is appropriate to examine BI strategies because BI technology is wide spread throughout most industry sectors including banking, finance, insurance and security, manufacturing, and retail (Olszak, and Zeimba, 2006). Data warehousing, an underlying foundation of most BI, is thought to be one of the more recent technologies that is influenced by institutional forces (Swanson and Ramiller, 2003). This ubiquitous nature of BI technology may influence different organizations to adopt BI in order to gain legitimacy within their environment. Therefore, institutional theory can provide insight into our understanding of various BI strategies including BI data collection strategies.

Competitive Pressure

I also examine the effect of competitive pressure on BI data collection strategies. Research about competitive pressure has its origin in strategic management and has been used extensively in understanding adoption, innovation, and diffusion of information technology in information systems research (Mata et al., 1995). Competitive pressure is defined as "the degree of pressure that the company feels from competitors within the industry" (Zhu and Kramer, 2005, p. 70). In a competitive environment, a firm can have a sustained competitive advantage only if it implements strategies not implemented by other firms within the same environment (Mata et al., 1995). The implementation of different strategies by different organizations can lead to organizational changes that are different for different organizations within the same environment. Thus, competitive pressure is different from institutional pressure. Competitive pressure helps explain why organizations function differently within the same environment as opposed to institutional forces which explains why organizations are similar.

The competitive pressure within which an organization operates is a driving force behind innovative business strategies in an organization (Bradford and Florin, 2003; Thong, 1999). There are different ways in which firms address competitive pressure. One way is to incorporate new innovations that alter the rules of competition by changing the industry structure within which they operate (Millar, 1985). Another way is to constantly evaluate current strategies and alter them to keep up with the competition (Premkumar et al., 1997). Technology adoption is also a way that organizations employ to address competitive pressure (Robertson and Gatignon, 1986). Finally firms may forge partnerships between different groups such as executives in engineering, manufacturing, marketing, and information systems in order to leverage a common vision and design new business systems as a means to address competitive pressure (Doll and Vonderembse, 1987).

Researchers within IS have mainly used competitive pressure to investigate the innovation and diffusion of different technologies within different organizations (Grover, 1993; Thong, 1999), the use of information systems in different industries (Doll and Vonderembse, 1987; Kim and Michelman, 1984), and how information technology changes the way an organization competes in a given environment (McFarlan and Warren, 1984, Parsons, 1983; Porter and Millar, 1984; Porter, 1987). For example, the adoption of computer-based inter-organizational systems by firms within an industry sector is due to the competitive pressure faced by those firms (Grover, 1993). Research has shown competitive pressure to be one of the major driving forces behind the integration of different information systems in hospitals (Kim and Michelman, 1984). Table 4 gives a brief overview of IS related competitive pressure research.

IS researchers have further examined the role of competitive pressure in the adoption of technologies such as data warehousing (Hwang et al., 2004), and EDI (Riggins and Mukhopdyay, 1994; Iacovou et al., 1995). Iacovou et al. (1995) posit competitive pressure to be one of the main driving forces behind the adoption of EDI by small firms. They suggest “as more competitors and trading partners become EDI-capable, small firms are more inclined to adopt EDI in order to maintain their own competitive position” (p. 470). This can be seen in the case of BI strategies also.

Table 4: IS Related Competitive Pressure Research

Concept	Studies	Content
Use of IS in small business	Chen et al.. (2000) Iacovou et al.. (1995) Thong (1999)	These studies examines the importance of use of information technology in small business to address competitive pressure
Use of IS in health care	Kim and Michelman (1985)	This study examines factors influencing the strategic role of information technology within the health care industry
Adoption of Data Warehousing technology	Hwang et al.. (2004)	This study indicates competitive pressure to be highly influential in the adoption of data warehousing technologies
IS and Competitive advantage	Mata et al.. (1995) McFarlan and Warren (1984) Parsons (1983) Porter (1987) Porter and Millar (1984) Rackoff et al.. (1985) Robertson and Gatignon (1986)	These studies address the use of information technology to achieve competitive advantage
Adoption of inter-organizational systems	Grover (1993) Riggins and Mukhopadyay (1994)	These studies indicate competitive pressure to be one of the factors that influence the adoption of inter-organizational systems in an organization

Research indicates competitive pressure to be very influential in the adoption of data warehouses – an underlying technology for BI (Hwang et al., 2004). Competitive pressure is also one of major factors that influenced First American Corporation (FAC) to adopt BI strategies. FAC adopted BI strategies to address the increasing competitive pressures from rival banks (Cooper et al., 2002). Furthermore, research has shown competitive pressure to be an influential factor that affects strategic decisions in an organization (Bradford and Florin, 2003; Porter, 1987).

Decisions regarding BI in an organization are strategic and involve top management (Eckerson, 2006; Moss and Atre, 2003; Williams and Williams, 2006; Yeoh et al., 2005). Furthermore, faced with competitive pressure firms may reexamine their current strategy for managing data and implement different strategies to leverage their data and stay ahead of competition. Therefore, competitive pressure may be highly relevant in understanding the data collection strategies that organizations employ for BI.

Attributes of BI

In this section, I explore and assign attributes to BI based on the purpose for which a BI project is initiated. BI is primarily used to support decision-making (Gould, 2001; Massa and Testa, 2004; Negash, 2003; On, 2006; Thomsen, 2003). However, the purpose of BI is more than just to support decision-making (Azoff and Charlesworth, 2004; Chou et al., 2005; Clark et al., 2007; Lonnqvist and Pirttimaki, 2006). Some of the reasons for implementing BI include enabling organizations to manage the flow of data and business information (Lonnqvist and Pirttimaki, 2006; Clark et al., 2007), presenting the business information in a timely and easily understandable way to the decision-makers (Azoff and Charlesworth, 2004; Chou et al., 2005), and identifying new business opportunities, cost-cutting ideas and reacting quickly to retail demand (Dragoon, 2003; Gessner and Volonino, 2005).

Furthermore, although there are well documented benefits of BI projects, it is important for organizations to articulate their reasons for implementing BI and relate it to the overall strategic business goals of the organization to achieve success with BI (Gangadharan and Swami, 2004; Moss and Atre, 2003). I define the purpose of BI as "the primary reasons that an organization initiates a BI project."

Data intensive applications such as ERP integrate the transactional data from different units such as finance, inventory management, HR, and purchasing and store them in master database for organizational planning (Chou et al., 2005). However, ERP systems do not support data analysis and decision support process (Chou et al., 2005). Companies rely on BI to make sense of the transactional data collected by ERP and other data intensive applications (Gould, 2001). Organizations further utilize BI to identify and control the vast flow of business information around and within the organization (Lonnqvist and Pirttimaki, 2006). Thus organizations implement BI to get a better understanding of strategic matters and trends that affects the business leading to informed decision-making (Chou et al., 2005; Gould, 2001; Lonnqvist and Pirttimaki, 2006). Firms, also implement BI to manipulate the existing data and generate various aspects of business views to empower employee decision capabilities (Chou et al., 2005).

BI assists in strategic and operational decision making by delivering insight into the existing business, creating forecast based on historical data, and answering specific non-routine questions (Marshall et al., 2004; Negash, 2004). For example, Office Depot, which runs a chain of around nine hundred and eighty stores in nine countries, implemented BI to manage and get better insight into its sales data (Cox, 2001). Thus, one of the primary reasons an organization undertakes a BI initiative is to better understand the current business and to derive decision-support benefit.

Another reason organizations implement BI is to achieve a single consistent view of business information (Eckerson, 2003; On, 2006; Watson et al., 2004). Enterprise data is constantly changing especially when organizations goes through acquisitions and mergers (Eckerson, 2003; On, 2006). Therefore, obtaining a single consistent version of business information is important for aiding in strategic and tactical decision making and for managing business process efficiently (Eckerson, 2003; On, 2006).

Obtaining a single version of the truth with regard to enterprise information helps in achieving high quality data and better data analysis (Eckerson, 2003; Watson et al., 2004). Having a single view of enterprise wide information also facilitates the development of new applications and saves time for users (Watson et al., 2004). It also avoids conflicts among different stakeholders within the organization because they have access to the same information (Massa and Testa, 2005). Thus, BI is used to provide consistent information across the enterprise and to various stakeholders in an organization. Sherwin-Williams, a leading developer, manufacturer, and distributor of architectural coatings and related products implemented BI to create a decision-support infrastructure that supports a single view of the supply chain (Watson et al., 2001). Similarly, 3M a manufacturing company initiated its BI project to obtain a single consistent view of its enterprise wide information (Helmaan, 2002).

Another purpose of BI is to enable organizational transformation. Here, the purpose of BI is to change the existing business model of an organization and to support the implementation of new business model to take advantage of external market (Watson, 2006). Thus, organizations initiate BI projects to find new ways of competing in the market. Harrah's entertainment is a well known example of an organization that implemented BI to enable organizational transformation (Lal, 2004; Watson, 2006). Harrah's entertainment adopted a brand approach where different casinos operated in an integrated manner as opposed to the existing paradigm of gaming industry where casino managers ran their properties independently (Watson and Volonino, 2002). Harrah's entertainment initiated BI project to support their new business strategy and thus become a leading organization in the gaming industry (Watson, 2006; Watson and Volonino, 2002).

Thus, based on the above discussions the reasons an organization may undertake BI initiative can be classified into three major categories:

- To understand current business and derive decision-support benefits
- To provide a single version of the truth
- To enable organizational transformation

Research indicates that the purpose for which data is collected influences the data collection strategies (Sen and Sinha, 2005; Watson, 2006; Williams and Williams, 2004). Therefore, the purpose of BI plays an important role in understanding the BI data collection strategies employed by organizations. In this dissertation, I further assign attributes to BI such that the each purpose of BI has an associated BI attribute. These attributes are insightfulness, consistency, and organizational transformation. Thus, the purpose of understanding current business and deriving decision-support benefits can be associated to the insightfulness attribute of BI. Similarly, the purpose of providing single version of the truth and enabling organizational transformation can be associated with the consistency and the transformation attributes of BI respectively. Simply stated, organizations leverage the insightfulness attribute of BI to understand their current business. Similarly, organizations leverage the consistency and the organizational transformation attributes of BI to provide single version of the truth and to enable organizational transformation respectively.

BI Data Collection Strategies

This section gives a detailed description of the different BI data collection strategies that are used in an organization during BI implementation. BI data collection refers to collecting and providing clean, consistent, high quality, and integrated data for BI applications (Eckerson, 2006; Marshall et al., 2004; Moss and Atre, 2003). The literature on BI and data warehousing suggests two strategies that can be employed for collecting and integrating data for BI purposes (Breslin, 2004; Jukic, 2005; Jukic, 2006).

The first strategy involves collecting, integrating, and storing all the data present in the organization into a single repository called the enterprise wide data warehouse (Ariyachandra, and Watson, 2005; Breslin, 2004; Jukic, 2005; Jukic, 2006). Extensive infrastructure planning is required for implementing this strategy (Ariyachandra and Watson, 2005; Watson and Haley, 1998). It can be a daunting task to define the requirements of such an initiative in advance (Sen and Sinha, 2005). As this strategy consists of collecting, integrating, and storing the majority of the data present in the organization into the data warehouse, I term this the comprehensive data collection strategy.

The comprehensive data collection strategy takes a data-centric approach where data is collected, integrated, and then tested (Moss and Atre, 2003; Sen and Sinha, 2005; Watson and Haley, 1998). The application programs for analyzing the data are written after the data is integrated (Sen and Sinha, 2005; Watson and Haley, 1998). Implementing a comprehensive data collection strategy is very time consuming and expensive (Watson and Haley, 1998; Watson et al., 2001). The funding and the initiative for the comprehensive data collection strategy generally stems from the IT unit of the organization (Watson and Haley, 1998). The manufacturing company 3M is an example of an organization that employed this strategy for implementing BI (Francis, 1995; Helmaan, 2002). 3M initiated a BI project to consolidate entire company information and to achieve the goal of having a single version of truth (Francis, 1995; Helmaan, 2002). This was done by collecting and integrating data from all of 3M's divisions into a single repository (Francis, 1995). Furthermore, the architecture for integrating all the data within the organization was planned and designed initially before implementing the strategy (Francis, 1995), which is an important factor in the comprehensive data collection strategy. The project was initiated by Mark Lahr, manager of 3M's IT data warehousing department (Helmaan, 2002).

Other examples of organization that implemented comprehensive data collection strategy for implementing BI include FAC and Universal Studios, Hollywood (Cooper et al., 2000; Smalltree, 2006). To achieve competitive advantage and become the innovative leader in the financial services industry, FAC employed the comprehensive data collection strategy and collected and integrated all the data present within the organization and stored it into a single repository (Cooper et al., 2000). Similarly, Universal studio, Hollywood also employed the comprehensive data collection strategy and integrated all its data sources to better manage their business (Smalltree, 2006).

The second strategy involves collecting and integrating data to provide solutions to a particular business unit initially. This occurs generally in response to some problem faced by that business unit or the organization. The driving force behind such a strategy is a single or a small set of applications that can provide potential benefits (Watson and Haley, 1998). Here, the BI application is seen as a powerful problem-solving tool that can enable access to relevant integrated data and thus enhance the decision making process of individual business units (Massa and Testa, 2005). Therefore, I term this strategy as the problem driven strategy for BI data collection.

The problem driven strategy takes an application-centric approach where the application required to solve the specific problems drives the collection and integration of relevant data sources (Sen and Sinha, 2005; Watson and Haley, 1998). This strategy generally involves building individual data marts that can integrate the required data sources and provide the necessary solutions to each business units (Breslin, 2004; Hwang and Cappel, 2002; Jukic, 2006). As the usage of BI continues, the amount of data collected slowly expands, and the data from different data sources are integrated to assist other business units. The initial cost required for this initiative is less compared to initiating an enterprise wide BI architecture as it can be completed quickly (Watson and Haley, 1998; Watson et al., 2001). This type of strategy is ideal for achieving quick win solution and can also serve as proof-of-concept for bigger BI initiatives (Watson and Haley, 1998). The funding and initiative for the problem driven strategy generally stems from individual business units within the organization (Watson and Haley, 1998).

The Hudson's Bay Company implemented BI using the problem driven strategy. Initially the company started with implementing a single data mart to support a single business unit. Then the data warehousing team added more data marts to support other business units. Finally, in 2003, they consolidated all the data marts to implement an enterprise wide data warehouse (Anonymous, 2007). Other examples of organizations that employed the problem driven strategy for BI data collection includes Kingspan Insulation (KI) that manufactures building materials and Office Depot which runs a chain of supply stores (Cox, 2001; Kelly, 2006). KI implemented BI to create reports to help in decision making (Kelly, 2006). In, KI each business area has a representative who controls the integration of data that is needed to create the reports important for that particular business area (Kelly, 2006). Thus, KI employs problem driven strategy for collecting and integrating data required for their BI. Similarly, Office Depot also employed problem driven strategy for its BI implementation (Cox, 2001). Office Depot faced the problem of managing and keeping track of their sales data coming from around 982 stores from across nine countries (Cox, 2001). In order to solve this problem, Office Depot collected and integrated all the sales data within the organization (Cox, 2001). Furthermore, the BI was mainly implemented to assist the sales division (Cox, 2001). Thus, here, data was collected and integrated to solve a particular problem faced by a particular division. Table 5 provides a summary of different authors that have examined these BI data collection strategies.

Research Model and Hypotheses

This section integrates the discussions given in the prior sections into a cogent research model. The research model is provided in Figure 2, and the following discussions address its development.

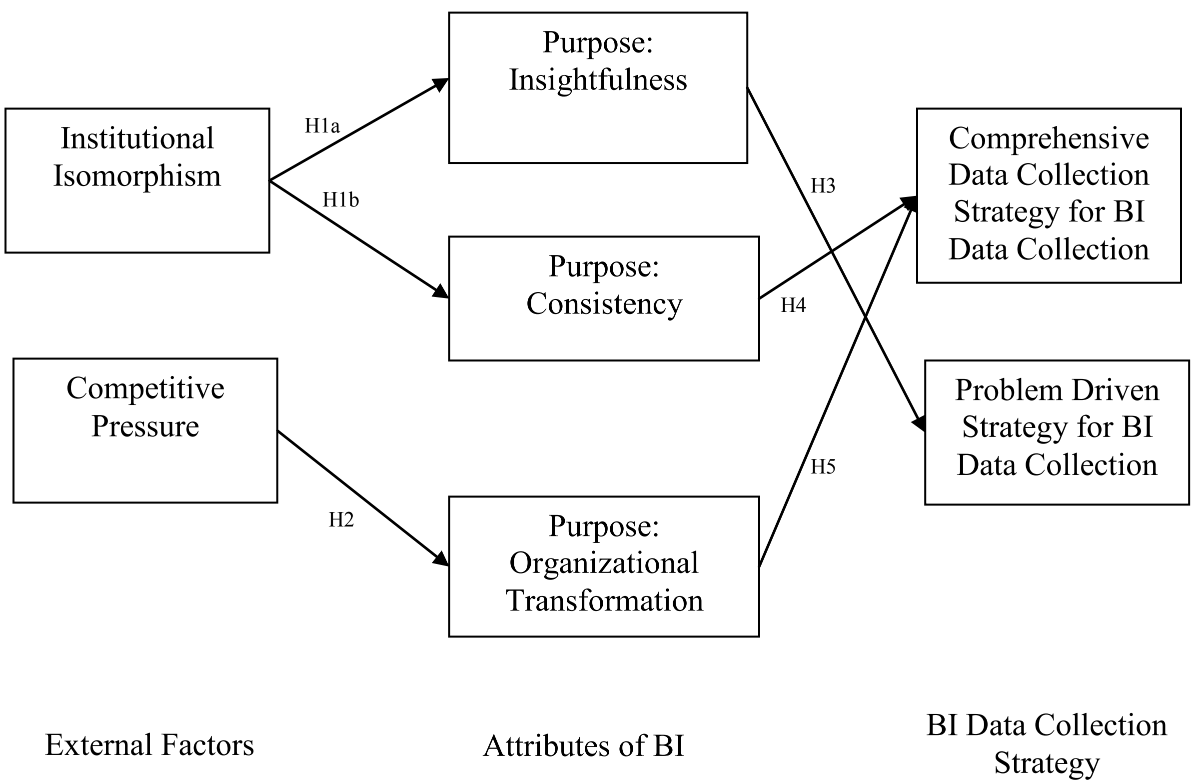

Figure 2: Research Model for BI Data Collection Strategy

Table 5: BI Data Collection Strategies

Author	Comprehensive Data Collection Strategy	Problem Driven Strategy	Purpose of the article
Jukic (2005)	The integration of all data occurs within a central data warehouse	A set of commonly used dimensions is designed first. Fact table corresponding to the subject of analysis is then added.	This article examines into different data modeling strategies for BI
Manglik & Mehra (2005)			This article examines different patterns of data integration
Anderson-Lehman et al. (2004)		The primary focus of building BI was to support pricing and revenue management decisions based on journey information. The warehouse initially integrated flight schedule data, customer data, and inventory data.	This article presents a case study on the successful use of BI by Continental Airlines
On (2006)			This article examines into managing data (data integration, data quality, semantic reconciliation, & meta data management) for BI purposes
Watson et al. (2004)		BCBSNC developed DW to address the problem related to information access and reporting capabilities	This article examines the driving forces, the development, and the governance of data warehouse at BCBSNC
Cooper et al. (2000)	All data regarding the clients such as client behaviors, client buying patterns, and client value positions were integrated and placed in a single data warehouse “VISION”	The main purpose of initiating the BI project was to have a better understanding of their customers	This article describes the development and use of data warehouse by FAC to become the innovative leader in the financial services industry
Watson et al. (2001)		Sherwin-Williams initially integrated data related to sales and then slowly expanded to include data related to cost information, raw materials, and point-of-sale data from major customers	This article compares and contrasts the top-down and bottom-up approach for developing data warehouse and describes Sherwin-Williams’ strategy for integrating data
Schwartz (2006)		The main purpose of initiating a BI project was to improve data quality. The focus was chiefly on integrating customer related data	This article presents a case study on the use of BI by IHOP

Author	Comprehensive Data Collection Strategy	Problem Driven Strategy	Purpose of the article
Gangadharan & Swami (2004)	The electronic and electrical manufacturing company (case study) uses a comprehensive data collection strategy as they create a central source of information by developing a comprehensive data warehouse		This article describes the different stages involved in implementing a BI project and gives an example of BI implemented by an electronic electrical manufacturing company in India
Helmaan (2002)	Integrated all the data present to achieve the goal of "single version of the truth"		This article provides excerpts of interview of Mark Lahr (manager of 3M's IT Data Warehousing Department) with Helmaan (author of this article)
Kelly (2006)		Each business area has a representative who controls the integration of data needed to help create the reports important for that particular business area	This article examines in to how Kingspan Insulation (manufacturer of building materials) have used BI
Shin (2002)		The insurance company used a problem driven approach to implement their DW. Initially they built the DW to support compliance monitoring application. Here, they integrated data pertaining to subject areas of client, field, policy, product, geography, and reference.	This article examines the implementation of data warehousing by an insurance company.
Cipolla (2001)	A DW was implemented that contains all customer orders worldwide for all marketing channels	A DW & BI solution was implemented in stages. The initial implementation was to solve the problem of customer satisfaction.	This article presents a case study about a multi-national, multi-product corporation that successfully implemented DW.
Widom (1995)	The author defines data warehouse to be one that integrates data using a comprehensive data collection strategy		This article outlines a general data warehousing architecture and discusses some technical issues suitable for research in data warehousing.
TDWI (2007)		Initially the company started with implementing a single data mart to support a single business unit. Then the DW team	This article examines the implementation of DW & Bi by Hudson's Bay Company

Author	Comprehensive Data Collection Strategy	Problem Driven Strategy	Purpose of the article
		added more data marts to support other business units. However, in 2003 the company switched its strategy to implement an enterprise wide data warehouse by consolidating all the data marts	
Chung et al. (2003)			This article examines implementing a knowledge map framework for discovering and analyzing information on the web
Jarke et al. (1999)		The authors argue that DW initiative is undertaken to fulfill particular business purpose.	This article address the quality issues concerned with the implementation of DW
Kelly (2006)		Newell Rubbermaid company implemented BI to cut inventory levels and warehouse costs	This article examines how Newell Rubbermaid has used BI
Kuhn et al. (2005)	The holistic approach that the authors talk about for managing information is akin to the comprehensive data collection strategy for integrating data		This article presents a holistic approach for BI that would enable organization create value from data
March & Hevner (2007)	The authors imply all the data within the organization should be loaded in to the data warehouse to support strategic decision-making		This article examines the link between data warehousing and strategic decision-making
Zeng et al. (2006)		The authors imply that it is necessary to first define the problem before data can be located for BI purpose	This article reviews the concept of BI and addresses some issues that organizations face during the implementation of enterprise BI.
Zangaglia (2006)	The deployment of Data-Warehouse-Centric Patterns for BI would involve a comprehensive data collection strategy for data collection	The deployment of Data-Mart-Centric Patterns for BI would involve a problem driven approach for data collection	This article addresses the different issues that an organization may face during the implementation of a BI solution and gives suggestions for tackling these issues.
Smalltree (2006)		Jefferson Medical Center initiated its BI project to measure the productivity of its	This article provides a report on how Jefferson Medical Center implemented BI

Author	Comprehensive Data Collection Strategy	Problem Driven Strategy	Purpose of the article
		investments in healthcare technology and services. The BI integrates data from its patient accounting, payroll and other internal systems.	
Gray & Watson (1998)	"Conventional data warehouse that provides data on and supports the entire enterprise" (p. 84)	"A miniature data warehouse designed to support a particular business unit or department" (p. 84)	This article address the current status and the future of data warehousing
Smalltree (2006)	To manage their business Universal Studio Hollywood initiated a BI project. "They started with ticketing data and incorporated all the 10 source systems into the new BI system"		This article provides a report on how Universal Studio Hollywood implemented BI
Cox (2001)		The office depot initiated a BI project to make sense of their sales data from around 982 supply stores.	This article provides a report on how and why Office Depot implemented BI
Manchur (1997)		The author advocates a problem driven approach for implementing BI starting with identifying the problem and then identifying the data source that can be used to resolve the problem	This article proposes five steps to transform data into knowledge for gaining competitive business advantage.
Scheese (1998)		The author advocates a scaled down goal oriented approach for implementing data warehouse and then slowly expanding it for other business solutions.	This article examines data warehousing practices in Healthcare industries.
Baker & Baker (1999)	A data warehouse integrate information across all business functions and departments	A data mart focuses on a single specific area of business	This article addresses the importance of implementing data warehouses and data marts to manage vast amount of data in an organization.
Dobbs et al. (2002)	The authors suggest that all the existing data must be integrated and loaded into a repository		This article examines the data warehousing and Business intelligence practice in companies across a range of industries in UK
Watson & Wixom	In this article, the authors imply		This article address the current status of BI

Author	Comprehensive Data Collection Strategy	Problem Driven Strategy	Purpose of the article
(2007)	that all the data present in an organization should be collected and integrated in a data warehouse, and this data warehouse should form the source for different data marts used for different functional areas		
Manglik (2006)	The author advocates an enterprise BI approach where in all the data within the enterprise is first integrated and stored in the data warehouse.		This article examines the different factors that constrain the adoption of BI in an organization.

The independent variables are the institutional isomorphism and the competitive pressure. The three major attributes of BI (Insightfulness, consistency, and organizational transformation) act as the mediating variables. The two BI data collection strategies – comprehensive data collection strategy and problem driven strategy are the dependent variables.

The Role of Institutional Isomorphism in BI Data Collection Strategies

Institutional isomorphism arises from political influence and the need for legitimacy (DiMaggio and Powell, 1983). Institutional isomorphism also stems from the cultural expectations of society and other organizations in the industry within which a firm operates (Lai et al., 2006; Liang et al., 2007). For example institutional pressure exerted on the organization for the adoption of EDI arises from dominant suppliers and customers (Teo et al., 2003). Furthermore, institutional isomorphism can also happen in an indirect way such as backing of high authority or top management (Roy and Seguin, 2000). In such cases failure to take advantage of the resources available to implement technology such as BI that has a high face value (Anderson-Lehaman, 2004; On, 2006) can be interpreted as a sign of incompetence (Roy and Seguin, 2000).

Regulatory agencies and industry associations may also exert institutional pressure on the firms in some industries. For example, it is imperative that organizations adhere to compliance imposed on them by mandates such as Health Insurance Portability and Accountability Act (HIPAA) and Sarbanes-Oxley Act (SOX). As punishment for non-compliance gets stricter, firms are not only forced to be compliant with these regulations but are also forced to prove their compliance to the regulatory agencies and the outside world (Russom, 2008; Wray, 2008). Therefore, organizations may be compelled to initiate a BI project for the purpose of improving data quality, eradicating inconsistency in data, and providing a single version of the truth (Eckerson, 2003; On, 2006; Russom, 2008; Wray, 2008). Thus institutional isomorphism is related to the consistency attribute of BI.

Furthermore, IS practitioners share a grasp of various problems faced within their discipline. They develop a body of knowledge and establish norms of good practice that helps managers implement strategies and information systems efficiently within their organization (Swanson and Ramiller, 1997). Organizational decision makers within an industry sector may be forced to employ these norms and standards that are institutionalized in their industry to gain legitimacy (Lu, 2002). Thus, the implementation of BI strategies within an organization may be dictated by the action of other firms within the industry. A failure to implement a BI strategy to support decision-making may cause business partners, competitors, customers, investors, and other stake holders to question the decision-making ability of the firm and thereby the legitimacy of the firm as it does not adhere to the norms of its industry (Abraham et al., 2004).

Institutional isomorphism can also stem from organizations copying the best practices of other organizations that they perceive to be successful (Lai et al., 2006; Liang et al., 2007). Organizations generally try to imitate other organizations when they are faced with uncertainty and when their understanding of technologies is weak (DiMaggio and Powell, 1983; Roy and Seguin, 2000). Furthermore, the best practices for implementing BI and the decision-support benefits that can be derived by implementing BI are shared through journal articles, white papers, and conferences organized by the data warehousing institutes. In this way, institutional isomorphism can influence organizations to implement BI for deriving decision-support benefits.

Thus, it is seen that institutional isomorphism acts as a driving force behind the implementation of BI for achieving high data quality and deriving decision-support benefits. Therefore, institutional isomorphism is related to the insightfulness attribute of BI.

Therefore, I hypothesize that

> H1a: There exists a positive relationship between institutional isomorphism and BI insightfulness.
>
> H1b: There exists a positive relationship between institutional isomorphism and BI consistency.

The Role of Competitive Pressure in BI Data Collection Strategies

Competitive pressure has been recognized as an important factor in the adoption, innovation, and implementation of information systems by different organizations to achieve a competitive edge over other firms operating within the same industry (Brad and Florin, 2003; Gatignon and Robertson, 1989; Iacovou et al., 1995; Mata et al., 1995; Zhu and Kramer, 2005; Zhu et al., 2006). It drives the businesses to be highly innovative and has shown to increase the likelihood of innovation adoption (Kimberly and Evanisko, 1981; Link and Bozeman, 1991; Tornatzky and Klein, 1982; Thong, 1999). It also increases the uncertainty within the industrial environment and thereby increases the necessity to implement new information systems to deal with this uncertainty (Ettlie and Bridges, 1982; Ettlie, 1983; Thong, 1999). Furthermore, previous research has shown organizations to adopt and implement technologies such as EDI, data warehouse, and other computer based inter-organizational technologies in response to the high competitive pressure faced by the organization (Grover, 1993; Hwang et al., 2004; Riggins and Mukhopadyay, 1994).

Competitive pressure can also influence the selection of different strategies in an organization (Bradford and Florin, 2003). Organizations operating under high competitive pressure needs to constantly assess its strategies and keep changing its strategy to address the competition (Premkumar et al., 1997). Faced with competitive pressure, organizations focus on implementing strategies that have not been implemented by other firms within their industry sector (Mata et al., 1995). Organizations achieve this by either cutting cost, differentiating themselves from other firms through the product they offer or the service they offer, or by creating new value propositions for their various stake holders (Cooper et al., 2000; Porter and Millar, 1985; Watson, 2006). Thus, organizations address competitive pressure by changing the ways they compete in the market and bringing about a complete organizational transformation. BI helps in organizational transformation by supporting the new business strategies (Watson, 2006). This can be seen in the case of FAC, which when faced with competitive pressure initiated BI to differentiate itself in terms of service provided to the customer (Cooper et al., 2000; Watson, 2006). Therefore, competitive pressure leads to organizations leveraging the organizational transformation attribute of BI.

Therefore I hypothesize that

> H2: There exists a positive relationship between the competitive pressure faced by an organization and the organizational transformation attribute of BI.

The Role of BI Attributes on BI Data Collection Strategies

BI Insightfulness

One of the primary reasons organizations initiate BI implementation is to understand current business and to derive decision-support benefits, i.e., leverage BI insightfulness attribute. BI aids in getting a better understanding of strategic matters and trends that affect their business

(Gould, 2001). BI further assists in empowering employee decision capabilities by manipulating the existing data and generating various aspects of the business views (Chou et al., 2005). However, in order to do so it is necessary for the BI application to identify, control, mine, organize, and present the relevant data to the decision-maker (Lonnqvist and Pirttimaki, 2006; Manchur et al., 2004). This further helps the decision-maker in understanding current business. The decision-makers can then mine this data and use this integrated data to support decision making. For example, Office Depot implemented BI using a problem driven strategy to understand their current business. Office Depot had to manage the sales data coming from around nine hundred and eighty-two stores across nine countries (Cox, 2001). They implemented BI to make better sense of all the sales data flowing from the different stores and to assist the sales division in better serving their customers (Cox, 2001). Thus, here Office Depot used a problem driven strategy to collect and integrate all the sales data within the organization to understand their current business. Therefore, in order to leverage the BI insightfulness attribute Office Depot utilized the problem driven strategy to collect and integrate data.

Furthermore, data is also collected and integrated by individual business units within an organization for deriving decision-support benefits. For example, the organization Kingspan Insulation has different representatives who are in charge of collecting and integrating data necessary for their specific business unit (Kelly, 2006). Here, each business unit collect and integrate only those data that are useful for them (Gray and Watson, 1998). In these above mentioned cases the BI application is seen as a powerful problem-solving tool that can enable access to integrated data and assist the decision making process for individual business units (Massa and Testa, 2005). Thus, here the organization employs a problem drive strategy for BI data collection.

Therefore I hypothesize that

> H3: There exists a positive relationship between BI insightfulness and initiating a problem driven strategy for BI data collection.

BI Consistency

Another major reason organizations implement BI is to provide a single version of the truth to the various stake-holders. This relates to data governance and initiating a BI project to improve data quality and to remove inconsistencies (Eckerson, 2003; Watson, 2004). Thus, organizations implement BI to get high quality data and avoid inconsistencies to be compliant with different regulatory agencies such as HIPAA and SOX (Russom, 2008; Wray, 2008). Furthermore, providing the different stake-holders in an organization a single consistent view of business information helps in managing conflicts among the different stake-holders (Massa and Testa, 2005). A single comprehensive integrated view of enterprise wide data also allows saves time during data analysis and gives freedom to different users to develop their own application to exploit this integrated information (Watson, 2004). Thus, if the purpose of initiating BI is to obtain a single version of the truth it is necessary to use the comprehensive data collection strategy for BI data collection. For example, 3M, a manufacturing company implemented BI using the comprehensive data collection strategy for obtaining a single consistent view of its enterprise wide information (Helmaan, 2002).

Therefore, I hypothesize that

> H4: There exists a positive relationship between BI consistency and initiating a comprehensive data collection strategy for BI data collection.

Organizational Transformation Attribute of BI

The third reason organizations implement BI is to assist in organizational transformation. Here organizations develop new business model in order to take advantage of external market or to achieve a competitive advantage over other organizations within the same industry (Anderson-Lehman et al., 2004; Cooper et al., 2000; Watson, 2006). Organizational transformation is enabled by aligning redefining business objectives and aligning these business objectives with IT objectives (Henderson and Venkatraman, 1993; Maes et al., 2000). In order to do so it is important to understand and manage the flow of entire data within the enterprise (Bergeron et al., 2004; Burn and Szet, 2000; Egelhoff, 1982; Papp, 1999; Sumner, 1999). Therefore, it is important for organizations to have a single consolidated view of enterprise wide data to enable organizational transformation. Thus organizations adopt a comprehensive data collection strategy to enable organizational transformation. FAC is an example of an organization that implemented BI for organizational transformation by employing comprehensive data collection strategy for data collection (Cooper et al., 2000; Watson, 2006).

FAC initiated its BI project to enable organizational transformation. They adopted the business model of differentiating themselves from other banks in terms of the service provided to the customers. They used the comprehensive data collection strategy to implement their BI. They initially integrated the existing customer information system with retail revenue to identify the top revenue producers. Then, they started expanding their data warehouse to integrate other data sources that contained the contribution view for consumers and the net income after capital charges for consumers for understanding all aspects of their clients and profitability (Cooper et al., 2000).

Thus, when organizations implement BI for enabling organizational transformation, it is necessary for them to have a single consolidated view of enterprise wide data. Therefore, they employ a comprehensive data collection strategy for collecting and integrating BI data.

Therefore, I hypothesize that

> H5: There exists a positive relationship between the organizational transformation attribute of BI and initiating a comprehensive data collection strategy for BI data collection.

In the next chapter I discuss the research methodology used for testing these hypotheses, data collection strategies, and the operationalization of the constructs.

CHAPTER 3

METHODOLOGY

In this chapter the research methods used to test the hypotheses developed in Chapter 2 are presented. A detailed description is presented about the research design, sampling and data collection strategies, development of the research instrument, reliability and validity issues, and data analysis procedures. This chapter includes the following sections: 1) research design, 2) population, sampling frame and sample, 3) instrument design and development, 4) survey administration, and 5) data analysis.

Research Design

A field study research design is used to conduct this study. Field studies are non-experimental scientific investigations intended to assess the interactions and relationships among educational, psychological, and sociological variables in real social structures (Kerlinger and Lee, 2000). A field study is suited for investigating an institutional or social situation and discovering the relations among attitudes, behavior, perceptions, and values of individuals in that situation (Kerlinger and Lee, 2000). Therefore, a field study design is the most appropriate research design to conduct this study.

A formal survey is used to collect data. The purpose of surveys is to allow the researcher to make inferences about the characteristics of a population from a sample. Survey research provides the advantage of a wide scope, i.e., a large quantity of information can be gathered from a large population (Kerlinger and Lee, 2000)

Population, Sampling Frame and Sample

The goal of this study is to determine the factors that affect organizations' BI data collection strategies. Therefore, the target population for this study includes IT professionals and top level managers involved in developing and managing BI. Data is collected from a range of industries and organizations within the United States. The sampling frame consists of BI professionals maintained by a marketing research company, L.I.S.T. Inc. They maintain the BI Network e-mail list from B-EYE-Network.com web community, which is a collection of more than 60,000 BI developers and managers.

In survey methodology it is important to determine the appropriate sample size needed to conduct the study (Kerlinger and Lee, 2000). Appropriate sample size is determined by using *a priori* power analysis as suggested by Cohen (1988). The *a priori* power analysis involves sample size, effect size, and the probability of two types of errors (Type I error and Type II error) that can occur when carrying out a statistical test (Cohen, 1988; Kerlinger and Lee, 2000). Type I error refers to falsely rejecting the null hypothesis when it should not be rejected and type II error refers to falsely not rejecting the null hypothesis when it should be rejected (Cohen, 1988; Huck, 2004; Kerlinger and Lee, 2000). For a fixed sample size, if the probability of a type I error is reduced it increases the probability of type II error and vice-versa (Kerlinger and Lee, 2000). The sample size should be selected such that it decreases the probability of the occurrence of both Type I and Type II errors.

To conduct a priori power analysis it is necessary to specify the amount of power desired, statistical significance (α level), and the effect size. For survey methodology, power of 0.8 and α level of 0.05 are generally recommended (Chin, 1998). Effect sizes are likely to be small in new areas of research inquiry and the generally recommended effect size is 0.2 (Cohen, 1988). The sample size for this study is calculated using these statistics with a free general power analysis software application, G*Power 3 (Faul et al., 2007). Assuming an effect size of 0.2, α level of 0.05, and a power of 0.8, the required sample size estimated by the G*Power 3 software is 70 for the research model.

Instrument Design and Development

In survey research the effectiveness of the survey instrument depends on the content and the wording of the questions in the instrument. An effective survey instrument includes questions that are brief, concise, and carefully ordered (Armstrong and Overton, 1971; Schuman and Pressor, 1981). The terminology used in the instrument should be clear and easy to understand (Mangione, 1995).

The survey instrument used in this study is developed in several steps. First, the survey was reviewed by IT/BI academic experts. Modifications were made to the survey items based on their comments regarding the ambiguity, sequencing, and flow of the questions.

The survey instrument for this study consists of four parts (Appendix A). The first part of the survey captures the demographic data of the respondents. The second part of the survey includes items for measuring the independent variables. The third part of the survey instrument includes items that measure the mediating variables, and the final part of the survey instrument will include items for measuring the dependent variables. The following section describes the operationalization of all variables in the study. Table 6 presents a summary of items, sources, and prior tests of scale properties.

Independent Variables

The research model includes two independent variables; competitive pressure and institutional isomorphism. Four items are used to measure competitive pressure, developed from three different studies: Thong (1999), Hwang et al. (2004), and Zhu et al. (2006). Four items are used to measure *institutional isomorphism,* adapted from Liang et al. (2007).

Mediating Variables

There are three mediating variables in the model. They are BI insightfulness, BI consistency, and organizational transformation attribute of BI. These three variables fall under the overarching umbrella of attributes of BI. Insightfulness, consistency, and organizational transformation attribute are measured with four items each. I found no previously validated scales measuring these constructs, thus the items were developed based on reading and interpretation of prior research on the topics.

Dependent Variables

There are two dependent variables in the model that tap BI data collection strategies. They are comprehensive BI data collection strategy and problem driven BI data collection strategy. I found no previously validated scales to measure BI data collection strategies. Therefore, I rely on data warehousing strategies, an underlying foundation of BI data collection (Eckerson, 2003; Moss and Atre, 2003; Watson, 2006) to develop measures for BI data collection strategies. In this model there are four items measuring the construct comprehensive data collection strategy and six items measuring the construct problem driven data collection strategy. The items for measuring these constructs are developed from the studies; Watson and

Haley (1998), Breslin (2004), Ariyachandra and Watson (2005), Jukic (2005; 2006), and Sen and Sinha (2005).

Table 6: Variables Used in Prior Research

Construct Names	**Sources**	**Number of Items**	**Reliability**	**Developed[1]/ Adapted[2]**
Competitive Pressure	Achrol and Stern (1988), Bagozzi (1984), Thong (1999), Hwang et al.. (2004), Zhu et al.. (2006)	4	NA	Developed
Institutional Isomorphism	Liang et al.. (2007)	4	0.852	Adapted
Insightfulness	Gould (2001), Watson and Volonino (2002), Eckerson (2003), Watson et al.. (2004), Massa and Testa (2005), Lonnqvist and Pirttimaki (2006), Watson (2006)	4	NA	Developed
Consistency		4	NA	Developed
Transformation		4	NA	Developed
Comprehensive Data Collection Strategy	Watson and Haley (1998), Breslin (2004), Ariyachandra and Watson (2005), Jukic (2005; 2006), Sen and Sinha (2005)	4	NA	Developed
Problem Driven Data Collection Strategy		6	NA	Developed

[1] Developed indicates that the items for the questionnaire are based on the articles but not taken directly from the article. In these cases there is no existing reference of every item from which to draw.
[2] Adapted indicates that the survey items were directly taken from the study conducted by the authors and modified for the purpose of this study.

Survey Administration

An online survey is used to obtain sample data. The process of questionnaire administration was completed in two steps. The first step included emailing a cover letter detailing the purpose of the study along with the hyperlink to the instrument. Refer to Appendix A for a copy of the cover letter. However, I was unable to send a reminder to the same group of recipients. Therefore, I emailed the hyperlink to the survey instrument to a different but smaller group of recipients two weeks after sending the initial email. This was done to attempt to increase the number of respondents. To further help increase response rate I included in the cover letter a statement ensuring confidentiality of responses (Dillman, 2000).

Non-response Bias

Non-response bias can occur when some respondents fail to return the survey instrument (Armstrong and Overton, 1977). If non-response bias is not addressed properly, it could lead to misleading and erroneous conclusions (Fox and Tracy, 1986). Non-response bias can be assessed by comparing the response of early respondents to that of late respondents (Churchill, 1979). Late respondents are very similar to non-respondents as they are less eager to participate and require additional prompting. Therefore, if there is no statistically significant difference between the characteristics of early respondents and late respondents, then I can infer that there is no significant difference between non-respondents and respondents (Compeau and Higgins, 1995). In this study, I compared the demographic and the responses of the respondents from the first email to the demographics and the responses of the respondents of the second email using t tests.

Data Analysis

Content Validity Assessment

Content validity refers to the sampling adequacy or the representativeness of the survey instrument's content (Kerlinger and Lee, 2000). Content validity can be ensured by conducting thorough research on the topic of interest and by consulting with experts within the field of interest (Churchill, 1979; Huck, 2004). The survey instrument for this study was developed in several steps with this in mind. First, the survey items were based on constructs and variables in prior BI or IT research. Because of limited existence of validated items in the literature, however, I relied heavily on feedback from field based experts for content validity assessment. The first draft of survey was reviewed by academic experts in the BI/IT field. The items in the survey were assessed for clarity, flow, and order. Feedback received from these experts was analyzed and the survey was further modified based on their comments.

Construct Validity Assessment

Construct validity relates to whether the scales used for measuring a construct adequately measure that construct (Huck, 2004; Kerlinger and Lee, 2000). Ascertaining the unidimensionality of the items used to measure a construct is one way to establish construct validity. Exploratory factor analysis is one of the most frequently used methods to evaluate unidimensionality when the psychometric properties of the items are largely unknown.

Principle component factor analysis with a Varimax rotation is used to assess all the variables in the research model. Dimensionality of each factor is evaluated by inspecting the factor loadings. Items having factor loadings more than 0.5 on the construct on which they are supposed to load is considered to be satisfactory measures of that construct (Hair et al., 1998).

Items having a factor loading of at least 0.3 on other factors were evaluated to find out whether they measure another factor (Hair et al., 1998). I further conducted a confirmatory factor analysis on the resulting factors to verify the dimensionality and confirm that the items result in the number of factors specified (Byrne, 1998).

Two other aspects of construct validity are convergent validity and discriminant validity (Huck, 2004). Convergent validity was demonstrated by providing evidence that items measuring the same construct are highly correlated to each other (Campbell and Fiske, 1959). Discriminant validity indicates that "one can empirically differentiate the construct from other construct that may be similar" (Kerlinger and Lee, 2000, p. 672). Adequate discriminate validity was demonstrated by providing evidence that items measuring different constructs do not highly correlate with each other (Campbell and Fiske, 1959).

External Validity Assessment

External validity refers to the generalizability or the representativeness of the survey instrument (Kerlinger and Lee, 2000). The respondents of this study include BI developers and managers from a range of industries and organizations that have implemented BI and therefore the results of the study can be generalized to the population of BI developers and managers implementing BI solutions in their organizations.

Reliability Assessment

Kerlinger and Lee (2000) define reliability as the "lack of distortion or precision of a measuring instrument" (p. 643). Internal consistency is one of the most widely used indicators of reliability (Cronbach, 1951). Internal consistency evaluates to what extent data are consistent to the items within the scale. Cronbach's alpha is used to assess the internal consistency of a multi-item measurement scale (Huck, 2004), following Nunnally's suggestion that a set of items with Cronbach's alpha greater than 0.8 is considered to be internally consistent. This dissertation uses Cronbach's coefficient to evaluate the reliability of multi-item measurement scales.

Hypothesis Testing

The final step in the data analysis is to test the research hypotheses. Component based structural equation modeling (SEM) is used for testing the research hypotheses stated in the previous chapter. The advantage of SEM lies in its ability to estimate series of interrelated dependence relationships simultaneously (Hair et al., 1998). Other advantages of SEM includes the decrease in measurement error by the use of confirmatory factor analysis, the flexibility in modeling relationships with multiple predictors, and the means of testing the overall model rather than individual coefficients (Chin, 1998; Hair et al., 1998). This technique is "particularly helpful when one dependent variable becomes an independent variable in subsequent dependence relationships" (Hair et al., 1998, p. 578). In this study, I predict the purpose of BI based on the external factors. The attributes of BI further becomes the mediating variable for predicting the data collection strategies. Table 7 shows the statistical tests associated with each hypothesis.

Table 7: Hypothesis and Statistical Tests

Hypothesis	Statistical Tests
H1a: There exists a positive relationship between institutional isomorphism and BI insightfulness.	$\eta_{is}= \gamma_0+\gamma_1 ii+\varepsilon$
H1b: There exists a positive relationship between institutional isomorphism and BI consistency.	$\eta_{cy}= \gamma_0+\gamma_1 cp+\varepsilon$
H2: There exists a positive relationship between the competitive pressure faced by an organization and organizational transformation attributes of BI.	$\eta_{tn}= \gamma_0+\gamma_1 cp+\varepsilon$
H3: There exists a positive relationship between BI insightfulness and initiating a problem driven strategy for BI data collection.	$\eta_{pds}= \beta_0+\beta_1 is+\varepsilon$
H4: There exists a positive relationship between BI consistency and initiating a comprehensive data collection strategy for BI data collection.	$\eta_{cds}= \beta_0+\beta_1 cy+\varepsilon$
H5: There exists a positive relationship between the organizational transformation attribute of BI and initiating a comprehensive data collection strategy for BI data collection.	$\eta_{cds}= \beta_0+\beta_1 tn+\varepsilon$

*** Notations

is – insightfulness
cy – consistency
tn – organizational transformation
pds- problem driven data collection strategy
cds- comprehensive data collection strategy
ii – institutional isomorphism
cp – competitive pressure

CHAPTER 4

DATA ANALYSIS AND RESULTS

The data analysis and the results of the study are presented in this chapter. This chapter is organized into two sections. The first section provides a comprehensive description of the data collection procedures and a summary of the demographic characteristics of the respondents. The second section describes the general data analysis procedures that are used, followed by the results of the analysis.

Data Collection

A survey method is used to collect data for the study. The target population for this study includes IT professionals and top level managers involved in developing and managing BI. The list of IT professionals for the study was provided by a market research company L.I.S.T Inc. This market research company maintains a data base of over 60,000 IT professionals from various industry sectors such as government, financial service, manufacturing, and retail, who are involved in developing and managing BI and data warehousing. Emails were sent out to 7500 IT professionals by this marketing research company. The email consisted of a brief description of the survey and the benefits of participating in the survey along with the link to the survey itself. Two weeks after the first email, a second email was sent. A total of 65 responses were received, thus giving a response rate of 0.9%. This result is not unexpected for web-based surveys (Basi, 1999). Dislike of surveys, time constraints, and lack of incentives are some of the reasons for not completing the survey (Basi, 1999). Although, the response rate seems low, approximately 87% of the respondents who clicked on the link actually completed the survey.

Two surveys out of the 65 were not usable as the respondents failed to answer majority of the questions. Therefore, the usable sample size is 63.

Non-response bias was assessed by comparing the responses to the first email with the responses to the second email. This method has been shown to be useful for determining whether non-response bias is present (Karahanna, Straub, and Chervany, 1999; Ryan, Harrison, and Schkade, 2002). T-tests were used to examine the differences between the two groups on the basis of independent variables, mediating variables, and the dependent variables. The result of the comparison is presented in Table 8a. The test indicates no significant difference between the respondents in the first and the second email at a 0.05 significance level on these variables.

Table 8a: T-tests for Nonresponse Bias

	T - Value	**P - Value**
Institutional Isomorphism	-0.892	0.376
Competitive Pressure	0.969	0.336
Organizational Transformation attribute of BI	0.076	0.940
Consistency	-1.505	0.137
Insightfulness	-0.873	0.386
Problem Driven Data Collection Strategy	1.394	0.168
Comprehensive Data Collection Strategy	-0.770	0.444

Further, independent samples t-tests (for continuous variables) and chi-square tests (for categorical variables) were also carried out to examine the difference between the two groups based on the demographic variables. The result of the comparison is presented in Table 8b & 8c. The tests indicate no significant difference between the respondents in the first and second email at a 0.05 significance level on these variables.

Table 8b: t-Tests for Nonresponse Bias (Demographics)

	T - Value	P - Value
Organizational Experience	0.830	0.410
BI Experience	0.272	0.786

Table 8c: Chi Square Tests for Nonresponse Bias (Demographics)

	Chi-Square Value	P - Value
Organizational Annual Revenue	3.405	0.492
Organizational Type	10.529	0.309
Primary Job Function	10.542	0.160
BI Classification	0.663	0.718
BI Orientation	0.226	0.634
Organizational Size	3.297	0.654

The demographic profile of the respondents is given in Table 9. The average organizational experience of all respondents is approximately 11 years and their average experience with working in BI area is approximately 10 years. Thus, in general these IT professionals have significant experience with BI within their organization and hence appropriate for answering questions in this study.

Table 9: Descriptive Statistics on Organizational Experience and BI Experience

	Mean	Max	Min
Organizational experience (in years)	11.13	36	1
Experience with BI (in years)	10.26	25	0.5

The respondents also represent a broad sample with respect to type of organization (Table 10) and also the size of organization both in terms of number of employees (Table 11) and the annual organizational revenue (Table 12).

Table 10: Organizational Type

	No. of Respondents	Percentage
Manufacturing	3	4.8 %
Services	5	7.9 %
Financial services/banking	8	12.7 %
Healthcare	6	9.5 %
Government	6	9.5 %
Educational	5	7.9 %
Insurance	8	12.7 %
Transportation	3	4.8 %
Communications	4	6.3 %
Others	15	23.8 %

Table 11: Organizational Size

	No. of Respondents	Percentage
Less than 100	6	9.5 %
100 - 499	4	6.3 %
500 - 999	4	6.3 %
1000 - 4999	15	23.8 %
5000 - 10000	12	19 %
More than 10000	22	34.9 %

Table 12: Organizational Total Annual Revenue

	No. of Respondents	Percentage
Less than $100 million	8	12.9 %
$100 million - $499 million	6	9.7 %
$500 million - $1 billion	12	19.4 %
More than $1 billion	35	56.5 %
Don't know / Not sure	1	1.6 %

The largest percent of the respondents are from financial services and insurance companies (12.7 %), followed by health care and government industries (9.5 %), educational and services (7.9 %), communications (6.3 %), and manufacturing and transportation industries (4.8 %). Approximately 24% of the respondents belong to other organizational sectors, which includes energy, media information, utilities, and consulting services. The respondents also range from organizations having employees less than 100 to organizations having more than 10,000 employees. Approximately 35% of the respondents were from organizations having more than 10, 000 employees, and approximately 57% of the employees were from organizations that had annual revenue greater than one billion dollars.

In addition, 70% of the respondents indicated having a technical orientation and the remaining 30% of the respondents indicated a business orientation with respect to BI (Table 13). About 29% of the respondents indicated that their organization has a BI competency center.

Table 13: BI Orientation

	No. of Respondents	Percentage
Technical	44	69.8
Business	19	30.2

Table 14 and Table 15 present the primary job function of the respondents with respect to BI and the main sponsor of the BI in their organizations respectively. Approximately 32% of the respondents were in charge of developing BI architecture and infrastructure within their organization. Approximately 21% of the respondents took care of the overall management of BI in their organization. Eleven percent of the respondents were business analysts and 2% were business users. A majority of the respondents indicated their chief operations officer (COO) to be the main sponsor of BI in their organization (36.5%), followed by line of business managers

(12.7%), and the chief financial officer (CFO) (11.1%). Approximately 10% of the respondents indicated the CEO of their company as the chief sponsor for BI and 19% of the respondents indicated as having no sponsors.

Table 14: Primary Job Function

	No. of Respondents	Percentage
Overall management of BI	13	20.6 %
Developing BI architecture and infrastructure	20	31.7 %
Evaluating and purchasing of new BI Technologies	1	1.6 %
Systems maintenance and operations	4	6.3 %
BI competency center employee	1	1.6 %
Business analyst	7	11.1 %
Business user	1	1.6 %
Others	16	24.2 %

Table 15: Main Sponsor of BI

	No. of Respondents	Percentage
CEO	6	9.5 %
CFO	7	11.1 %
COO	23	36.5 %
CIO/IT management	0	0 %
BI competency center	4	6.3 %
Line of business manager	8	12.7 %
No main sponsor	12	19 %
Don't know	1	1.6 %
others	2	3.2 %

The majority of respondents indicated they used BI in the areas of finance (63.5%), followed by marketing and sales (38.1%), supply chain (27%), human resources (23.8%), and order management (19%). Around 33% of the respondents indicated that they used BI in other areas such as operations, customer care, click tracking, capacity planning, actuarial, regulatory/compliance, and clinical metrics. Table 16 provides the descriptive statistics regarding the area where BI was used by the respondents.

Table 16: Areas for using BI

	No. of Respondents	Percentage
Financial	40	63.5
HR	15	23.8
Marketing	24	38.1
Sales	24	38.1
Supply Chain	17	27
Order Mgmt	12	19
Others	21	33

Data Analysis Procedure

The measurement properties of the instrument are examined by assessing the construct validity (Hair et al., 1998; Kerlinger and Lee, 2000). Dimensionality and reliability are two widely used indicators of construct validity (Kerlinger and Lee, 2000). Factor analysis and Cronbach's alpha are the tools used to evaluate these properties, respectively in this study. Exploratory factor analysis is commonly used to evaluate dimensionality (Beatty et al., 2001). It allows the researcher to examine the correlation among the items that is supposed to measure a specific construct. It further derives factor loadings that represent the correlation between an item and the construct it is supposed to measure.

Principal component factor analysis with a Varimax rotation was used to examine the dimensionality of the items in the study. A separate factor analysis was conducted for the independent, mediating, and the dependent variables rather than a single factor analysis wherein the loadings of each indicator on several factors are examined. Conducting a single factor analysis on all the 30 indicators simultaneously would result in a correlation matrix of over 430 relationships, which would not provide reliable or meaningful results (Jones and Beatty, 2001; Gefen and Straub, 2005).

Hair et al. (1992) recommends the sample size to be at least four or five times the numbers of variables present in a factor. There are no more than twelve items in any of one factor analyses; therefore the sample size of 63 is adequate to carry out the analyses. The criteria for extracting the number of factors was based on the number of factors the items were purported to load as dictated by theory. The dimensionality of each of the factors extracted was evaluated by inspecting the factor loadings (Hair et al., 1998). Items having factor loadings more than 0.5 on the construct on which they are purported to load are considered to be satisfactory measure of that construct (Hair et al., 1998). Items having factor loadings more than 0.45 on other factors are considered to have cross loaded and thus are not unique indicators of a given construct.

The independent variables for the study are institutional pressure and competitive pressure. For the independent variables, eight items were hypothesized to load on two factors. The factor analysis yielded two distinct factors and all the items loaded on their respective factors with a loading of at least 0.5 for the given set of data. There was no cross loading (Table 17). The total variance explained by the model is 59.66%.

Table 17: Factor Analysis of Independent Variables

	1	**2**
IP2	0.806	0.102
IP3	0.762	-0.116
IP1	0.744	-0.046
IP4	0.680	0.094
CP2	0.059	0.846
CP3	-0.027	0.831
CP4	0.183	0.809
CP1	-0.353	0.519

IP = Institutional isomorphism; CP = Competitive pressure.

After the factor analysis, the reliability of each factor was examined. Internal consistency is one of the most widely used indicators of reliability (Cronbach, 1951). Internal consistency is the extent to which each item is consistent with the items within the scale. Cronbach's alpha is most often used to assess the internal consistency of a multi-item measurement scale (Huck, 2004). A Cronbach's alpha of 0.7 is generally considered acceptable (Hair et al., 1998), though 0.6 may be acceptable for newly defined scales (Nunnally, 1978; Robinson, Shaver, and Wrightsman, 1994). Cronbach's alpha for the extracted factors are above 0.70 indicating the measures are internally consistent. Table 18 shows the factor analysis results along with the Eigen values for each of the factors extracted and the Cronbach's alpha scores.

Table 18: Factor Analysis of Independent Variables

	Components	
Items	Institutional Isomorphism	Competitive Pressure
IP2	**0.806**	0.102
IP3	**0.762**	-0.116
IP1	**0.744**	-0.046
IP4	**0.680**	0.094
CP2	0.059	**0.846**
CP3	-0.027	**0.831**
CP4	0.183	**0.809**
CP1	-0.353	**0.519**
Mean	**3.681**	**3.275**
Variance Explained	**30.11%**	**29.55%**
Eigen Values	**2.409**	**2.364**
Cronbach's Alpha	**0.735**	**0.750**

IP = Institutional isomorphism; CP = Competitive pressure.

Convergent validity and discriminant validity are two other indicators of construct validity (Huck, 2004). Convergent validity can be demonstrated by providing evidence that items measuring the same construct are highly correlated to each other (Campbell and Fiske, 1959). Evidence of factor loadings above 0.5 demonstrates adequate convergent validity for the independent variables. Discriminant validity indicates that "one can empirically differentiate the construct from other construct that may be similar" (Kerlinger and Lee, 2000, p. 672). Adequate discriminant validity can be demonstrated by providing evidence that items measuring different constructs do not highly correlate with each other (Campbell and Fiske, 1959). There was no cross-loading with any other items using 0.3 as the cross-loading criteria, thus the independent variables exhibit adequate discriminant validity.

The mediating variables for this study include BI Insightfulness (the purpose of BI to provide insight), BI Consistency (the purpose of BI to provide consistency), and Organizational transformation attribute of BI (the purpose of BI to provide organizational transformation). Similar to the assessment of independent variables, I used exploratory factor analysis and Cronbach's alpha to assess the measurement properties of the scale. Principal component factor analysis with a Varimax rotation was used to examine the dimensionality of the items in the study. The criteria for extracting the number of factors was based on the number of factors the items were purported to load as dictated by theory.

For the mediating variables, twelve items were hypothesized to load on three factors. The initial run of the factor analysis for the mediating variables is given in Table 19. After examining the loadings, I removed the items PC1 and PI3 because they exhibited cross loading with components 1 and 2 and did not load with their respective hypothesized factors (Table 19). The removed items included one question from the construct purpose of BI to provide insight, and the other question from the construct purpose of BI to provide consistency. Careful examination of these questions revealed that these questions were not properly worded and could have led to some confusion. For example, the item "PI3: Identify and process the required information into condensed knowledge" used to measure the construct purpose of BI to provide insight could be misinterpreted as the purpose of BI for processing information rather than identifying required information as it originally intended. Similarly, the item "PC1: Improve the quality of data that underlies our decision making" used to measure the construct purpose of BI to provide consistency seems to measure the purpose of BI to provide quality rather than consistency.

Table 19: First Run Factor Analysis of Mediating Variables

	1	**2**	**3**
OT3	0.765	0.202	0.093
OT2	0.746	-0.061	0.091
OT1	0.723	0.092	-0.177
OT4	0.630	0.053	0.200
PC3	-0.080	0.785	0.144
PC4	-0.012	0.774	-0.065
PC2	0.111	0.718	0.251
PC1	0.381	0.484	0.107
PI3	0.303	0.475	0.134
PI2	0.016	0.144	0.772
PI1	0.015	0.128	0.752
PI4	0.145	0.063	0.625

OT = Organizational transformation attribute of BI; PC = BI consistency; PI = BI insightfulness.

The results obtained by running the factor analysis after removing the items PC1 and PI3 is given in Table 20. After the removal of these items the factor analysis yielded three distinct factors, and all the remaining items loaded on their respective factors with a loading of at least 0.5 for the given set of data. There was no further cross loading. The total variance explained by the model is 58.85%.

Table 20: Second Run Factor Analysis of Mediating Variables

	Component		
	1	**2**	**3**
OT2	0.793	-0.01	0.073
OT3	0.750	0.098	0.126
OT1	0.712	0.025	-0.147
OT4	0.677	0.108	0.177
PC3	0.008	0.870	0.133
PC4	0.057	0.802	-0.057
PC2	0.138	0.695	0.266
PI2	-0.001	0.108	0.794
PI1	0.037	0.178	0.731
PI4	0.122	-0.006	0.641

OT = Organizational transformation attribute of BI; PC = BI consistency; PI = BI insightfulness.

After the factor analysis, the reliability of each factor was examined. Cronbach's alpha was used to assess the reliability of the factors. A Cronbach's alpha of 0.7 is generally considered acceptable (Hair et al., 1998). However, a Cronbach's alpha greater than 0.5 is acceptable for preliminary research (Nunnally, 1967; Peterson, 1994; Robinson et al., 1991). The Cronbach's alpha for the extracted factors are above 0.5 indicating the measures are internally consistent for this newly developed scale. Table 21 shows the final factor analysis results along with the Eigen values for each of the factors extracted and the Cronbach's alpha scores.

Evidence of factor loadings above 0.5 demonstrates adequate convergent validity for the mediating variables. The cross-loadings of less than 0.3 for each of the items for which they were not supposed to load exhibits evidence of adequate discriminant validity for the mediating variables.

The dependent variables for this study are Comprehensive Data Collection Strategy and the Problem Driven Data Collection Strategy. Principal component factor analysis with a Varimax rotation was used to examine the dimensionality of the items in the study. The criteria for extracting the number of factors was based on the number of factors the items were purported to load as dictated by theory.

Table 21: Factor Analysis of Mediating Variables

Items	Org. Transform	Consistency	Insightfulness
OT2	**0.793**	-0.010	0.073
OT3	**0.750**	0.098	0.126
OT1	**0.712**	0.025	-0.147
OT4	**0.677**	0.108	0.177
PC3	0.008	**0.870**	0.133
PC4	0.057	**0.802**	-0.057
PC2	0.138	**0.695**	0.266
PI2	-0.001	0.108	**0.794**
PI1	0.037	0.178	**0.731**
PI4	0.122	-0.006	**0.641**
Mean	**3.845**	**4.402**	**4.060**
Eigen Values	**2.194**	**1.949**	**1.742**
Variance Explained	**21.94%**	**19.49%**	**17.42%**
Cronbach's Alpha	**0.693**	**0.719**	**0.588**

OT = Organizational transformation attribute of BI; PC = BI consistency; PI = BI insightfulness.

For the dependent variables, ten items were hypothesized to load on two factors. The initial run of the factor analysis for the dependent variable is given in Table 22.

Table 22: Factor Analysis of Dependent Variables

	1	**2**
PDDC2	0.866	-0.017
PDDC1	0.842	-0.206
PDDC3	0.832	-0.158
PDDC6	0.772	-0.249
PDDC5	0.454	-0.225
PDDC4	0.117	0.032
CDC4	-0.212	0.877
CDC3	-0.247	0.873
CDC1	-0.177	0.761
CDC2	0.115	0.548

PDDC = Problem driven data collection strategy; CDC = Comprehensive data collection strategy.

After examining the loadings, I initially removed the item PDDC4 because it did not show adequate loadings on any of the factors. The removed item was from the Problem Driven Data Collection Strategy construct. A closer look at the item (PDDC4: BI was implemented to achieve quick win solution) revealed that this item indeed should not have been a part of the data collection strategy as its focus is more on BI implementation rather than the data collection strategy used for BI implementation.

The results of the factor analysis after the removal of the item PDDC4 is shown in table 22 below. After removal of this item the factor analysis yielded two distinct factors, and all the remaining items loaded on their respective factors with a loading of at least 0.5 for the given set of data except PDDC5. Because, this is not a previously validated scale, and after reexamining the wordings of PDDC5, I decided to retain it with a loading of 0.458. There was no further cross loading (Table 23). The total variance explained by the model is 63.36%.

Table 23: Factor Analysis of Dependent Variables

	Component	
	1	**2**
PDDC2	0.872	0.032
PDDC1	0.851	-0.164
PDDC3	0.841	-0.114
PDDC6	0.784	-0.208
PDDC5	0.458	-0.208
CDC4	-0.251	0.869
CDC3	-0.288	0.862
CDC1	-0.222	0.746
CDC2	0.083	0.549

PDDC = Problem driven data collection strategy; CDC = Comprehensive data collection strategy.

After the factor analysis, the internal consistency of each factor was examined using Cronbach's alpha. Cronbach's alpha for the extracted factors are above 0.70 indicating the measures are internally consistent for this newly developed scale. Table 24 shows the factor analysis results along with the Eigen values for each of the factors extracted and the Cronbach's alpha scores.

Table 24: Factor Analysis of Dependent Variables

Items	Problem Driven Data Collection	Comprehensive Data Collection
PDDC2	**0.872**	0.032
PDDC1	**0.851**	-0.164
PDDC3	**0.841**	-0.114
PDDC6	**0.784**	-0.208
PDDC5	**0.458**	-0.208
CDC4	-0.251	**0.869**
CDC3	-0.288	**0.862**
CDC1	-0.222	**0.746**
CDC2	0.083	**0.549**
Mean	**3.010**	**3.347**
Eigen Values	**3.218**	**2.484**
Variance Explained	**35.76%**	**27.60%**
Cronbach's Alpha	**0.837**	**0.780**

PDDC = Problem driven data collection strategy; CDC = Comprehensive data collection strategy.

Evidence of factor loadings above 0.5 also demonstrates adequate convergent validity for the dependent variables. The cross-loadings of less than 0.3 for each of the items for which they were not purported to load exhibits evidence of adequate discriminant validity for the dependent variables.

A confirmatory factor analysis was then conducted using the partial least squares technique (Smart-PLS) to further assess the validity of the constructs used in the model. PLS was also used to test the hypothesis. PLS has many advantages over other statistical techniques used for analyzing data. PLS can be used to analyze all the paths in one analysis (Barclay, Thomson, and Higgins, 1995; Gefen, Straub, and Boudreau, 2000; Komiak and Benbasat, 2006). It has the capability to test the structural and measurement models concurrently (Chin et al., 2003). This technique, further, does not require the homogeneity and normal distribution of the data set (Chin et al., 2003). Another major advantage of PLS is its ability to handle smaller sample size. Although PLS is not the universal solution for very low sample sizes (Marcoulides and Saunders, 2006), the minimum sample size advocated for the use of the PLS technique should be greater than ten times either the number of independent constructs influencing a single dependent construct, or the number of items contributing to the most formative construct (Chin, 1998; Wixom and Watson, 2001; Garg et al., 2005). This dissertation does not have any formative constructs, and no more than two independent constructs influence a single dependent construct. Thus, even though the software G*Power 3 estimated the required sample size to be seventy to carry out ordinary least square regression analysis to test the hypotheses, a sample size of twenty is sufficient for carrying out the PLS technique for my dissertation. The collected and cleaned data set of 63 respondents adequately satisfies this requirement. Therefore, PLS was chosen over ordinary least square regression to test the hypotheses. SmartPLS version 2.0.M3 (Ringle, Wende and Will, 2005) is used to analyze the theoretical model.

PLS provides the analysis for two models: (1) a measurement model and (2) a structural model. The measurement model describes the relationship of measured variables to their own latent variables or the theoretical constructs, which is done by assessing the reliability and the validity of the measures (Komiak and Benbasat, 2006; Tenenhaus, Vinzi, Chatelin, and Lauro, 2005). The structural model gives the relationship between the theoretical constructs (Komiak and Benbasat, 2006; Tenenhaus et al., 2005).

Measurement Model

Convergent validity is evaluated by examining the average variance extracted (AVE) and the composite reliability of the constructs (Barclay et al., 1995; Chin, 1998; Hu, Lin, Whinston, and Zhang, 2004; Komiak and Benbasat, 2006). The AVE is the amount of variance explained by the indicators of a particular construct relative to the amount of variance captured due to the measurement error (Chin, 1998; Hu et al., 2004, Komiak and Benbasat, 2006). An adequate model should have an AVE greater than 0.5 (Chin, 1998; Hu et al., 2004; Komiak and Benbasat, 2006). The results of the item loadings and the AVE scores for the constructs are given in Tables 25 and 26 respectively.

Table 25: Item Loadings

	IP	CP	PI	PC	OT	CDC	PDDC
IP1	0.830775						
IP2	0.913882						
IP3	0.636761						
IP4	0.487737						
CP1		0.590664					
CP2		0.843555					
CP3		0.768835					
CP4		0.831992					
PI1			0.732617				
PI2			0.606192				
PI4			0.807036				
PC2				0.842655			
PC3				0.832018			
PC4				0.710581			
OT1					0.708015		
OT2					0.261329		
OT3					0.436579		
OT4					0.803576		
CDC1						0.745085	
CDC2						0.342536	
CDC3						0.941811	
CDC4						0.934502	

	IP	CP	PI	PC	OT	CDC	PDDC
PDDC1							0.69427
PDDC2							0.550438
PDDC3							0.798808
PDDC5							-0.19646
PDDC6							0.81659

IP = Institutional isomorphism; CP = Competitive pressure; PI = BI insightfulness; PC = BI consistency; OT = Organizational transformation attribute of BI; CDC = Comprehensive data collection strategy; PDDC = Problem driven data collection strategy.

Table 26: Average Variance Extracted for the Latent Variables

	AVE
Institutional Isomorphism (IP)	0.542180
Competitive Pressure (CP)	0.585947
BI Insightfulness (PI)	0.518501
BI Consistency (PC)	0.635749
Organizational Transformation attribute of BI (OT)	0.351478
Comprehensive Data Collection Strategy (CDC)	0.608196
Problem Driven Data Collection Strategy (PDDC)	0.425701

The AVE for the construct Organizational Transformation is 0.352. Therefore, the indicator variable (OT2) having the least path weight (0.261) for that construct was removed to improve the AVE. The results for the item loadings and the AVE of the constructs after the removal of the item OT2 is given in Tables 27 and 28 respectively.

Table 27: Item Loadings (OT2 removed)

	IP	CP	PI	PC	OT	CDC	PDDC
IP1	0.830727						
IP2	0.913917						
IP3	0.636851						
IP4	0.487539						
CP1		0.607857					
CP2		0.826907					
CP3		0.771619					
CP4		0.830641					
PI1			0.732531				
PI2			0.606170				

	IP	CP	PI	PC	OT	CDC	PDDC
PI4			0.807109				
PC2				0.841784			
PC3				0.832011			
PC4				0.711972			
OT1					0.730408		
OT3					0.550072		
OT4					0.827822		
CDC1						0.756379	
CDC2						0.354338	
CDC3						0.936400	
CDC4						0.927962	
PDDC1							0.69426
PDDC2							0.550449
PDDC3							0.798809
PDDC5							-0.19648
PDDC6							0.816579

IP = Institutional isomorphism; CP = Competitive pressure; PI = BI insightfulness; PC = BI consistency; OT = Organizational transformation attribute of BI; CDC = Comprehensive data collection strategy; PDDC = Problem driven data collection strategy.

Table 28: Average Variance Extracted for the Latent Variables

	AVE
Institutional Isomorphism (IP)	0.542156
Competitive Pressure (CP)	0.584657
BI Insightfulness (PI)	0.518490
BI Consistency (PC)	0.635915
Organizational Transformation attribute of BI (OT)	0.507121
Comprehensive Data Collection Strategy (CDC)	0.608906
Problem Driven Data Collection Strategy (PDDC)	0.425698

After the removal of the item OT2, the AVE of the latent variable OT improved from 0.352 to 0.507, which is the desired value (Chin, 1998; Hock and Tingle, 2006; Hu et al., 2004; Komiak and Benbasat, 2006).

The AVE for the construct Problem Driven Data Collection Strategy is 0.426. Therefore, the indicator variable (PDDC5) having the least path weight (-0.197) for that construct was removed to improve the AVE. Tables 29 and 30 indicate the final item loadings and the final AVE scores for all the constructs respectively in the model . After the removal of the item PDDC5, the AVE scores of the latent variable PDDC improved from 0.426 to 0.699. The final AVE scores for all the constructs are above 0.5 (Table 30).

Table 29: Final Item Loadings (OT2 & PDDC5 removed)

	IP	**CP**	**PI**	**PC**	**OT**	**CDC**	**PDDC**
IP1	0.832927						
IP2	0.914500						
IP3	0.635169						
IP4	0.478005						
CP1		0.607864					
CP2		0.826897					
CP3		0.771616					
CP4		0.830645					
PI1			0.664304				
PI2			0.711686				
PI4			0.794257				
PC2				0.841328			
PC3				0.831863			
PC4				0.712847			
OT1					0.730445		
OT3					0.550103		
OT4					0.827787		
CDC1						0.756483	
CDC2						0.354270	
CDC3						0.936371	
CDC4						0.927929	
PDDC1							0.805482
PDDC2							0.696935
PDDC3							0.904984
PDDC6							0.916667

IP = Institutional isomorphism; CP = Competitive pressure; PI = BI insightfulness; PC = BI consistency; OT = Organizational transformation attribute of BI; CDC = Comprehensive data collection strategy; PDDC = Problem driven data collection strategy.

Table 30: Final Average Variance Extracted for the Latent Variables

	AVE
Institutional Isomorphism (IP)	0.540502
Competitive Pressure (CP)	0.584655
BI Insightfulness (PI)	0.526214
BI Consistency (PC)	0.635993
Organizational Transformation attribute of BI (OT)	0.507131
Comprehensive Data Collection Strategy (CDC)	0.608904
Problem Driven Data Collection Strategy (PDDC)	0.698448

Composite reliability is a measure of the internal consistency. The composite reliability of all the constructs are above 0.7 (Table 31), which is the suggested bench mark for an adequate model (Barclay et al., 1995; Chin, 1998; Fornell and Larcker, 1981; Komiak and Benbasat, 2006).

Table 31: Composite Reliability of the Latent Variables

	Composite Reliability
Institutional Isomorphism (IP)	0.816586
Competitive Pressure (CP)	0.847368
BI Insightfulness (PI)	0.768181
BI Consistency (PC)	0.839058
Organizational Transformation attribute of BI (OT)	0.750390
Comprehensive Data Collection Strategy (CDC)	0.849800
Problem Driven Data Collection Strategy (PDDC)	0.901579

The AVE scores (Table 30 and the composite reliability scores, Table 31) indicate that the constructs used in this model have adequate convergent validity.

Discriminant validity is evaluated by examining the relationship between the square root of AVEs and the correlation among the latent variables (Chin, 1998; Fornell and Lacker, 1981; Gefen and Straub, 2005; Komiak and Benbasat, 2006). For the constructs to exhibit adequate discriminant validity, the square root of the AVEs should be greater than the correlation among the latent variables. This means that the variance shared by the construct and its indicators is more than that shared with other constructs (Fornell and Larcker, 1981; Komiak and Benbasat, 2006). The relationship between the square root of AVEs and the correlation among the constructs for this study is shown in Table 32. The square root of all the AVEs (diagonal elements) is greater than the correlations among the constructs (non-diagonal elements). This indicates satisfactory discriminant validity of all the constructs.

Table 32: AVE and Correlations among Latent Constructs

	Composite Reliability	**AVE**	**IP**	**CP**	**PI**	**PC**	**OT**	**CDC**	**PDDC**
IP	0.816586	0.540502	**0.735188**						
CP	0.847368	0.584655	0.008645	**0.764627**					
PI	0.768181	0.526214	0.197318	0.104614	**0.725406**				
PC	0.839058	0.635993	0.362607	0.213317	0.252077	**0.797492**			
OT	0.750390	0.507131	0.104411	0.183192	0.214917	0.216344	**0.712131**		
CDC	0.849800	0.608904	0.208594	0.188842	0.214392	0.314433	0.27058	**0.780323**	
PDDC	0.901579	0.698448	0.022395	-0.05011	-0.19382	-0.11505	-0.05943	-0.3718	**0.835732**

IP = Institutional isomorphism; CP = Competitive pressure; PI = BI insightfulness; PC = BI consistency; OT = Organizational transformation attribute of BI; CDC = Comprehensive data collection strategy; PDDC = Problem driven data collection strategy.

Structural Model (Hypotheses Testing)

In PLS, the structural model represents the relationship between the theoretical constructs. Figure 3 represents a graphical depiction of the structural model. The recommended bootstrapping with a sample size of 500 was used to estimate the significance of the path coefficients (Chin, 1998; Majchrzak, Beath, Lim, and Chin, 2005).

The hypotheses shown in Table 33 were evaluated using one-tailed t-test because the hypotheses are unidirectional in nature. The path coefficients, t-values, and their respective p-values for the hypotheses are given in Table 34.

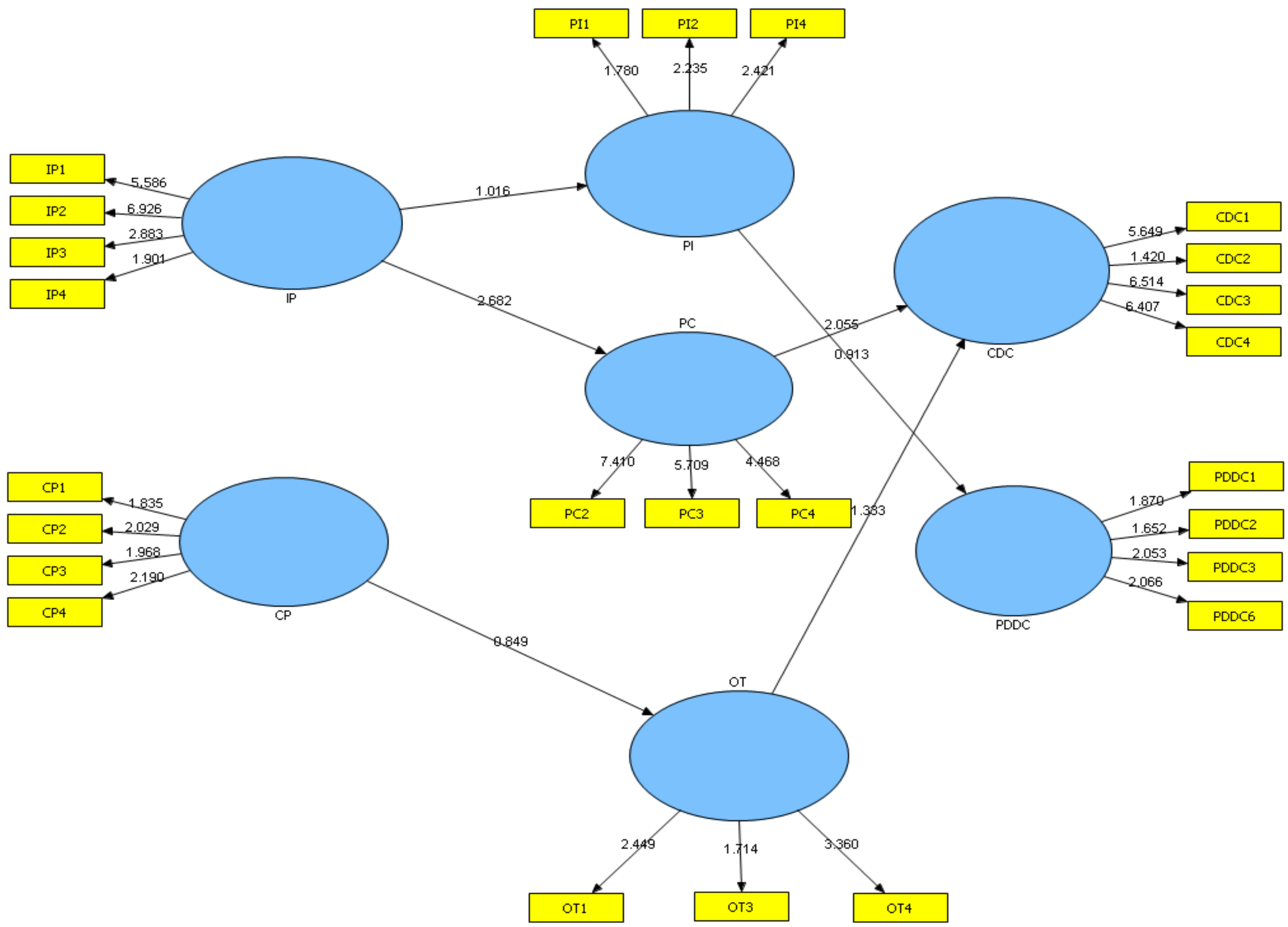

Figure 3: PLS Results for the Hypothesis Tests. [IP = Institutional isomorphism; CP = Competitive pressure; PI = BI insightfulness; PC = BI consistency; OT = Organizational transformation attribute of BI; CDC = Comprehensive data collection strategy; PDDC = Problem driven data collection strategy.

Table 33: Summary of Hypotheses

H1a	There exists a positive relationship between institutional isomorphism and BI insightfulness.
H1b	There exists a positive relationship between institutional isomorphism and BI consistency.
H2	There exists a positive relationship between the competitive pressure faced by an organization and organizational transformation attributes of BI.
H3	There exists a positive relationship between BI insightfulness and initiating a problem driven strategy for BI data collection.
H4	There exists a positive relationship between BI consistency and initiating a comprehensive data collection strategy for BI data collection.
H5	There exists a positive relationship between the organizational transformation attribute of BI and initiating a comprehensive data collection strategy for BI data collection.

Table 34: Path Coefficients, t Values, and p Values

Hypotheses	**Path coefficients**	**t-values**	**p-values**
H1a	0.187	1.016	0.155061
H1b	**0.355**	**2.682**	**0.003780*** **
H2	0.183	0.849	0.198144
H3	-0.196	0.913	0.180842
H4	**0.269**	**2.055**	**0.020200****
H5	**0.212**	**1.383**	**0.083642***

*p < 0.10 **p < 0.05 ***p<0.01

Hypotheses 1a-b and 2 suggest that there exists a relationship between the external environmental factors and BI attributes, i.e., the purpose for which organizations initiate a BI project. Hypotheses H3-5 suggest that there exists a positive relationship between the BI attributes (purpose for which a BI project is initiated) and the strategy used for collecting data for initiating such a project. I found evidence to support the hypotheses H1b, H4, and H5. I found no support for the hypotheses H1a, H2, and H3.

Hypothesis H1B examines the relationship between institutional isomorphism and the purpose of BI to provide consistency of data and information. It suggests that there exists a positive relationship between institutional isomorphism and BI consistency. The analysis indicates a statistically significant t-value of 2.682. Therefore, the result supports this hypothesis.

This means that if an organization is subjected to institutional pressure then they initiate the BI project for providing consistency to data and information.

Hypothesis H4 examines the relationship between the purpose of BI to provide consistency to data and information and the comprehensive data collection strategy for BI. It suggests that there exists a positive relationship between BI consistency and initiating a comprehensive data collection strategy for BI. The analysis indicates a statistically significant t-value of 2.055. Therefore, the result supports this hypothesis. Hypothesis H5 examines the relationship between the purpose of BI to help in organizational transformation and the comprehensive data collection strategy. It suggests that there exists a positive relationship between the organization transformation attribute of BI and initiating a comprehensive data collection strategy for BI. The analysis indicates a statistically significant (at 10%) t-value of 1.383. Therefore, the result supports this hypothesis.

This means that if an organization initiates a BI project either for the purpose of providing consistency to data and information or for the purpose of bringing about an organizational transformation then they adopt the comprehensive data collection strategy for collecting data for such an initiative.

Hypothesis H1a examines the relationship between institutional isomorphism and the purpose of BI to provide insight into an organization's current business. It suggests that there exists a positive relationship between institutional isomorphism and BI insightfulness. The analysis does not indicate a statistically significant t-value (1.016). Therefore, the result does not support the hypothesis. This means institutional pressure does not influence an organization to initiate a BI project for the purpose of providing insight to their current business.

Hypothesis H2 examines the relationship between competitive pressure and the purpose of BI for organizational transformation. It suggests that there exists a positive relationship between competitive pressure faced by an organization and the organizational transformation attributes of BI. The analysis does not indicate a statistically significant t-value (0.849). Therefore, the result does not support this hypothesis. This indicates competitive pressure alone does not influence an organization to initiate a BI project for bringing about an organizational transformation.

Hypothesis H3 examines the relationship between the purpose of BI to provide insight into current business and the problem driven data collection strategy for BI. It suggests that there exists a positive relationship between BI insightfulness and initiating a problem driven data collection strategy for BI. The analysis did not indicate a statistically significant t-value (0.913). Therefore, the result did not support this hypothesis. Thus, these results suggest that a BI project initiated for providing insight into an organization's current business influences a problem driven data collection strategy.

Table 35 gives a summary of the results of the hypothesis testing.

Table 35: Summarized Result of Hypothesis Testing

	Hypothesis	Result
H1a	There exists a positive relationship between institutional isomorphism and BI insightfulness.	Not Supported
H1b	**There exists a positive relationship between institutional isomorphism and BI consistency.**	**Supported**
H2	There exists a positive relationship between the competitive pressure faced by an organization and organizational transformation attributes of BI.	Not Supported
H3	There exists a positive relationship between BI insightfulness and initiating a problem driven strategy for BI data collection.	Not Supported
H4	**There exists a positive relationship between BI consistency and initiating a comprehensive data collection strategy for BI data collection.**	**Supported**
H5	**There exists a positive relationship between the organizational transformation attribute of BI and initiating a comprehensive data collection strategy for BI data collection.**	**Supported**

Post Hoc Examination

To further evaluate the robustness of the theoretical model and to rule out other possible relationships not hypothesized in the theoretical model, I examined an alternative model (Assadi and Hassanein, 2009; Gefen, 2000; Segars, 1997).In this model (called the saturated model) all the independent variables were associated with all the mediating variables, and all the mediating variables were associated with all the dependent variables (Figure 4).

In a covariance based SEM, this is done by comparing the fit indices of the two models, especially the chi-square, however; in a component based SEM (PLS) this is done by examining and comparing the path significance for both the models (Assadi and Hassanein, 2009; Gefen, 2000). The path coefficients, t-statistics, and the significance in the theoretical model and the alternative model are given in Table 36.

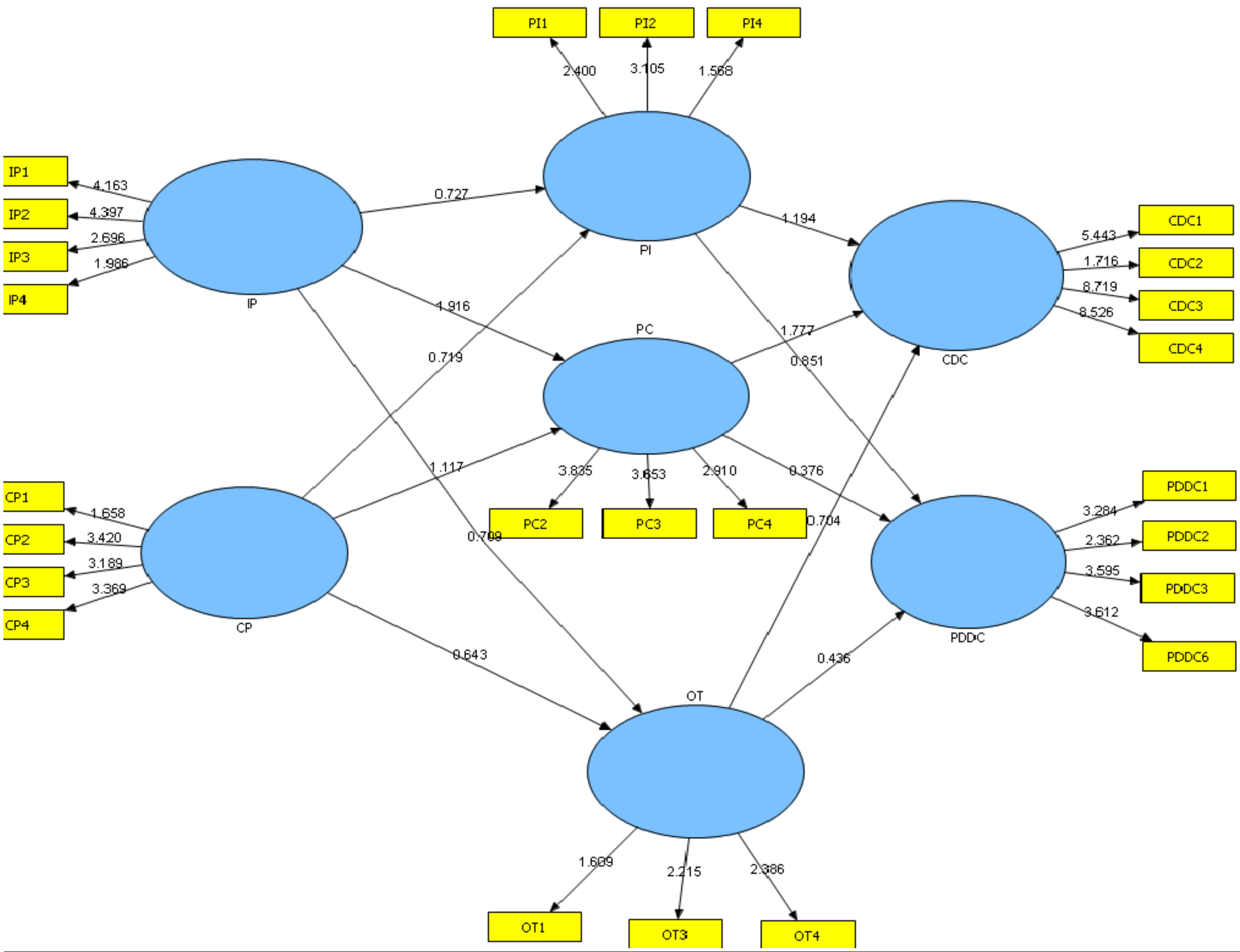

Figure 4: PLS Results for the Alternative Saturated Model. [IP = Institutional isomorphism; CP = Competitive pressure; PI = BI insightfulness; PC = BI consistency; OT = Organizational transformation attribute of BI; CDC = Comprehensive data collection strategy; PDDC = Problem driven data collection strategy.]

Findings lend support for the robustness of the theoretical model. T-statistics and the path coefficients indicate that the hypothesized relationships in the theoretical model are stronger than the relationships tested in the alternative model. In addition only two hypothesized paths are significant in the alternative model as opposed to three in the theoretical model. Therefore, I conclude that the theoretical model is robust and conforms better to the data than the alternative model.

Table 36: Path Coefficients, t Values, and p Values for the Fully Saturated Model

	Theoretical Model			Alternative Model		
	Path Coefficients	**T-Test**	**Sig**	**Path Coefficients**	**T-Test**	**Sig**
IP→PI	0.187	1.016	0.155061	0.124	0.727	0.23378
IP → PC	**0.355**	**2.682**	**0.00378*** **	**0.335**	**1.916**	**0.02797****
IP→OT				0.174	0.709	0.23933
CP→PI				0.150	0.719	0.23624
CP→PC				0.224	1.117	0.13227
CP→OT	0.183	0.849	0.198144	0.114	0.643	0.26026
PI→CDC				0.190	1.194	0.11652
PC→CDC	**0.269**	**2.055**	**0.02020****	**0.248**	**1.777**	**0.03809****
OT→CDC	**0.212**	**1.383**	**0.083642***	0.126	0.704	0.24088
PI→PDDC	-0.196	0.913	0.180842	-0.140	0.851	0.19759
PC→PDDC				-0.062	0.376	0.35354
OT→PDDC				-0.100	0.436	0.33151

*p<0.10; **p<0.05; ***p<0.01. IP = Institutional isomorphism; CP = Competitive pressure; PI = BI insightfulness; PC = BI consistency; OT = Organizational transformation attribute of BI; CDC = Comprehensive data collection strategy; PDDC = Problem driven data collection strategy.

I further conducted a post-hoc analysis to investigate the relationship between the different BI attributes and the different data collection strategies. The pearson correlation matrix for BI attributes and BI data collection strategies are given in Table 37 and Table 38 respectively.

Table 37: Pearson Correlation Matrix for BI Attributes

	PIAV	**PCAV**	**OTAV**
PIAV	1	0.259**	0.119
PCAV	0.259**	1	0.161
OTAV	0.119	0.161	1

**p<0.05. PIAV = Aggregate score for BI Insightfulness; PCAV = Aggregate score for BI Consistency; OTAV = Aggregate score for the Organizational Transformation Attribute of BI.

Table 38: Pearson Correlation Matrix for BI Data Collection Strategies

	PDDCAV	**CDCAV**
PDDCAV	1	-0.378***
CDCAV	-0.378***	1

***p<0.01. PDDCAV = Aggregate score for Problem Driven Data Collection Strategy; PCAV = Aggregate score for BI Comprehensive Data Collection Strategy.

It is seen from Table 37 that there exists a positive correlation significant at the 0.05 level between the BI Insightfulness attribute and the BI consistency attribute. However, these attributes are not correlated with the organizational transformation attribute of BI. Similarly, from Table 38, it is seen that there exists a negative correlation significant at the 0.01 level between the problem driven data collection strategy for BI and the comprehensive data collection strategy for BI. This suggests that these two strategies are mutually exclusive, i.e., while initiating a BI project for a specific purpose, organizations either implement the problem driven data collection strategy or the comprehensive data collection strategy for BI for that purpose. They do not implement both the strategies together.

Summary

This chapter provides the data analysis and the results from the study. Descriptive summaries of the data, validity and reliability among the variables of interests and PLS analysis are presented. The next chapter provides a detailed discussion regarding the results found in this chapter.

CHAPTER 5

DISCUSSION AND CONCLUSIONS

This dissertation examines the influence of external environmental factors on BI data collection strategies with the BI attributes (purpose for which the BI is implemented) as the mediating factor. This chapter is organized in the following way. It first presents a discussion about the findings and then provides the limitation of this study. It then proceeds to give the theoretical and managerial implication of this study and then finally concludes by providing directions for future research and conclusion.

Discussion of Research Findings

External Environmental Factors and BI Attributes

Hypotheses 1a-b and 2 propose that there exists a positive relationship between external environmental factors and BI attributes, i.e., the purpose for which BI is implemented. The external environmental factors investigated in this dissertation are institutional isomorphism and competitive pressure. The BI attributes examined are BI insightfulness, BI consistency, and organizational transformation attribute of BI.

Institutional Isomorphism and BI Attributes

Hypothesis H1b which proposes that there exists a positive relationship between institutional isomorphism and BI consistency. This means when subjected to institutional pressure organizations implement BI for the purpose of providing consistency to data and information. Findings support this hypothesis. This suggests that organizations leverage the BI consistency attribute to cope with pressure exerted by stakeholders. This might be particularly so for pressure from regulatory agencies, industry associations, and powerful vendors, suppliers, and customers. These stakeholders may exert pressure on a company for accuracy and consistency in reporting or other externally visible information. BI may be one response firms make to this pressure in efforts to provide consistency of data and information and thereby strengthen the legitimacy of their information. BI can help provide a single version of the truth for an organization's stakeholders. Findings, however, do not support the hypothesized relationship between Institutional Isomorphism and the BI Insightfulness attribute (H1a). This implies that institutional pressure is not linked to a firm's implementation of BI to gain insight into the current business. One possible explanation for this is that insight into the current business is not directly motivated by external pressures, but rather is driven by internal issues. For example, gaining insight into the current business might be manifest by efforts to better understand what their data tells them about customer buying patterns or account defaults. Although external stakeholders i.e., regulatory agencies or external auditors, could directly prompt the desire for such insight, it may be more likely that the desire arises directly from the organization's internal desire to enhance efficiency or effectiveness.

Competitive Pressure and BI Attributes

Hypothesis H2 proposes that there exists a positive relationship between the competitive pressure faced by an organization and the organizational transformation attribute of BI. My findings did not provide sufficient evidence to support this hypothesis. One possible explanation for this is that competitive pressure is not strong enough to prompt organizations to initiate a BI project for organizational transformation. Rather, competitive pressure may motivate firms to gain efficiencies in more focused areas. For example, using BI to better understand customers or to enhance customer service is a common starting point for BI initiatives (Williams and Williams, 2006). Even firms whose BI is more mature may still respond to a perceived competitive pressure with a specific instantiation of BI. Another possible explanation is that when firms are faced with increased competitive pressure one response is to reduce costs rather than seek organizational transformation, which may be perceived as more costly, unless they are far behind or far ahead of their competitors (Boone, 2000; Vives, 2006). Initiating a BI project requires high investments (Gessner and Volonino, 2005). Therefore, faced with high competitive pressure, initiating a BI project for organizational transformation may not be perceived as the best option for the organization.

BI Attributes and BI Data Collection Strategies

Hypotheses 3, 4, and 5 propose that there exists a positive relationship between BI attributes, i.e., the purpose for which a BI project is initiated and BI data collection strategies. The BI attributes investigated in this dissertation are BI insightfulness (purpose of BI to provide insight in to the current business), BI consistency (purpose of BI to provide consistent data and information), and organizational transformation attribute of BI (purpose of BI to assist in organizational transformation). The BI data collection strategies examined in this dissertation includes comprehensive data collection strategy and problem driven data collection strategy. Hypotheses H4 & H5 were significant, and Hypothesis H3 was not. I discuss the significant hypotheses first and then move on to the hypothesis that was not significant.

Hypothesis H4 proposes that there exists a positive relationship between BI consistency and initiating a comprehensive data collection strategy for BI data collection. The findings are consistent with the hypothesized relationship between BI consistency and comprehensive data collection strategy for BI data collection. This indicates that in order to leverage the consistency attribute of BI organizations adopt the comprehensive data collection strategy for collecting data for BI. Thus, the result suggests that when organizations implement BI to provide clean and consistent information to their various stakeholders then they collect, integrate, and store the entire data present in the organization.

Hypothesis H5 proposes that there exists a positive relationship between the organizational transformation attribute of BI and initiating a comprehensive data collection strategy for BI data collection. Results of the data analysis indicate evidence to support this hypothesis. This means that if an organization initiates a BI project for the purpose of bringing about an organizational transformation then they adopt comprehensive data collection strategy for collecting data for such an initiative. Organizational transformation includes developing new business models to take advantage of the external market (Anderson-Lehman et al., 2004; Cooper et al., 2000; Watson, 2006). In order to do so, it is critical for the organizations to have a single consolidated view of their enterprise wide data. Therefore, organizations, in order to leverage the organizational transformation attribute of BI collect, integrate, and store the entire data present within the organization.

Hypothesis H3 proposes that there exists a positive relationship between BI insightfulness and initiating a problem driven strategy for BI data collection. My findings do not provide sufficient evidence to support this hypothesis. One possible explanation for this could be that majority of the BI guidelines suggests laying out the infrastructure for collecting and integrating all the data within the organization before implementing a BI solution (Ariyachandra and Wathson, 2005; Breslin, 2004; Jukic, 2005; Jukic, 2006). Therefore, irrespective of the purpose for initiating a BI project, BI users may be biased towards the comprehensive data collection strategy for the collection of data for BI. The nature of BI insightfulness could be another reason for the lack of support for this hypothesis. Managers need to isolate and differentiate the context within which they need better understanding of their business. This context could be the current business environment, competitors, customers, economic issues, and markets (Lonnqvist and Pirttimaki, 2006). Having identified the need for insight into business within a specific context, the managers can then identify, collect, and integrate the relevant data source to address the problem area. However, BI insightfulness focuses on the overall understanding of the organization's current business rather than any specific context.

Limitations of the Study

This study is subject to some possible limitations with respect to sample size and diversity of the respondents. Although a sample size of 63 was statistically sufficient for the analyses I conducted, a larger sample size may have allowed for more robust and/or comprehensive analyses. Further, the diversity of the respondents is another limitation of this study. For example, seventy percent of the respondents had technical orientation with respect to BI, whereas only thirty percent of the respondents had business orientation with respect to BI. Thus, this could have shifted the focus more on BI data collection strategy and less on the external environmental factors. This may further, have caused the non-significant result between competitive pressure and the organizational transformation attribute of BI.

The potential for the existence of common method variance is another possible limitation of this study (Liang et al., 2007; Malhotra, Kim, and Patil, 2006; Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). Common method variance refers to the systematic error that might be included in the study due to potential respondent biases. This is common in survey studies where the same respondent responds to the survey items in a single questionnaire at the same point in time (Kemery and Dunlap, 1986; Lindell and Whitney, 2001; Malhotra et al., 2006). This could cause spurious correlation among the shared variables due to the common method used to collect the data (Bagozzi, 1980; Buckley, Cote, and Comstock, 1990; Malhotra et al., 2006). In order to minimize this effect I separated the items measuring independent variables, mediating variables, and dependent variables into different sections.

Research Contributions and Implications

This study has implications for both academicians and practitioners. The model proposed in this dissertation contributes to the BI literature in many ways. First, it extends the current research in BI by proposing and testing a cogent framework for understanding and studying BI data collection strategies. Prior studies within this area have examined some factors that affect the selection of different data warehousing architectures (Ariyachandra and Watson, 2005). However, these studies are more descriptive in nature and not grounded in theory. Furthermore, these studies examine the data warehousing architectures from the perspective of factors that arise from within an organization and they are largely silent about external environmental factors. This dissertation provides an empirical and theoretically grounded lens through which to better understand the motivators and success factors associated with collecting the vast quantities of data required for BI by investigating into the data warehousing strategies, research about competitive pressure, and institutional theory.

Another contribution is identifying the major BI purposes based on BI literature and assigning attributes to BI such that each purpose of BI has an associated BI attribute. I also developed and validated scales to measure these BI attributes. Literature in BI implementation always suggests making a case for undertaking a BI initiative (Moss and Atre, 2003; Williams and Williams, 2007). Although, there are studies that give the benefits of implementing BI, little research has investigated into BI purpose and captured the perception regarding BI attributes. This study contributes to filling this research gap and investigates the influence of external environment on these BI attributes and the influence of these BI attributes on BI data collection strategies. Further, based on data warehousing and BI literature, I developed and validated scales for measuring data collection strategies for BI. There are no previously validated instruments for capturing the perception regarding BI attributes and BI data collection strategies. This is the first step in BI implementation literature and can further be used to determine the success of BI implementation.

The results obtained in this dissertation also have managerial implications. Results indicate that there exists strong correlation between institutional isomorphism and BI consistency. Thus, organizations when faced with institutional pressure can initiate a BI project to provide consistency of data and information. Further results from this dissertation also show evidence of correlation between BI consistency and comprehensive data collection strategy for BI and organizational transformation attribute of BI and comprehensive data collection strategy for BI. This indicates that if managers are initiating a BI for either providing consistency of data and information or to assist in organizational transformation then a comprehensive data collection strategy would be the best suited approach for such an initiative. Thus, from a practitioner perspective this dissertation provides managers with a mental model on which to base decisions about the data required to accomplish their goals of BI.

Future Research

This study examines the influence of external environmental factors on BI data collection strategies when mediated by BI attributes. Institutional isomorphism and competitive pressure forms the independent variable for this study. However, there are also other internal factors such as technical issues, organizational infrastructure, information interdependence between organizational units, and resource constraints (Ariyachandra and Watson, 2005; Breslin, 2004; Schick, 2006; Sen and Sinha, 2005) that may affect the BI data collection strategies. Expanding this study to include these factors is a future research direction. Further, in this study I have mainly focused on the mimetic pressure dimension of institutional isomorphism. Future research might also examine the two other dimensions (coercive pressure and normative pressure).

Further, in this study I have developed three attributes for BI based on the literature on purpose of BI. There are, however, other attributes of BI. Thus, future research could explore the impact of institutional and competitive pressures on other BI attributes. Leveraging the right BI attributes and selecting the proper BI data collection strategies may improve the success of BI implementation. Therefore, another direction for future research includes examining the relationship between BI attributes, BI data collection strategies, and BI success. Further research direction also includes refining the survey instruments used in the current dissertation, collecting diverse data, and running a more comprehensive analysis.

Summary and Conclusions

This study examines the influence of external environmental factors on BI data collection strategies when mediated by BI attributes, i.e., the purpose for which BI project is initiated. Institutional theory, research on competitive pressure, and literature on BI and data warehousing were used to develop the hypotheses. Through the use of PLS, the study verified that there exists a positive relationship between institutional isomorphism and BI consistency. The study also indicated that there exists a positive relationship between BI consistency and comprehensive data collection strategy and there exists a positive relationship between the organizational transformation attribute of BI and comprehensive data collection strategy.

BI technology has pervaded every large industry sector including banking, finance, insurance and security, government, manufacturing, retail, and services. Therefore, understanding BI attributes and BI data collection strategies may prove vital for the success of any BI initiative. This study may serve as a first step in understanding the influence of external environmental factors on BI attributes and BI data collection strategies.

APPENDIX A

COVER LETTER

Dear Participant,

I would like to invite you to take part in this research project, which is being carried as part of the requirements for me to earn my Ph.D. in Business Computer Information Systems from the University of North Texas (UNT). The project examines the factors influencing Business Intelligence (BI) data collection strategies in an organization. Results of this study can provide guidance for managers in optimal data collection strategies for their BI. It should take you **approximately 15 minutes** to complete the survey.

Your candid responses to each statement and question are very important for the success of this project. Every feasible effort will be made to preserve anonymity and confidentiality. All results will be examined in the aggregate. No individual responses will be published and the raw information will be accessible only to me and the University of North Texas faculty on my dissertation committee.

Participation is completely voluntary, and you may end the survey at any time simply by stopping and/or not submitting the survey. You may decline to answer any particular question that you are uncomfortable with or feel is not appropriate. Completion of the survey will indicate that you have given permission to use your responses.

This research project has been reviewed and approved by the UNT Institutional Review Board (IRB). You may contact the IRB at 940-565-3940 with any questions regarding your rights as a human subject. If you have questions concerning this study, please feel free to contact me at 940.565.3174 (RamakriT@unt.edu) or the faculty sponsor of this project, Dr. Mary C. Jones at 940.565.3167 (jonesm@unt.edu).

Thank you very much for your participation and your time.

Sincerely,

Thiagarajan Ramakrishnan
Ph.D. Candidate
Information Systems

APPENDIX B

SURVEY INSTRUMENT

Factors Influencing BI Data Collection Strategies: An Empirical Investigation

Demographics	
1.	What is your organization's total annual revenue? a. Less than $100 million b. $100 million to $499 million c. $500 million to $1 billion d. More than $1 billion e. Don't know / not sure
2	What sector best describes your organization? a. Manufacturing b. Services c. Financial services / banking d. Healthcare e. Government f. Pharmaceutical g. Educational h. Insurance i. Transportation j. Communications k. Others (Please Specify) ___________

3	Which of the following best describes your job function? a. Overall management of BI b. Developing BI architecture and infrastructure c. Financial planning of BI d. Evaluating and purchasing of new BI technologies e. Systems maintenance and operations f. BI Competency Center employee g. Business analyst h. Business user i. Others (Please specify) ___________
4	How would you classify yourself? a. New entrant to BI b. Intermediate c. Advanced
5	Would you classify yourself as having a "technical" or "business" orientation when it comes to BI? a. Technical b. Business

6	Who is the main sponsor of BI in your organization? a. CEO b. CFO c. COO d. CIO / IT management e. BI Competency Center f. Line of business manager g. There is not a main sponsor in my organization h. Don’t know i. Others (Please specify) ___________
7	Does your organization have a BI Competency Center? a. Yes b. No c. If so, where does it report? ___________
8	Who is your primary BI vendor? ___________
9	For which of the following areas do you personally use BI? a. Financial b. Human Resource c. Marketing d. Sales e. Supply Chain f. Order Management g. Others (Please specify) ___________

10	What is the approximate number of employees in your organization? a. Less than 100 b. 100 to 499 c. 500 to 999 d. 1000 to 4999 e. 5000 to 10000 f. More than 10000
11	Approximately how long have you been working in your current organization? __________
12	Approximately how long have you been working with BI? __________
13	What is your job title? __________

Please rate the following on a scale of 1 (Very Low) to 5 (Very High)					
	Very Low	**Somewhat Low**	**Neither Low Nor High**	**Somewhat High**	**Very High**
The ease with which my customers can switch to a competitor	1	2	3	4	5
The level of rivalry among businesses within my industry sector	1	2	3	4	5
The level of competitor domination in my industry	1	2	3	4	5
The business resources held by the top four companies in my industry	1	2	3	4	5

Please rate the following questions on a scale of 1 (strongly disagree) to 5 (strongly agree)					
Other firms that have implemented BI in my industry	**Strongly Disagree**	**Somewhat Disagree**	**Neither Disagree Nor Agree**	**Somewhat Agree**	**Strongly Agree**
Have greatly benefitted	1	2	3	4	5
Are favorably perceived by other firms within the industry	1	2	3	4	5
Are favorably perceived by their suppliers	1	2	3	4	5
Are favorably perceived by their customers	1	2	3	4	5

Please rate the following questions on a scale of 1 (strongly disagree) to 5 (strongly agree)					
If you have implemented more than one BI application or one set of BI applications, please pick one of them and answer the following questions about only that one. For example, if you have implemented BI for both supply chain and financial support, please choose only one for purposes of answering these questions.					
We implemented BI to	**Strongly Disagree**	**Somewhat Disagree**	**Neither Disagree Nor Agree**	**Somewhat Agree**	**Strongly Agree**
Understand the meaning behind business information	1	2	3	4	5
Understand the stock and flow of business information within and around the organization	1	2	3	4	5
Identify and process the required information into condensed knowledge	1	2	3	4	5
Understand current matters and trends that affect the business	1	2	3	4	5
Improve the quality of data that underlies our decision	1	2	3	4	5

making					
Provide consistent and reliable data on which to base decisions	1	2	3	4	5
Provide different stakeholders with a single consistent view of business information	1	2	3	4	5
Provide a consolidated view of information in the organization	1	2	3	4	5
Develop new business models	1	2	3	4	5
Redefine business objectives	1	2	3	4	5
Change existing business processes	1	2	3	4	5
Support strategic business objectives	1	2	3	4	5

Please rate the following questions on a scale of 1 (strongly disagree) to 5 (strongly agree)					
In my organization	**Strongly Disagree**	**Somewhat Disagree**	**Neither Disagree Nor Agree**	**Somewhat Agree**	**Strongly Agree**
All or most of the data present in the organization was collected, integrated, and stored in a single repository to implement BI	1	2	3	4	5
The BI application program for analyzing data were written after data integration	1	2	3	4	5
All or most **functional areas** in the organization contributed data for this BI	1	2	3	4	5
All or most **business units** in the organization contributed data for this BI	1	2	3	4	5
Only specific data requested by specific business units was collected and integrated to	1	2	3	4	5

implement BI					
Only specific data necessary to solve some specific problem or problems were collected and integrated to implement BI	1	2	3	4	5
A single or small set of applications was the driving force for determining the requirements for data collection and data integration	1	2	3	4	5
BI was implemented to achieve quick win solutions	1	2	3	4	5
The initiative for BI arose from an individual **business unit** that requested a BI solution	1	2	3	4	5
Only specific data required by one or a few **functional areas** was collected and integrated to implement BI	1	2	3	4	5

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