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Competitive Advantage Factors And Diffusion Of Business

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COMPETITIVE ADVANTAGE FACTORS AND DIFFUSION OF BUSINESS INTELLIGENCE AND DATA WAREHOUSING

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COMPETITIVE ADVANTAGE FACTORS AND DIFFUSION OF BUSINESS INTELLIGENCE AND DATA WAREHOUSING

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ABSTRACT

This research represents two streams of study. The first measures the level of adoption for Business Intelligence (BI) and Data Warehousing (DW). The second identifies those factors that contribute to the competitive advantage offered by BI/DW. Together, these two research streams expand the body of knowledge in three ways: (1) quantifying the adoption of BI/DW in both academia and practice, (2) leveraging competitive advantage theory and existing academic research to validate those factors statistically significant to competitive advantage for BI/DW programs, and (3) providing a comprehensive view of the BI/DW space. This research extends the body of knowledge for Information Systems (IS) and Information Technology (IT) in the academic community. It also offers practitioners guidance in allocating limited resources.

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CHAPTER 1. COMPREHENSIVE RESEARCH IN BUSINESS INTELLIGENCE AND DATA WAREHOUSING

This research had two objectives: (1) to measure the level of adoption for Business Intelligence (BI) and Data Warehousing (DW) and, assuming a high level of adoption, (2) to identify those factors that contribute to the competitive advantage of BI/DW programs. This research extends the body of knowledge for Information Systems (IS) and Information Technology (IT) in the academic community as well as provides needed guidance for practitioners who must allocate their limited resources judiciously.

1.1 The Theory and Strategy of Competitive Advantage

Competitive advantage theory defined by Michael Porter is central to this research. According to Porter, establishing synergy among a company's activities creates strategy. The success of a strategy depends largely on integrating many activities well, as opposed to excelling at only one. As Porter stated, without synergy among activities, no distinctive or sustainable strategy is possible (Porter, 1996).

Strategic fit among several activities is the cornerstone of creating and sustaining competitive advantage. Interlocking and synchronizing several activities is simply more difficult for competitors to emulate. Therefore, an organization's position established on a system of multiple activities is more sustainable than one built on individual activities (Porter, 1996).

Taking Porter's model, then, one can argue that establishing a sustainable competitive advantage in BI/DW requires a network of interrelated BI/DW activities. The challenge is to

identify which activities to focus on. To that end, this research identifies factors of BI/DW initiatives that significantly contribute to the overall maturity and success of a program.

1.2 Background of Business Intelligence and Data Warehousing

The early focus of relational databases was online transactional processing (OLTP), designed to support daily business operation requirements (Chen, Soliman, Mao, & Frolick, 2000). Using Codd's normalization rules, operational systems are typically optimized for fast inserting and updating of data (Codd, 1985). As companies expanded the applications they supported, and the amount of data stored increased, attention turned to providing user access for reporting and decision support. However, a different architecture was needed such that transactional data from operational systems could be extracted, transformed, integrated, and stored to support reporting requirements (Devlin & Murphy, 1988). The DW is designed to collect disparate data from operational systems and uniquely store that data to allow end users ready access for analysis. A DW is defined by four features: subject-oriented, integrated, non-volatile, and time-variant (Inmon, 1992).

A DW is intended to provide integrated data from operational systems organized for reporting, whereas BI is intended to provide actionable information. Business Intelligence can be defined as a set of concepts and methodologies to improve decision-making through use of facts and fact-based systems (Gonzales & Wells, 2006). Simply stated, BI provides the ability to transform data into usable and actionable information for business and organization purposes. The term BI combines data architectures, technical architectures, analytic tools, and methodologies (Turban, Aronson, Liang, & Sharda, 2007).

There is significant synergy and overlap between DW and BI. While a DW is the core repository (Turban et al., 2007), BI requires an information infrastructure to provide actionable insight to decision makers (Beyer, 2009). The synergy between BI and DW has caused them to be viewed as one entity. An industry report (Gartner, 2009) noted, “BI/DW is a strategic initiative that has the potential to deliver significant insights unavailable through other means.” The close relationship between BI and DW is why this research examines both disciplines as a single body of published work, reflecting a continuum of applications, technologies, and techniques to support better decision making.

1.3 Two Research Streams

Before attempting to identify activities that should be included in BI/DW strategy, it is critical to establish first whether or not BI/DW is effecting organizational change. If BI/DW proves to be widely adopted, then careful examination of specific success factors is relevant. On the other hand, if BI and DW are merely fads with little long-term impact on organizational change, then it is better not to continue significant research in this area considering the likelihood that another fad will appear and supplant BI/DW.

Therefore, this research is a blend of two interrelated research streams. The first stream studies the level of adoption of BI/DW in both academia and practice. The objective of this effort is to answer the first question: Are BI/DW activities impacting organizational change? Based on findings in this research, further examination of those activities will be considered. Specific factors that contribute to a successful BI/DW program will be analyzed to address the second research question of which factors offer the greatest competitive advantage.

For example, is having a high ratio of power users to standard users important? Or is establishing a standard technical architecture important? These questions are both considered by practitioners and lobbied by consulting groups and participating vendors. As explained by Porter, strategy is about making tradeoffs. A BI/DW program must decide where to allocate limited budgets and resources, and focus those resources on activities that make significant contributions to the program's success, strategy, and sustained competitive advantage.

1.3.1 Trends and Levels of Adoption

This study extends current BI/DW research by studying the discourse life cycle of IS fashion waves to determine levels of adoption. Using bibliographic methodology and applying diffusion of innovation and management fashion theories, BI/DW-related papers and articles were gathered from both academic research and practitioner journals, published from 1995 to 2009. Formal diffusion models were employed to examine the level of adoption of BI/DW based on these papers and articles. Findings will demonstrate mixed-influence fashion waves of BI/DW across the academic and private sector communities. Moreover, practitioners are influenced more by external factors compared to academic communities. And academic research diffusion progresses differently from practitioner literature diffusion, with academic research diffusion comparatively slower.

1.3.2 Factors for Competitive Advantage

Current research studies IT determinants of competitive advantage and corporate performance, including leadership, skill, and infrastructure. Significant contribution of this study to current IT research comes from studying the impact of these factors on achieving competitive

advantage in BI. This study presents a causal relationship model of an organization's BI leadership, BI skill, and BI infrastructure and its competitive advantage and performance.

1.4 A Comprehensive View

This author leveraged diffusion models, factor analysis, and structured equation modeling as a continuum of analytic techniques in order to answer a series of research questions posed in three distinct but related stages. The first stage addresses the most fundamental research question: Is BI/DW broadly adopted? Answering this question determines if subsequent research questions warrant investigation.

Based on quantitative evidence that supports the broad adoption of BI/DW, a second stage of research questions must be examined. For example, which factors are significant in explaining BI/DW competitive advantage? Moreover, are those factors consistent with established research regarding the IT competitive advantage factors of leadership, skill and infrastructure?

The third stage of this research examines questions focused on validating or rejecting established theory; specifically, can the theoretical model of IT competitive advantage and its three constructs of leadership, skill, and infrastructure be applied to the BI/DW space and fitted to the identified factors of success exposed in the second stage of this research?

This research expands the body of knowledge by addressing the series of research questions and traversing analytic techniques in a continuum of investigation and examination to provide a comprehensive view and better understanding of the BI/DW space.

CHAPTER 2. TRENDS AND LEVELS OF ADOPTION IN ACADEMIC RESEARCH AND PRACTICE

This chapter describes the study design for quantifying the trends in BI/DW and the level of adoption in the academic community as well as in practice. Findings for this research stream are also reported.

2.1 Diffusion of Business Intelligence and Data Warehousing

The primary step of this research was to determine the level of adoption for BI/DW. The rationale was that wide adoption was necessary to justify careful examination of those aspects of BI/DW that are significant to its success. On the other hand, a lower level of adoption would signal that the space would be marginalized or even supplanted by new terms and technology (Gonzales et al., 2011).

Justifying and demonstrating the effectiveness of IS grows increasingly critical as firms look to become more competitive and efficient. The challenge for both BI and DW has been explaining their mixed success. Some organizations have gained solid benefits, while others have not achieved original expectations (Watson, Goodhue, & Wixom, 2002). Also, recent *Computerworld* and other studies cited BI as a top skill for IS professionals in 2010 (Brandel, 2010; Luftman & Ben-Zvi, 2010).

The interest in BI/DW and its usefulness as a managerial tool is typical of all new management approaches: Is it a passing fad, or an enduring fashion? The question is of particular concern to IS researchers and practitioners because IS/IT is driven by technological opportunities (Landry & Banville, 1992). In the 1980s, there was considerable debate about the value of graphs versus tables, but in general little difference exists between the two (DeSanctis, 1984), and

interest subsequently disappeared. Other technologies, such as Computer-aided Software Engineering (CASE) and e-commerce, have evolved into widely accepted and valued tools (Gil & Bhattacherjee, 2009). Bibliographic research has identified IS “fashion waves” based on neo-institutional theory and has suggested that a management fashion is a belief that a certain management technique leads to rational progress (Bakersville & Myers, 2009). Findings recommended that IS researchers should participate more directly through the use of action and practice research, demonstrate flexibility by dropping research topics that have lost the interest of practitioners, provide more practitioner-oriented publication outlets, and create new publication outlets with shorter review cycles (Bakersville & Myers, 2009).

Other research (Gil & Bhattacherjee, 2009) raised the question: Are issues fashions or diffused innovations? While generally agreeing with the findings stated above, researchers differed in how fashion waves should be analyzed. They generally suggested that research should be viewed from the perspective of diffusion, which considers the changing rate of acceptance. Consider the following (entirely hypothetical) example, where one topic (A) represents a fad, and another topic (B) represents a fashion wave (see Table 1 for raw data and Figure 1 for the cumulative graph). As illustrated, topic A clearly started strong; but over time the total (cumulative) number (i.e., diffusion) of articles diminished, while topic B publications have endured and even accelerated. For the last five time periods, the slope of the linear regression for topic A is 1.0, while the corresponding slope for topic B is 11.00.

Table 1. Illustrative Data

Time Period	Topic A		Topic B	
	No.	Total	No.	Total
1	2	2	0	0
2	6	8	2	2
3	8	16	3	5
4	5	21	5	10
5	4	25	6	16
6	4	29	8	24
7	2	31	10	34
8	1	32	11	45
9	1	33	11	56
10	0	33	12	68

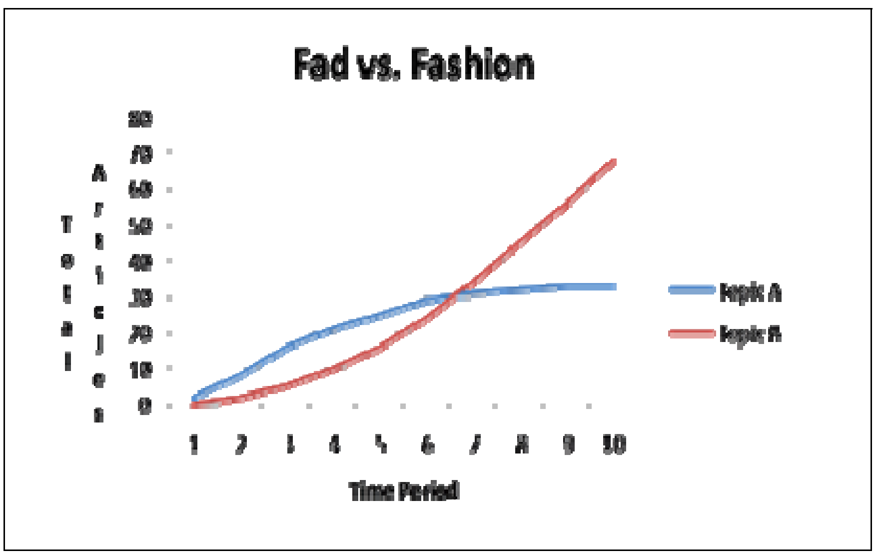

Figure 1. Cumulative Data Trends

One of the most important contemporary BI/DW literature reviews (Jourdan, Rainer, & Marshall, 2008) was published in ten leading journals from 1997 to 2006 in an attempt to establish BI-centric research categories.

However, there are no current research articles that validate or reject the notion that BI or DW represents technologies/techniques that are broadly adopted. A few researchers (Wexelblat

& Srinivasan, 1999) have made the claim that DW was in fact a fad that was advanced by many who were impressed by claims but never fully realized the purported value. Conversely, in the private sector, BI diffusion is generally viewed as an area of growth (Wixom & Watson, 2001).

This study considered the diffusion of BI/DW research based on accepted diffusion models, using bibliographic research in both published academic journal articles and practitioner papers and articles (Gil & Bhattacherjee, 2009). Several subordinate questions are also addressed: Are the academic and private sector communities synchronized? Which of the well-referenced diffusion innovation models best predict the diffusion of BI/DW? What are the differences between the scholarly and private sector research in terms of internal versus external influence?

If the different influences driving BI/DW diffusion are found to have similar patterns in scholarly research and the private sector, then it can be argued that BI/DW research and practice have similar information exchange patterns and drawbacks. If not, then influences driving IS research and IS practice are different, a fact which may eventually lead to isolation of the two communities and require bridges to be built for better exchange and communication. Additionally, if there is evidence of enduring BI/DW diffusion, we can consider potential opportunities for future research (Wixom & Watson, 2001).

Much attention has recently been given to the theory of innovation diffusion, which considers how a new idea spreads throughout the market over time. The ability to accurately predict new product diffusion concerns designers, marketers, managers, and researchers alike.

Innovation diffusion is defined as the process by which the innovation is communicated over external media channels or internal social systems (Rogers, 1995). The four fundamental components to the traditional diffusion process include (1) an innovation such as an idea,

product, or process; (2) communication channels such as radio, TV, and newspapers; (3) time as it pertains to the rate of adoption of the innovation; and (4) a social system consisting of individuals or organizations that represent potential adopters (Mahajan & Peterson, 1985).

The diffusion models with significant support are the external, internal, and mixed influence models (Dos Santos & Peffers, 1995; Bass, Krishnan, & Jain, 1994). The external model assumes that external sources of influence drive an organization's adoption of innovation. ATMs are an example of external influence where the manufacturers of the equipment aggressively promoted the adoption (Dos Santos & Peffers, 1995). The general form of the model is:

$$\frac{dN(t)}{dt} = a[\square N - N(t)]$$

Where: a = external influence, t = time, $\square\square N$ = potential total adopters, and $N(t)$ = population of adopters

The internal model assumes that influence comes from communication or social networks, such as the adoption of seed as a consequence of promotion by farm associations:

$$\frac{dN(t)}{dt} = bN(t)[\square N - N(t)]$$

Where: b = external influence, t = time, $\square\square N$ = potential total adopters, and $N(t)$ = population of adopters

The Bass mixed-influence model assumes that influence comes from both internal and external sources. The adoption process starts with mass media influencing early adopters. Individuals are influenced by internal communication early in the diffusion process, but the

impact declines in later periods. When plotted on a cumulative basis, this adoption rate creates a familiar S-shaped curve (Rogers, 1995).

$$\frac{dN(t)}{dt} = (a + bN(t))[\square N - N(t)]$$

This study uses all three models not only to validate or reject hypotheses offered, but also to determine which model best predicts the diffusion of BI/DW.

2.2 Diffusion Hypotheses

There is evidence of continued growth in BI/DW and its impact on organizations. The IDC studied 43 leading organizations in North America and Western Europe and found a median return on investment of 112% for business analytics projects using BI/DW (IDC, 2003). And a 2008 study (Gartner, 2008) concluded that BI was the top technology priority for three years in a row. Given this evidence, this research indicates that BI and DW are experiencing a fashion wave (Bakersville & Myers, 2009).

Understanding how BI/DW has diffused over time has significant ramifications for organizations considering new or continued investments in BI/DW. If the level of adoption for BI/DW exhibits an elongated S-curve (fashion wave), then one can infer that adopters have benefited from their investment, while limited diffusion may discourage organizations from further pursuit of BI/DW. And if BI/DW demonstrates sustained diffusion, the question arises, “Which diffusion model most accurately estimates BI/DW diffusion?” Therefore, the first hypothesis is:

$H1_{Diffusion}$: A mixed-influence model will more accurately predict the diffusion of BI/DW in both academic and practitioner literature.

Another goal of this study is to detect any difference in BI/DW diffusion between academic and practitioner literature. There are three perspectives to this question: (1) academic literature generally precedes practitioner literature (Clark, 2004); (2) academic and practitioner literature diffusion corresponds—similar diffusion curves in time, with little or no lag (Ruling, 2005); and (3) practitioner literature diffuses earlier than academic research (Ramiller, Swanson & Wang, 2008)—an example could be the Service Oriented Architecture area. Thus the second hypothesis is:

$H2_{Diffusion}$: BI/DW diffusion in academic literature will be lower than in practitioner literature.

Academics often discuss ideas with their peers, present their ideas at conferences, receive peer criticism and review, and then finally prepare papers for academic journals. In contrast, practicing managers often receive new ideas, as well as implementation success/failure stories and relevant product information, from vendor ads and articles in magazines, newspapers, and other external outlets (although peer networks also play an important role). Therefore, the third hypothesis is:

$H3_{Diffusion}$: In the diffusion of BI/DW the role of external influence will be greater for practitioner literature.

2.3 Research Design and Methodology

Publications were selected for analysis only if they were not centered on topics of BI or DW. The reason was twofold: (1) Journals on BI/DW do not represent a broad cross section of IT papers, which is the focus for this research stream; and (2) none of the BI-centric or DW-centric journals covered the entire 15-year time span studied in this research. Moreover, only

those articles that materially used the exact terms “Business Intelligence,” “Data Warehouse,” and “Data Warehousing” were selected for this study. Much of the literature that might be appropriate for BI could include terms such as data mining, statistical analysis, dashboards, and OLAP to name a few. Nevertheless, using exact terms provided consistency and reduced ambiguity regarding the selection process.

Five top scholarly journals and two practitioner periodicals were searched for references to at least one of the terms, “Business Intelligence,” Data Warehouse,” or “Data Warehousing,” in the body of a paper. The search covered a 15-year span, from 1995 to 2009, which afforded a comprehensive examination of the diffusion of BI/DW. The period encompasses the most prevalent activity for BI/DW, and follows two significant events: Bill Inmon, often considered the father of data warehousing, published his influential book (Inmon, 1992), and Ralph Kimball founded Red Brick Systems. There were two overriding constraints to selecting scholarly and practice journals for this preliminary study: (1) Only journals that were actively publishing the entire 15-year period were candidates, and (2) only journals that represented a cross-section of IT-centric content and not just BI/DW topics were considered. Some popular journals were therefore not selected, for example, the *Business Intelligence Journal*. This practitioner journal was not publishing the entire 15-year time span and it represents BI/DW-specific content.

Five academic journals were selected based on two criteria: first, at least one journal must represent general interest content and the other four specifically management information systems (MIS), and second, one journal had to be considered a “B” level journal while the other four were rated as “A/A+. The purpose was to include a cross-section of papers being published and consumed as opposed to simply selecting the top five MIS journals. Using the current rankings of journals by the Association for Information Systems coupled with publication

grading from Penn State and Washington State University, the following journals were selected: *MIS Quarterly*, *Information Systems Research*, *Journal of Management Information Systems*, *Management Science*, and *Information & Management*.

Practitioner periodicals were limited in part by their availability in LexisNexis. Two of the most popularly read were selected: *Computerworld* and *InfoWorld*. While this represents fewer periodicals than used for the academic sample, the number of articles selected is considerably higher (See Table 2 for a summary).

Table 2. Periodicals Selected

Academic Journals	No.	Magazines	No.
MIS Quarterly	34	Computerworld	1329
Information & Management	15	InfoWorld	886
Journal of Management Information Systems	10		
Management Science	40		
Information Systems Research	59		
Total:	**158**		**2,215**

The approach and process for selecting papers in this study were based on previous research (Abrahamson, 1991; Bakersville & Myers, 2009; Jourdan et al., 2008). For example, selected were the ten top IT journals, using the terms BI, DW, and Data Mining to identify potential papers spanning 1997 to 2006 (Jourdan et al., 2008). While this work identified articles for the purpose of categorizing the type of research being conducted, the intent was to simply identify and count relevant papers as data points for the three diffusion models and descriptive statistics. To that end, the three-phased process outlined below was designed.

Once the periodicals were identified, 75 specific searches (15 years times 5 journals) were conducted, one for each journal, for each year from 1995 to 2009. The three key phrases

searched for in each article were: “business intelligence,” “data warehouse,” and “data warehousing.” Phrases such as decision support, data mining, expert systems, or artificial intelligence were not included in the searches in order to reduce doubts regarding the paper selection. The specificity of this search process ensured consistency and repeatable results.

Although the initial search results were specific, several other filtering criteria ensured selection of only those papers relevant to the research. In order to be selected, one of the three key phrases must be used in the context of IS support systems and applications. If the article speaks of, for example, business intelligence in a literal sense as opposed to a reference to an IS-based system or application, then the paper was rejected. The paper was also rejected if the phrases were found only in the reference section, subject terms, key words, or author’s bio. Only those papers that used one or more of the three phrases within the body of the paper or its tables or notes, and conformed to an IS reference, were selected.

Final selection was conducted on a paper-by-paper basis. Since the vast majority of papers were stored in a PDF format, the Find option of Adobe Acrobat was used to determine if the candidate paper met all the criteria specified above. A test word was chosen at random from the paper in order to test that the Find option worked on the PDF version of the document. If the test search worked, then three separate searches were conducted, one for each of the key phrases.

The papers identified, selected, and categorized for this study serve as the data set for the three diffusion models: internal, external, and mixed-influence. The expressions for $N(t)$, and the cumulative number of adopters at time t, used for each of the models are outlined below (Mahajan & Peterson, 1985; Dos Santos & Peffers, 1995):

Internal model: m/(1+ ((m-m0)/m0)*exp(-b*m*t))
External model: (m*(1-exp(-(a)*t)))

Bass mixed-influence model: (m*(1-exp(-(a+b)*t)))/(1+(b/a)*(exp(-(a+b)*t)))

where *m* is the number of potential adopters, *m0* is the number of adopters at time *t* = 0, and other symbols have the same meaning as in Section 2.1. The nonlinear regression model of SPSS was used for each of the three diffusion models of this study.

2.4 Findings

The mixed-influence model (MM) demonstrated the most success in predictive quality for both the academic and practice research.

2.4.1 Bass Mixed-Influence Model: Academic Research

The results from the Bass MM appear in Figure 2. The findings suggest that both internal and external influences are affecting the diffusion of BI/DW in academic research. The fit of the MM to the cumulative academic articles published is significant with an R^2 of 0.998 (and an SSE of 398.061). The results provide additional support for $H1_{Diffusion}$ in the case of academic literature. The summary of parameter estimates appears in Table 3.

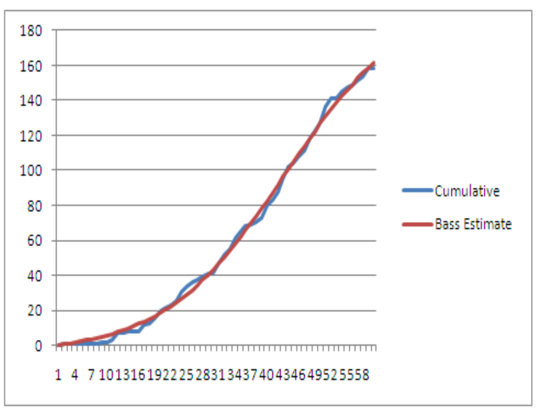

Figure 2. Academic Data Set Bass Mixed-Influence Model Distribution versus Actual Cumulative

Table 3. Scholarly Data Set Model Parameter Estimates

Parameter	MM Estimate	IM Estimate	EM Estimate
M	198.45***	187.286***	103221.85**
A	0.00186***	---	0.000022**
B	0.08709***	0.001***	---
R^2	0.998	0.997	0.868

M = % saturation level = total number of adopters

A = coefficient of external influence (e.g., media)

B = coefficient of internal influence/imitation (e.g., word of mouth)

*** = $p < 0.000$, ** = $p < 0.05$

2.4.2 Bass Mixed-Influence Model: Practitioner Articles

Shown is only the figure (Figure 3) for the Bass model for practitioner articles. The summary parameter estimates are given in Table 4. Based on the R^2 values, the Bass model provides the best fit for measuring diffusion of practitioners' literature. Thus support for $H1_{Diffusion}$ can also be found in the practitioners' literature. This also provides an answer to the first research question regarding the adoption level of BI/DW research in both communities.

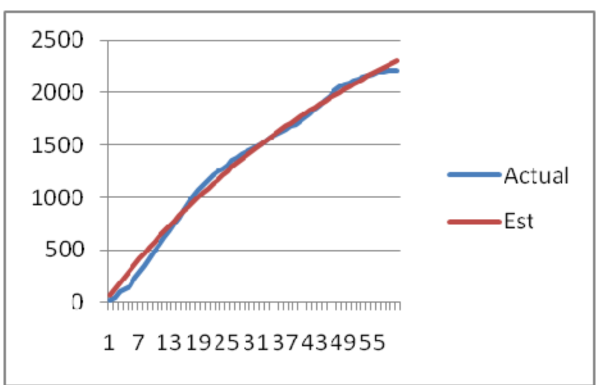

Figure 3. Practitioner Data Set Bass Mixed-Influence Model Distribution versus Actual Cumulative

Table 4. Practitioner Data for All Model Parameter Estimates

Parameter	MM Estimate	IM Estimate	EM Estimate
M	2610.6***	2193.08***	3444.44***
A	0.0207***	---	0.0182***
B	0.0228***	0000444***	---
R^2	0.9939	0.9765	0.9927

2.4.3 Comparison of Academic and Practitioner Diffusions

The inflection point (the maximum penetration rate), where incremental change in cumulative value is highest, occurred in the MM for academic diffusion at about the 43rd quarter, preceded by a rapid rise in adoption and followed by a level of sustained maturity. For practitioner diffusion, the MM results in an inflection point much earlier, at about the 3rd quarter. Clearly, the two mixed models differ in structure. This provides support for $H2_{Diffusion}$, that BI/DW diffusion in academic literature will be lower than in practitioner literature.

Using the results from the MM for both the scholarly and practitioner data sets, support is found for $H3_{Diffusion}$ as well as research question 2. The internal parameter estimate for the practitioner data set is 0.0207, whereas the internal parameter estimate for the scholarly data is 0.08909. The external parameter values for scholarly and practice data sets are 0.00186 and 0.0207, respectively. Then we consider the ratio of coefficients *b* and *a* (i.e., *b*/*a*): 1.101 for the practice data set and 46.823 for the academic data set, a marked difference. Thus, external influence makes a stronger impression on practitioner literature, although both models are mixed.

2.5 Level of Adoption Conclusion

In spite of the limitations cited above, this study contributes in several ways. The analysis demonstrates that BI/DW has achieved relatively significant diffusion over the 15 years from

1995 through 2009. Of the different diffusion innovation models (mixed, internal, and external), the mixed model more accurately estimates the diffusion of BI/DW. The Bass mixed-influence model suggests that both internal and external influences are promoting the adoption of BI/DW technology and techniques for both academic and practitioner literature.

Another important finding is that the diffusion in practitioner literature seems to be more influenced by external factors than is diffusion in academic literature. Finally, it can be observed that the practitioner periodical diffusion rate slows earlier than that of academic journals. This may be partly explained by the peer review process of published scholarly work.

The impact of these preliminary findings is particularly significant if they remain consistent as the study expands. They suggest that academic research in BI/DW is conducted in a closed community of peers. This situation may make the research results less relevant to or disconnected from practitioners. Conversely, the private sector may be overly influenced by external factors such as advertising, vendor messages, and outside consultants. When companies plan to make investments in BI/DW, they must guard against decisions being swayed by vendors and other external sources that may degrade the internal value of the effort. If this degradation is allowed to happen, academia and practice may become disconnected, consequently limiting the contributions of each community to the other and even limiting DW/BI growth in general.

Results show that for BI/DW diffusion, practitioners' research is being influenced more by external factors, while internal influence is predominant in academic research diffusion. One pertinent question arises: Is this only true for BI/DW diffusion or a result that holds true for all technologies such as BPR, CASE, e-commerce, and ERP? Empirical studies are needed to explore this question further.

CHAPTER 3. BUSINESS INTELLIGENCE AND DATA WAREHOUSING FACTORS FOR COMPETITIVE ADVANTAGE

This chapter introduces the second research stream based on a parametric study. Provided in this chapter are the literature review, hypotheses, study design, and data of the BI/DW factors for competitive advantage.

3.1 Competitive Advantage Factors

The essence of achieving competitive advantage is to have an effective strategy to cope with competition. The strongest competitive forces are of great importance in business strategy formulation (Porter 1979, 1980). Agility is essential to the innovation and competitive performance of firms in contemporary business environments. Firms are increasingly relying on IT, including process, knowledge, and communication, to enhance their agility (Sambamurthy, 2000).

IT-enabled competitive advantage is the process of leveraging IT resources (Porter, 1980; Sambamurthy, 2000) based on the theory of competitive advantage. According to Porter, the two main types of competitive strategies are cost and product differentiation. One can make a more meaningful analysis by breaking down factors that help a firm to achieve either a cost or a product differentiation advantage over competing firms.

The debate continues on which IT resources and other factors significantly contribute to competitive advantage. However, the factors of leadership, skill, and infrastructure are widely accepted as significant (Bharadwaj, 2000; Bhatt & Grover, 2005; Dehning & Stratopoulos, 2003; Sambamurthy, Bharadway, & Grover, 2003; Santhanam & Hartoro, 2003). These three factors increase a firm's differentiation component as well as the cost component of competitive

advantage. For example, investing in employees' leadership and skill training may initially increase operation costs. However, in the long run, a firm will cut the total cost of operations through innovative process planning by utilizing the leadership and skill of its employees. The same logic applies to the infrastructure factor. A planned initial investment in a firm's infrastructure generally increases its cost; however, this increase results in more effective information flow throughout the company.

Leveraging the IT-enabled competitive advantage research, this study focuses specifically on BI and DW and their impact to competitive advantage as measured by the established three constructs of leadership, skill, and infrastructure (Gonzales, Mahmood, & Gemoets, 2009). Using a proprietary database of BI maturity assessment survey data, this study attempts to validate or reject BI leadership, BI skill, and BI infrastructure as significant factors to competitive advantage. This study builds theoretical relational hypotheses between factors and tests them using statistical techniques in three phases: (1) principal component analysis (PCA), (2) confirmatory factor analysis (CFA), and (3) structured equation modeling (SEM). This paper presents the data analysis and findings from all three steps.

The following section provides a literature review of relevant studies that provide evidence to support the factors of leadership, skill, and infrastructure as offering significant competitive advantage. The section after that (3.3) presents the causal model and research hypotheses grounded in theory. Next, the research methods and related data are described in Section 3.4. The results and subsequent analysis are then reported in Chapters 5 and 6.

3.2 Literature Review

Focusing on current research (academic papers published since 2000), examined were several studies on IT-enabled competitive advantage, including archival (Bharadwaj, 2000; Dehning & Stratopoulos, 2003), theoretical (Weill, Subramani, & Broadbent, 2002; Sambamurthy et al., 2003), and survey (Wade, 2001; Wixom & Watson, 2001). These studies proposed theories and frameworks in an effort to explain and quantify the impact of IT-centric factors on business strategy and competitive advantage. While existing research varies on the factors and their significance, leadership (also identified as management), skill, and infrastructure emerged as widely accepted determinants.

Table 5. Factor Summary

	Factors for Competitive Advantage		
Academic Papers	IT Infrastructure	IT Skill	IT Leadership
Bharadwaj, 2000	X	X	X
Duliba et al., 2001			X
Feeny, 2001	X		
Wixom &Watson, 2001	X		X
Wade, 2001	X	X	X
Ross & Beath, 2002	X	X	X
Weill et al., 2002	X	X	X
Sambamurthy et al., 2003	X	X	X
Santhanam & Hartono, 2003		X	X
Dehning & Stratopoulos, 2003	X	X	X
Bhatt & Grover, 2005	X	X	X
Oh & Pinsonneault, 2007	X	X	X

Table 5 lists the three factors identified in the respective research contributing to competitive advantage. Each of these factors is briefly discussed here.

3.2.1 Leadership

Research has confirmed that effective IT leadership is a cornerstone to business strategy and competitive advantage (Bharadwaj, 2000). Research also suggests that it may take several years to cultivate and nurture a successful organization with the necessary internal relationships

for communication and coordination (Bhatt & Grover, 2005). As outlined in Table 5, there are 11 papers that recognize leadership as a factor for consideration (Bharadwaj, 2000; Duliba, Kauffman, & Lucas, 2001; Wixom & Watson, 2001; Wade, 2001; Ross & Beath, 2002; Weill et al., 2002; Sambamurthy et al., 2003; Santhanam & Hartono, 2003; Dehning & Stratopoulos, 2003; Bhatt & Grover, 2005; Oh & Pinsonneault, 2007).

3.2.2 Skill

Nine of the papers shown in Table 5 consider skill as a competitive advantage determinant. It is thought that a well-trained team is required to successfully implement and support leading technology and applications. However, establishing this highly skilled resource pool takes time. Current research suggests that organizational learning establishes a competitive advantage because it is difficult for competitors to emulate (Bhatt & Grover, 2005; Johannessen & Olsen, 2003; Dehning & Stratopoulos, 2003).

3.2.3 Infrastructure

As shown in Table 5, ten studies have identified infrastructure as a potential factor for competitive advantage. Some researchers view the establishment of leading edge-hardware and software as a differentiator that is difficult to emulate by competitors (Weill & Broadbent, 2000; Bharadwaj, 2000). Conversely, a few researchers have not been able to confirm the significance of infrastructure as a determinant for competitive advantage, based on the argument that IT hardware and software are widely available (Bhatt & Grover, 2005).

3.3 Research Hypotheses and Causal Model

A BI-enabled competitive advantage model is proposed in Figure 4. As shown, there are three factors, *BI leadership*, *BI skill*, and *BI infrastructure*, used to validate a BI-enabled

competitive advantage. Research concludes that IT contributes to corporate performance and competitive advantage through, for example, product or service innovation, corporate differentiation, process efficiency, cost reduction, and quality improvement (Porter, 1998).

The model defines the explicit and direct relationship among the three factors and competitive advantage as well as the causal relationships between the factors (Gonzales et al., 2009). Because technology infrastructure has been questioned in previous research as a significant factor, this study examines the potential impact of skill and leadership on Infrastructure.

3.3.1 BI Leadership

Previous research has identified leadership (Piccoli & Ives, 2005) and management (Dehning & Stratopoulos, 2003) of IT as significant to the success of an IT-enabled corporate strategy. The IT organization must foster its management skill over time in order to manage the technical environment, conceive of innovative techniques and approaches, and effectively scope inherent risks (Bharadwaj, 2000) associated with infrastructure investments and technology trends.

3.3.2 BI Skill

The skill of the BI team refers to the expertise required to evaluate, select, implement, build, and support the use of the technical environment. From an infrastructure perspective this includes hardware, operating systems, networks, and user-facing applications. Technical skill is critical to the performance of, for example, IT and its ability to contribute to competitive advantage (Dehning & Stratopoulos, 2003; Bharadwaj, 2000). Skilled resources and capabilities contribute to the overall performance of an organization (Sambamurthy, 2000).

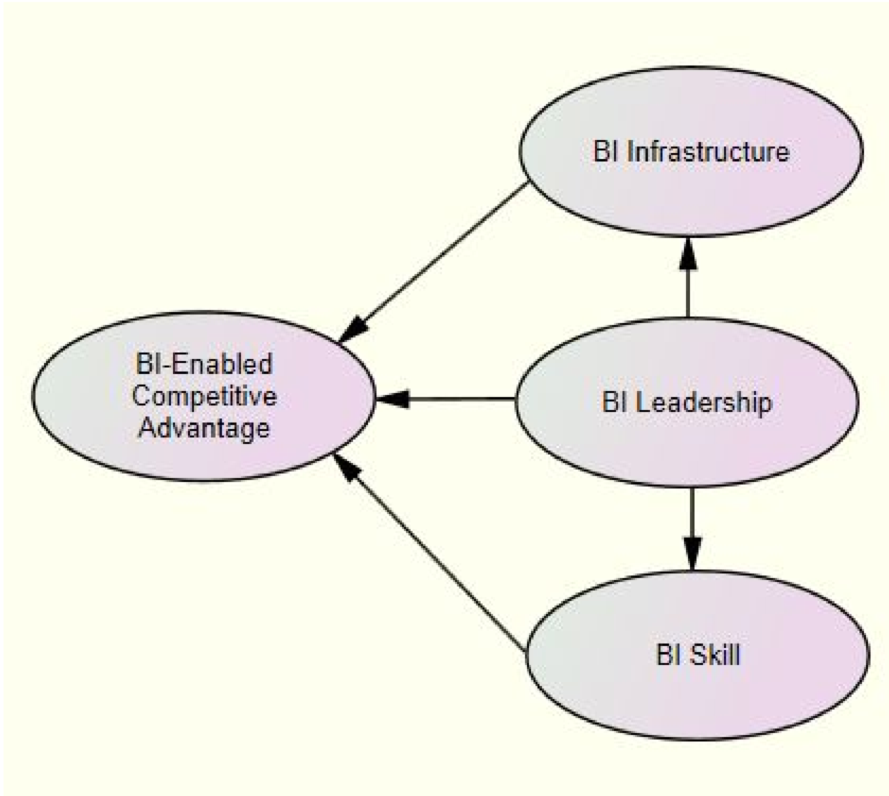

Figure 4. BI-enabled Competitive Advantage Model

3.3.3 BI Infrastructure

Successful BI infrastructure is considered difficult to imitate and is consequently a barrier to competitors and a source of competitive advantage (Oh & Pinsonneault, 2007). Infrastructure includes all hardware and software implemented in an environment to establish the platforms from which information is gathered, synthesized, and delivered to user communities to support operational and strategic decision making.

3.3.4 Research Hypotheses

Previous research suggests that competitive advantage is achieved in part by the contribution of technical resources and capabilities (Porter, 1979, 1980; Sambamurthy, 2000). This research therefore proposes five hypotheses, described below and illustrated in Figure 5.

Training and skill of a technology team has been established as a possible factor that, if nurtured over time, may prove difficult for competitors to emulate (Bharadwaj, 2000). Based on that research, the following hypothesis is offered:

$H1_{Factors}$: BI skill will positively impact the competitive advantage of the firm.

Technical infrastructure has been associated with the ability to deliver and maintain company support of the services (Weill & Broadbent, 2000). Based on existing research, the following is hypothesized:

$H2_{Factors}$: BI infrastructure will positively impact the competitive advantage of the firm.

Leading and managing a technical resource team and environment is widely accepted as a factor for competitive advantage (Dehning & Stratopoulos, 2003); consequently, the following is posed:

$H3_{Factors}$: BI leadership will positively impact the competitive advantage of the firm.

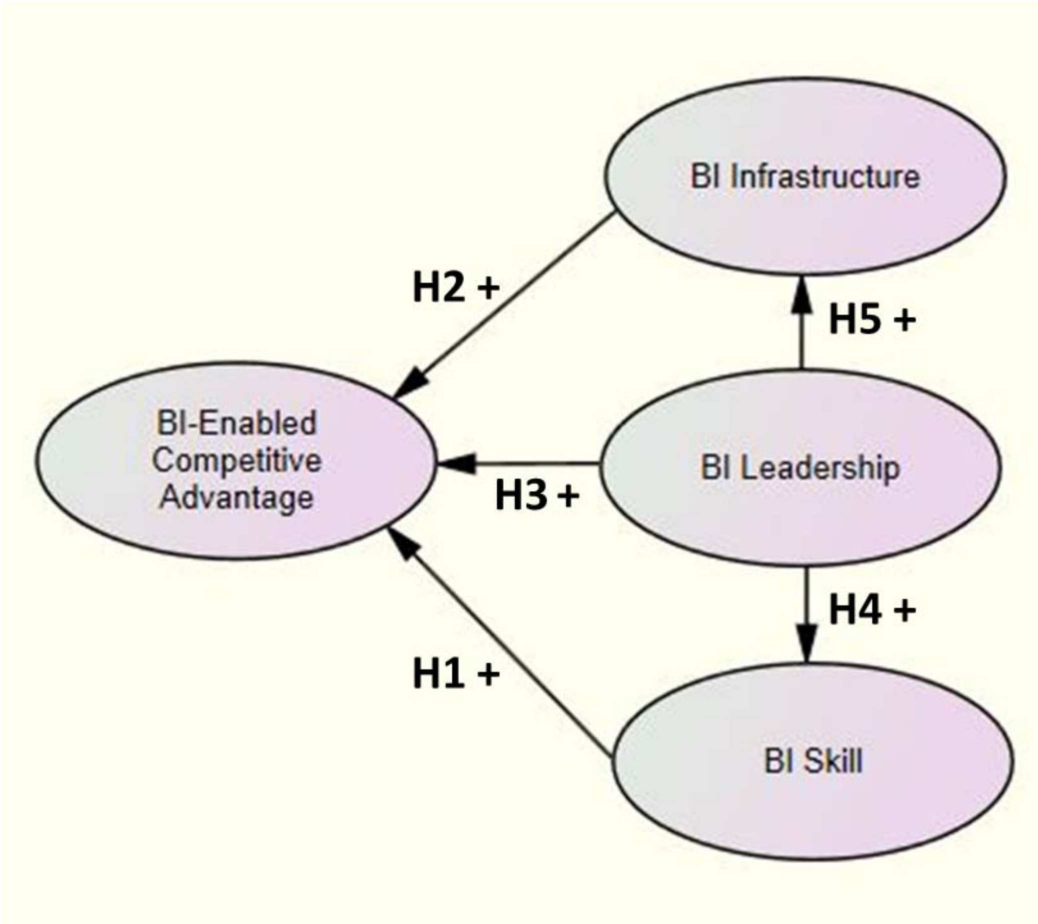

Figure 5. Hypotheses

There are two other hypotheses in this study that focus on the causal relationships between factors as outlined below.

Some research suggests that leadership is critical to the development of a mature, experienced technical team and, therefore, to the skill of the organization (Bharadwaj, 2000; Dehning & Stratopoulos, 2003; Sambamurthy et al., 2003). Moreover, it has been suggested that leadership is critical for an organization to gain the necessary support for sustained and aggressive investment in Infrastructure. Therefore, based on current research, the following two hypotheses are offered:

$H4_{Factors}$: BI leadership will positively impact BI skill.

$H5_{Factors}$: BI leadership will positively impact BI infrastructure.

3.4 Research Methodology and Design

This section describes the proposed design of the study as well as the data to be leveraged to validate or reject stated hypotheses. Empirical studies of IT factors for competitive advantage have focused on linear regression analysis that utilized proxies for each of the three factors (leadership, skill, and infrastructure) as independent variables in an attempt to measure the variance of the dependent variable, competitive advantage (Dehning & Stratopoulos, 2003). Linear regression does help to determine how much of the variance in the dependent variable is explained by the independent variables; however, it does not validate the use of factors, nor does it explain the causal relationships between latent variables.

Table 6. Surveys by Year

Year	Frequency	Percent	Cumulative Percent
2007	1,699	55.60%	55.60%
2008	957	31.30%	86.90%
2009	402	13.10%	100.00%
Total	3,058	100.00%	

To that end, this study leveraged three techniques: PCA, CFA, and SEM. The initial research will expose those factors that are most significant when attempting to measure the maturity of a BI/DW environment and will also execute SEM to explain the causal relationships between the factors themselves.

This research had exclusive access to a proprietary database of 3,058 self-assessment surveys that rate BI maturity. Individual representatives of corporations and organizations as well as BI consultants were participants who voluntarily took the survey by visiting the website

of The Data Warehousing Institute (tdwi.org/pages/assessments/benchmark-your-bi-maturity-with-tdwis-new-assessment-tool.aspx?sc_lang=en). The database of survey responses is considered a convenient sample. Moreover, bias exists in the data set because participants would need to be familiar with The Data Warehousing Institute to find the assessment. Nevertheless, the surveys represent organizations across the globe, from diverse industries (no industry bias), over a timeframe from 2007 to 2009. Table 6 provides a summary of the number of surveys taken by year.

Table 7 provides the frequency count of surveys by location. Participants were allowed one choice among Africa, Asia, Australia, Canada, Europe, Mexico/Central/South America, Middle East, United States, or Other.

Table 7. Surveys by Location

Geographic Area	Frequency	Percent	Valid Percent	Cumulative Percent
Africa	28	0.90%	0.90%	0.90%
Asia	144	4.70%	4.70%	5.60%
Australia	105	3.40%	3.40%	9.10%
Canada	240	7.80%	7.80%	16.90%
Europe	540	17.70%	17.70%	34.60%
Mexico/Central/South America	74	2.40%	2.40%	37.00%
Middle East	33	1.10%	1.10%	38.10%
Other	104	3.40%	3.40%	41.50%
USA	1790	58.50%	58.50%	100.00%
Total	3058	100.00%	100.00%	

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CHAPTER 4. PRINCIPAL COMPONENT ANALYSIS

Factor analysis begins with Principal Component Analysis (PCA). This chapter presents the formal steps taken to conduct PCA and reports the results.

4.1 Data Set Validation

Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were performed on the data set as part of PCA and were the first step toward identifying factors that are significant to BI-enabled competitive advantage. KMO measures whether the distribution of values in the data set are adequate for conducting factor analysis, while Bartlett's tests whether the correlation matrix is an identity matrix. As shown in Table 8, the KMO score is 0.946, which is considered "marvelous" based on the Kaiser scale (Venkaiah, Brahmam & Vijayaraghavan, 2011). The score for Bartlett's confirms that the data set does not produce an identity matrix.

Table 8. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.946
Bartlett's Test of Sphericity	Approx. Chi-Square	36752.163
	Df	703.000
	Sig.	0.000

Cronbach's alpha reliability test was also conducted to test validity. This type of reliability analysis facilitates the examination of the properties of measurement scales and the respective items of those scales. Cronbach's alpha tests the internal consistency of a model, based on the average inter-item correlation.

The coefficient of Cronbach's alpha normally ranges between 0 and 1, although there is no actual lower limit. As the coefficient approaches 1.0, the internal consistency of the items in the scale of the instrument grows. Rules of thumb have been widely accepted to interpret

Cronbach's alpha coefficient at a value > 0.9 to be excellent (George & Mallery, 2003). Table 9 outlines the Cronbach's alpha coefficient values for this data set.

Table 9. Cronbach's Alpha

Construct	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
BI Infrastructure	0.875	0.879	10
BI Leadership	0.675	0.679	4
BI Financial Commitment	0.684	0.712	4

Refer to Appendix D for the intraclass correlation coefficients for each of the three constructs.

4.2 Total Variance

The total variance explained by the components in PCA is shown in Table 10. The default procedure recommends focusing only on those factors with an eigenvalue greater than 1.0; consequently, only six components appear in Table 10, accounting for 47.567% of the variance explained.

Table 10. Total Variance Explained

	Initial Eigenvalues		
Component	**Total**	**% of Variance**	**Cumulative %**
1	10.008	26.338	26.338
2	2.077	5.466	31.804
3	1.845	4.854	36.658
4	1.563	4.112	40.770
5	1.535	4.039	44.809
6	1.048	2.758	47.567

4.3 Scree Plot and Rotated Component Matrix

A Scree plot is a line segment graph that illustrates the fraction of total variance in the data represented by each principal component. The components appear in decreasing order of contribution to total variance. Therefore, the plot is read left-to-right with the most important

components on the left. Those principal components considered significant are identified by a significant slope. It is recommended to retain all components above the point in the plot that begins to flatten out, referred to as the elbow or break in the plot (Catell, 1966). In this data set, the elbow is estimated at the 7th component, indicating that components 1 through 6 merit further examination. As illustrated in Figure 6, the first component demonstrates the steepest slope and therefore explains the most significant portion of variance. And while less significant than component 1, components 2 through 6 maintain some slope. After the 6th component, however, the slope begins to flatten.

A final step in PCA is the rotated component matrix. Table 11 shows results from Varimax rotation with Kaiser normalization. The 38 observed variables in Table 11 appear in order by most significant to least by components loaded. The objective of the rotation is to identify a *simple structure* described as a component with high factor loadings on one observed variable and low loadings on all others. In general, factor loadings of > 0.5 are considered high, and all else is considered low (George & Mallery, 2003). Based on this general rule, the rotated component matrix provides some interesting findings that are supported by a Scree plot.

The first three components seem to provide guidance on a simple structure. Component 1 identifies observed variables that mainly focus on *infrastructure*, such as Standards in Technology, Standards for Development, Adherence to those Standards, Definition and Rules, Developing Solutions, Data Models, Predominant Architecture, Business Metadata, and User Access. Trust in Data is also considered significant for component 1, but further research must be conducted to determine its inclusion here. All other factors have low load values for component 1.

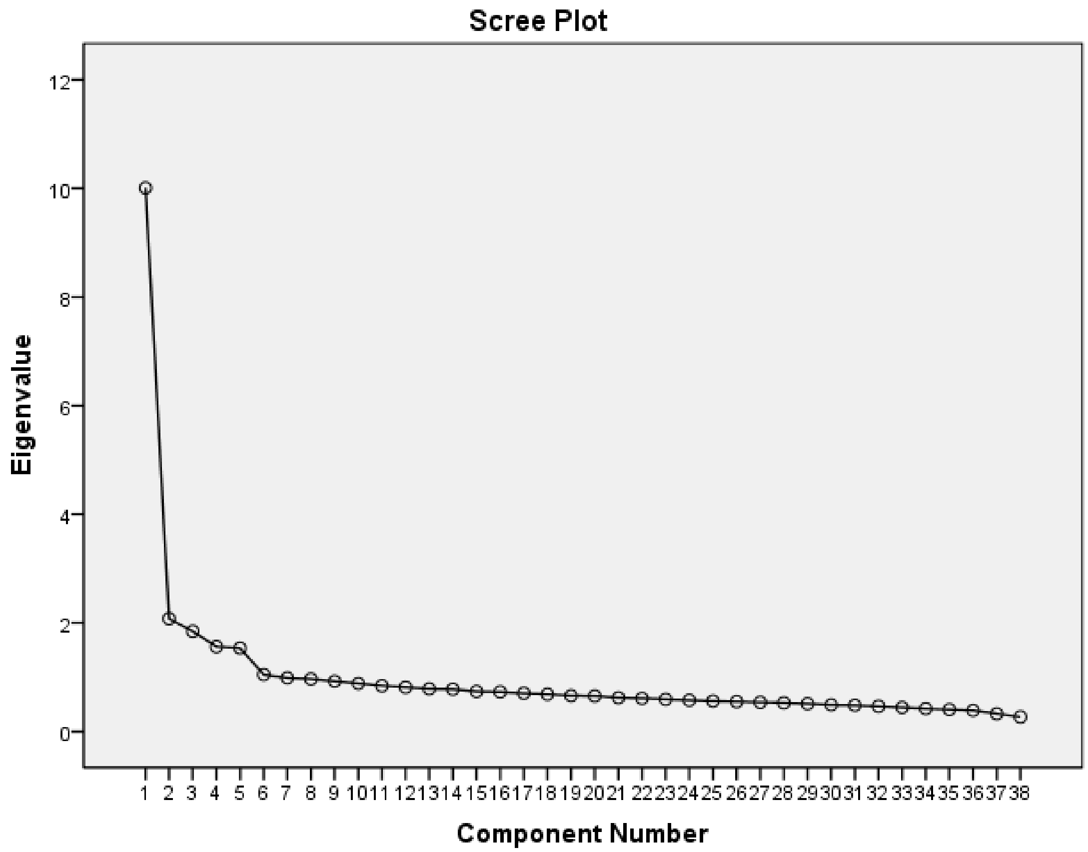

Figure 6. Scree Plot

Component 2 highlights variables that can be considered consistent with *leadership*: Executive, Committed, Accountable, and Sponsor. All other factors have low load values. And finally, component 3 identifies a unique set of factors that seem centered on finance, such as Funding, Annual Budget, Maintenance Budget, and Capital Investment. All other factors for component 3 have low load values. The other components are less consistent with regard to significant factors. For example, component 4 shows Apps, Data Sources, Project 90 Days, and Role as being significant. However, these factors are not focused on a particular issue or topic. Instead they seem to be disconnected and therefore may not be considered for further study. For the complete component analysis matrix refer to Appendix C.

The PCA findings provide important evidence to support future research to identify factors related to the measurement of BI-enabled competitive advantage. There are six findings of particular interest to subsequent research: (1) findings suggest that the data set is suitable for factor analysis; (2) of the 38 observed variables of the survey, 18 are significant; (3) these 18 variables seem to be grouped into three topics: infrastructure, leadership, and finance; (4) two of the topics are consistent with the proposed BI-enabled competitive advantage model, specifically BI infrastructure and BI leadership; (5) support for BI skill as affecting competitive advantage seems not to exist given the data set, and (6) financial commitment seems to be a significant topic for measuring BI success.

If proxies for BI skill included only such measures as the number of power users or the ratio (of power users to other user types), then there is little or no support in these initial findings for BI skill as a contributor to competitive advantage. However, previous research suggests other important measures for BI skill, such as the number of staff trained or the budget amount spent on training. Since these variables are not measured in the data set being studied, it is imperative that other data be studied that contain these factors before making any final conclusions regarding BI skill.

The PCA was used to start the process of validating the proposed BI-enabled competitive advantage model based on the survey data set. It is this data set that forms one limitation. It contains 38 measurements, many of which may serve as proxies to measure the impact of BI infrastructure, BI leadership, and BI skill. But many more variables that go beyond the 38 measurements of the data set may prove significant. Future research must pursue other data sets to fully validate or reject $H1_{Factors}$.

While this phase of the research does have limitations, these initial findings remain significant for the remaining two phases of this study and the pursuit of measuring BI-enabled competitive advantage

Table 11. Rotated Component Matrix (Abbreviated)

Rotation converged in 9 iterations	Component					
	1	2	3	4	5	6
STANDARDS in TECHNOLOGY	.736	.024	.232	.177	.093	.041
STANDARDS for DEVELOPING	.730	.090	.175	.187	.057	.112
ADHERENCE	.669	.031	.199	.105	.214	.016
DEFINITIONS and RULES	.662	.179	.121	.027	-.002	.234
DEVELOPING SOLUTIONS	.640	.150	.187	.136	.181	-.023
DATA MODELS	.589	.062	.097	-.079	.174	.163
PREDOMINANT ARCHITECTURE	.574	.069	.173	.096	.253	-.003
BUSINESS METADATA	.549	.227	-.056	.021	-.069	.338
USER ACCESS	.548	.050	.151	.090	.390	.169
TRUST the DATA	.502	.098	.114	.006	.438	.155
REPORTING for CASUAL USERS	.483	.206	-.060	.122	.212	.126
PROJECT MANAGERS	.472	.253	.131	.089	.052	.048
PROCESSES	.442	.389	.396	.092	.028	.163
SUCCESS	.433	.139	.254	.176	.381	.292
EXECUTIVE	.123	.644	.091	.026	.070	.165
COMMITTED	.106	.644	.417	-.062	.185	.048
ACCOUNTABLE	.113	.606	.408	-.085	.060	.168
SPONSOR	.179	.515	.036	.243	-.005	-.029
FUNDING	.217	.266	.610	-.050	.126	.075
ANNUAL BUDGET	.106	.098	.609	.154	.035	.138
MAINTENANCE BUDGET	.336	.136	.606	.206	.082	.111
CAPITAL INVESTMENT	.409	.057	.507	.195	.150	.069
ALLOCATES	.217	.311	.318	.189	.005	-.092
APPS	.117	.011	.103	.754	.149	.128
DATA SOURCES	.078	.103	.036	.741	-.082	.102
PROJECTS 90 DAYS	.214	.044	.167	.649	-.023	.118
ROLE	.077	.056	.080	.597	.277	-.078

CHAPTER 5. UNDERSTANDING CAUSAL RELATIONSHIPS USING STRUCTURED EQUATION MODELING

The final step to factor analysis and the BI/DW factors for competitive advantage research stream is to build a structured equation model (SEM) to validate or reject the hypotheses outlined in Chapter 3. This chapter presents the process and related findings for establishing and improving the model fit.

5.1 Structured Equation Model

The model shown in Figure 7 is based on the PCA conducted and presented in Chapter 4. As stated, the PCA found three significant components that covered 18 proxies. Figure 7 is the SEM that reflects the three components and their relevant proxies.

Labels were associated with each of the three latent variables shown in the model. Two of the labels, BI infrastructure and BI leadership, represent the constructs identified in Chapter 3 in both the literature review and hypotheses. The first component contains 10 proxies labeled *BI Infrastructure* as the proxies mainly focus on infrastructure. For example, Standards Technology, Data Model, Predominant Architecture, Data Access, and Standards for Developing reflect infrastructure-centric concepts consistent with previous research. The second component reflects the four proxies replicating those of the leadership construct found in the literature review and therefore was labeled *BI Leadership*. Both BI infrastructure and BI leadership represent those constructs in the hypotheses of this research. However, the PCA identified a third significant component that did not represent proxies associated with the construct in our literature review or with our hypotheses. Instead of *BI Skill*, the third construct was labeled *BI Financial Commitment* to better describe the four proxies of this latent variable.

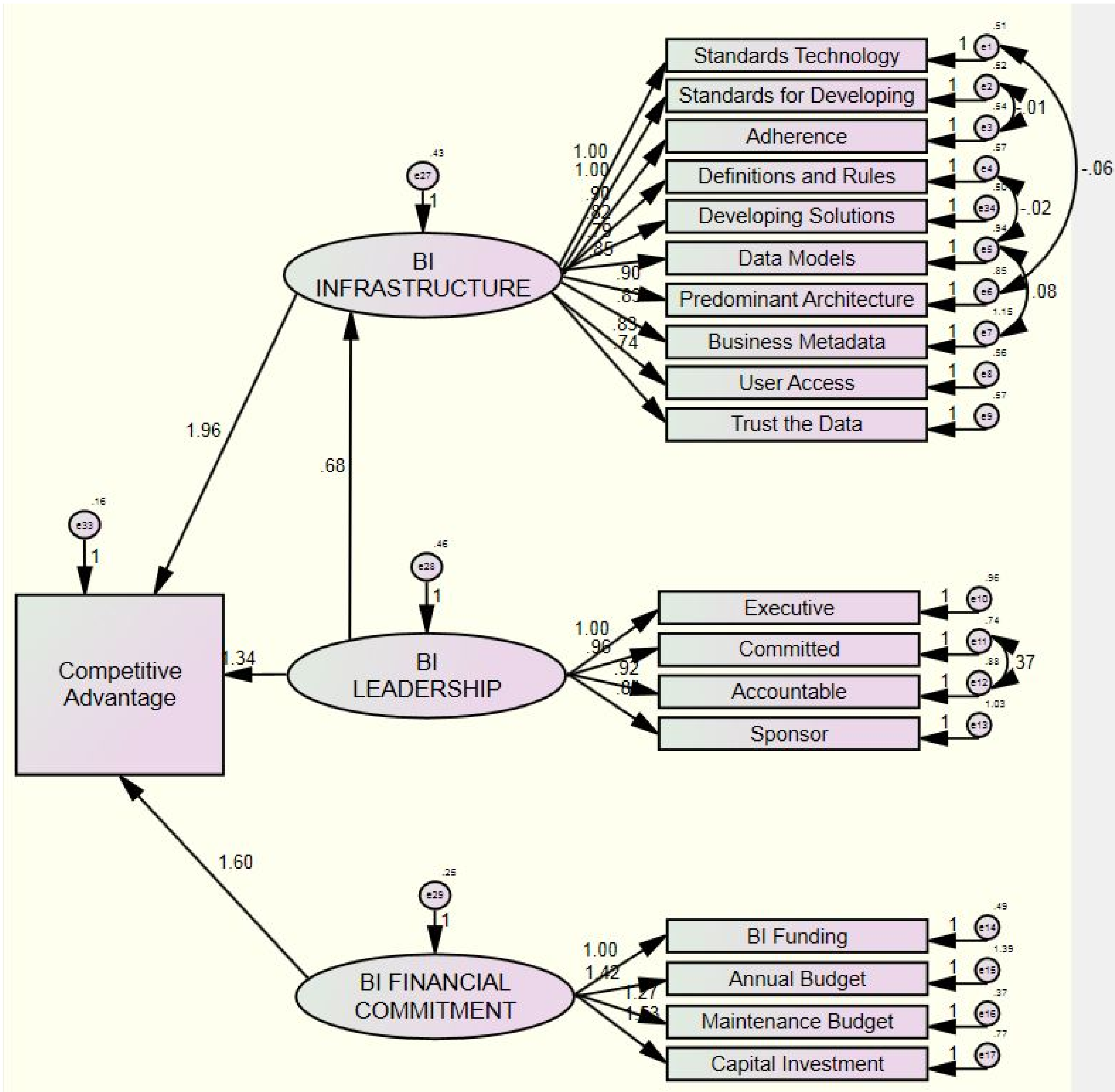

Figure 7. Base Structured Equation Model

Three steps were taken to validate the model in Figure 7: (I) base model test, (II) modification search for SEM, and (III) testing the final model. The first phase focuses on the results of the PCA and is consistent with factor analysis. The second phase is based on the common practice of attempting to improve the model fit, referred to as Modification Search for

SEM. And the third phase is reserved for testing the final model. For brevity, the following outline identifies the key steps.

Phase I—Base model with full data set

1. Identify and establish proxy correlations where appropriate and defendable
2. Test the base model in Figure 6 using the full data set

Phase II—Modification Search for SEM

3. Create two data sets, each with approximately 50% of the observations from the full data set, one labeled *Analysis Sample* and the other *Test Sample*
4. Using Modification Indices (MI), identify opportunity for model improvement and test with Analysis Sample
5. Using Residual Moments, identify opportunity for model improvement and test with Analysis Sample

Phase III—Test the final model

6. Establish a final model based on the updates in Phase II and test the model using the Test Sample

The results of these steps and a brief discussion are covered in the following section.

5.2 Findings

Table 12 outlines the key results from the model tests across all three phases of this analysis. Detailed results can be found in the appendices.

Table 12. Summary of Findings

	Phase I	Phase II		Phase II
	Base Model	Modification Index Model Update	Residual Moments Model Update	Test Final Model
Data Sets	Full Data Set	Analysis Sample	Analysis Sample	Test Sample
Measurements				
CMIN	3402.077	975.063	868.617	988.495
DF	144.000	143.000	126.000	126.00
GFI	0.905	0.934	0.939	0.930
AGFI	0.874	0.913	0.917	0.905
PGFI	0.686	0.703	0.692	0.685
RMSEA	0.086	0.062	0.062	0.067
Hoelter 0.05	156.000	271.000	271.000	236.000
Hoelter 0.01	168.000	292.000	293.000	256.000

5.2.1 Phase I

The first phase was conducted for two purposes. The first was to establish a base model consistent with the PCA findings discussed in Chapter 3 and in section 5.1, and to test this base model with the full data set. The second purpose was to attempt model improvement where possible while preserving the integrity of a PCA-based study.

In order to improve the model fit, identifying correlations between proxies is accepted practice and does not compromise the integrity of a PCA-based study. To that end, five correlations were established to the base model:

1. Standards of Technology with Predominant Architecture
2. Standards of Development with Adherence to Standards
3. Data Model with Definitions and Rules
4. Data Model with Business Metadata
5. Committed with Accountable

The adjustments to the base model are shown in Figure 7.

Running the base model using the full data set resulted in satisfactory results across all key measures, as shown in Table 12. While some measures are relatively consistent with generally accepted tolerances of a good model fit, other measures simply do not meet established standards. For example, RMSEA of 0.086 is slightly higher than 0.06 (Hu & Bentler, 1999); a value as high as 0.08 represents reasonable error approximation in the population (Browne & Cudeck, 1993; Byrne, 2001). Both Hoelter indices are considered low given the rule-of-thumb score of 200 (Hoelter, 1983) or higher to indicate that the proposed model adequately represents the sample. GFI and AGFI scores over 0.90 represent adequate fit (Joreskog & Sorbom, 1993). As shown in Table 12, the GFI score of 0.905 meets that standard, while the AGFI of 0.874 does not. A combination value of GFI > 0.905 and a PGFI of 0.686 are consistent with a good-fit model (Mulaik et al., 1989). Refer to Appendix E for a complete list of base model results.

Phase I adhered to the PCA-based methodology. The results across the key measures, while relatively positive, do not achieve widely accepted measurement levels that determine a good model fit to the data.

5.2.2 Phase II

Phase II is a post-hoc analysis to modify the original base model. As such, this analysis no longer represents a strict confirmatory factor analysis approach. Although it is a common practice to attempt to modify the model, often referred to as Modification Model Search for SEM, it is important to move from Phase I to Phase II in a systematic way. Modification to the original model is not performed haphazardly. Instead, guidelines have long been established that provide direction to a methodical approach for modifying the model to achieve better model fit

results (Chou & Bentler, 2002). The process attempts to add a parameter based strictly on theoretical grounding. For Phase II, there are three key steps: (1) creating non-overlapping sample data sets, one for modifying the model and the other to validate the final model (Phase III); (2) Modification Indices to add constraints; and (3) Residual Moments to potentially reduce model constraints.

5.2.2.1 Two Sample Data Sets

It was necessary to split the full data set into two data sets without overlapping observations. This was accomplished by taking the 3,058 observations and randomly selecting 50% of those observations for one data set referred to as the Analysis Sample. This data set was used to tune the SEM model. The remaining 50% of observation were copied into a second test data set referred to as the Test Sample. This data set was reserved for the final model validation in Phase III.

5.2.2.2 Modification Indices

With Modification Indices (MI) selected in AMOS version 18, the estimates were calculated based on the model in Figure 6 and using the Analysis Sample data set. The AMOS output reports MI based on the estimated value by which chi-square will be reduced. In this study, three MIs reported included adding a parameter constraint to the following constructs:

- BI Infrastructure → BI Financial Commitment
- BI Leadership → BI Financial Commitment
- BI Financial Commitment → BI Infrastructure

While adding the parameter BI Infrastructure → BI Financial Commitment was considered to have the most impact on Chi-square, there is no theoretical support for this

constraint. The same is true for BI Financial Commitment → BI Infrastructure. Current research (refer to literature review in Section 3.2) does not provide any guidance to suggest that either of these parameters are valid. However, theoretical support can be argued for the MI of BI Leadership → BI Financial Commitment by substituting the original hypothesis and literature that suggests that BI leadership does influence other factors of competitive advantage, such as BI skill (Bharadwaj, 2000; Dehning, & Stratopoulos, 2003; Sambamurthy et al., 2003).

Although the PCA did not identify proxies indicative of a BI skill construct as explained in Chapter 4 of this research, the exploratory analysis did identify a third component that was labeled BI financial commitment due to the proxy's similarity to financial aspects of a BI/DW program. Even though the data set did not support a BI skill construct, this research will leverage BI financial commitment and apply the same theoretical support established for the BI skill construct. In Section 3.3, it was hypothesized that BI leadership would have a positive influence on BI skill and BI infrastructure. These hypotheses are consistent with current literature. Consequently, it seems reasonable to hypothesize that BI leadership will positively impact the level of funding and other financial aspects of the BI/DW program. A parameter was then added to the model similar to the one hypothesized. A constraint is shown that BI leadership will impact BI financial commitment as illustrated in Figure 8.

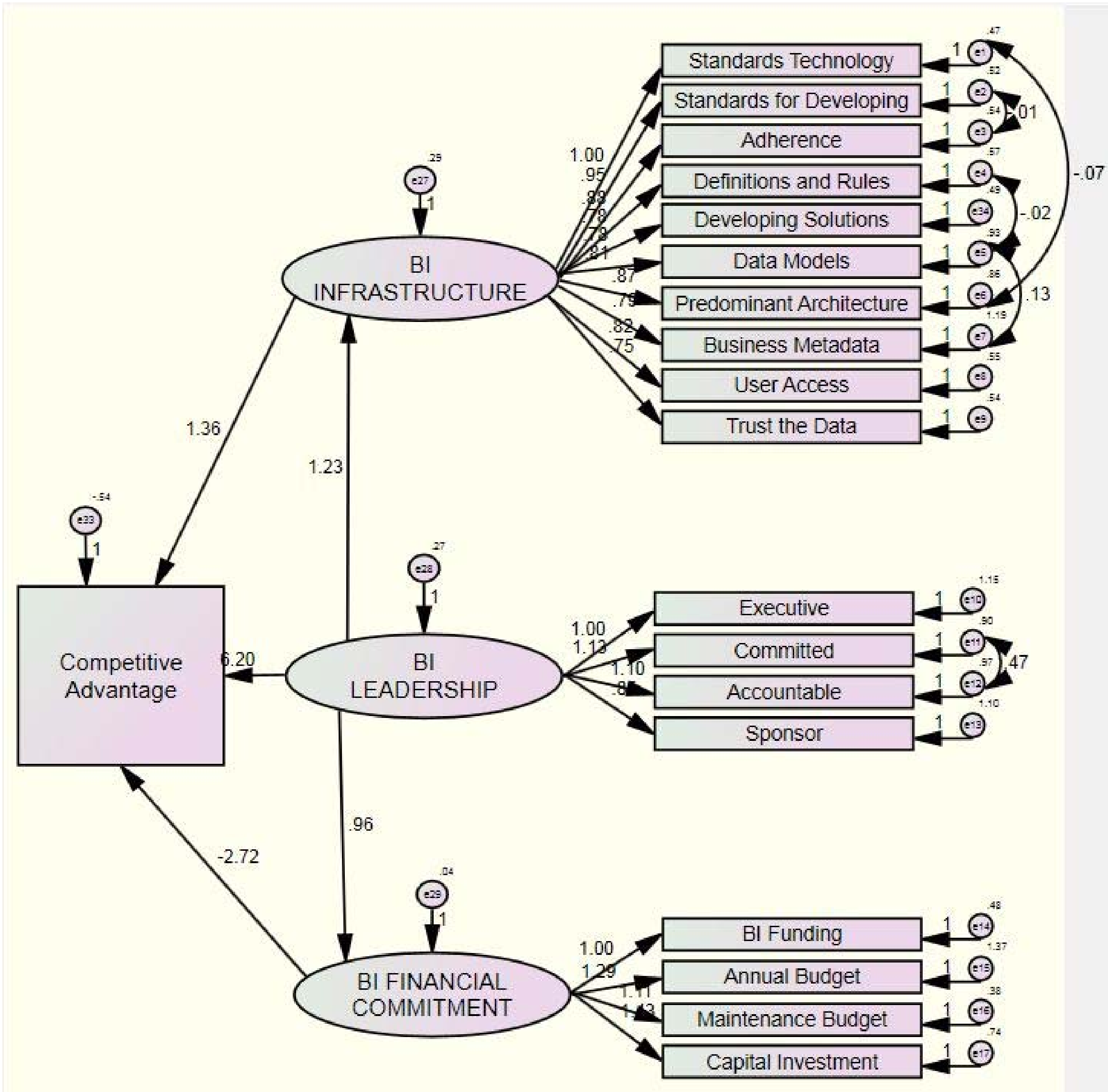

Figure 8. Modification Index Model Update

The model in Figure 8 was executed with the added parameter per the output of Modification Indices. Using the Analysis Sample data set, the parameter estimates were calculated with one less degree of freedom. Table 11 shows significant improvement across all key measures. The CMIN is reduced to 975.063; both GFI and AGFI now meet the conservative standards of > 0.90; the RMSEA is significantly closer to the objective of 0.50; and now both

Hoelter scores are above the 200 threshold. Essentially, the modified model meets all generally accepted measures of a model fitting the data. Refer to Appendix F for a complete list of results.

In order to test for statistical significance in the difference in chi-square, between the base model of 3402.077 and the MI modified model of 975.063, a chi-square difference test was conducted. The difference between the chi-square (CMIN) results for each model (2427.014) and the difference in degrees of freedom between the models (1) were entered into the CHISQ.DIST.RT function of Excel, and the *p*-value was calculated at 0. This means that the difference in chi-square between the base model and the MI modified model is statistically significant.

5.2.2.3 Residual Moments

Examining Residual Moments (RM) is the next step in modifying the model. Following similar steps described under MI, the RM is checked so that the results are reported by AMOS. RM reports those proxies with the highest residual values. Based on the Analysis Sample data set and the model shown in Figure 7, three RMs recommended were Capital Investment, Predominant Architecture, and Definitions and Rules. Capital Investment reported the highest residual value and therefore was selected for removal from the model. Capital Investment is a general metric used to identify the level of investment with an expected recovery over several years. Since the metric can cover a broad range of investment, it is likely to be less effective in measuring an organization's commitment to BI/DW when compared to, for example, BI/DW budget level.

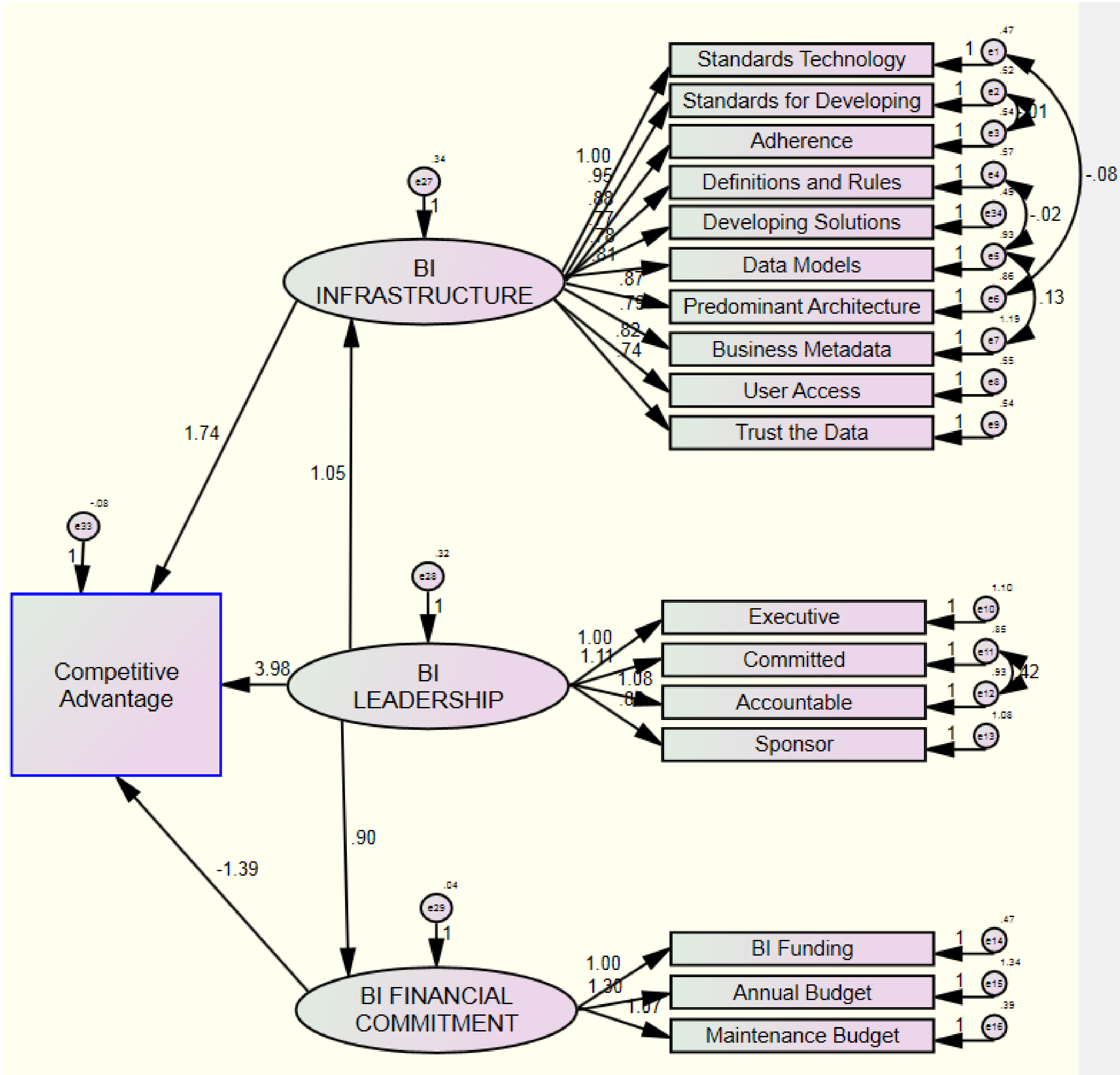

Figure 9. Residual Moment Model Update

Removing the Capital Investment proxy produces the model shown in Figure 9. Now only three proxies define the construct BI financial commitment, including BI Funding, Annual Budget, and Maintenance Budget. Executing the modified model using the Analysis Sample reports improved results across all key measures when compared to the MI model in Figure 8. As shown in Table 6, the chi-square value continues to drop, from 975.063 in the MI model to 868.617 in the RM model. Both the GFI and AGFI increase when compared to the MI model

results and are therefore well above the 0.90 threshold. The RMSEA and Hoelter scores remain relatively unchanged when compared to the MI model results. Given well-established rules of thumb, all key measures suggest that this model with the MI adjustment and the RM modification fits the data. Appendix G outlines a complete list of results from RM modification.

As with the MI model test, a chi-square test is conducted to determine if the difference in chi-square between the MI and RM models is statistically significant. This difference (975.063 – 868.617) is 106.446 and the difference in degrees of freedom between the models is 17. These values were included in the CHISQ.DIST.RT function resulting in 5.60504E-15, very near zero. In other words, the *p*-value suggests this difference between the models is statistically significant.

Given Modification Model Search for SEM standards, Phase II successfully improved the model fit by implementing one constraint identified in Modification Indices and removing one proxy based on the results for testing Residual Moments.

5.2.3 Phase III

The analysis effort enters Phase III given the success of Phase II. In this phase the final model, updated as a result of MI and RM adjustments, is now tested using a completely different data set specifically reserved for this phase, called Test Sample. This sample is used to validate the modified model built from the Analysis Sample shown in Figure 9.

Calculating estimates based on the final model and using the Test Sample produces the results shown in Table 13 in the Revised Model columns. While the results across all key measures are slightly different from the RM model, they are all within well-established

thresholds. Given these results, the final model shown in Figure 9 is a significant improvement from the base model and should be considered across all accepted measures as a good model fit.

Table 13. Final Model Test

	Revised Model	**Revised Model**
Data Sets	Analysis Sample	Test Sample
Measurements		
CMIN	868.617	988.495
DF	126.000	126.00
GFI	0.939	0.930
AGFI	0.917	0.905
PGFI	0.692	0.685
RMSEA	0.062	0.067
Hoelter 0.05	271.000	236.000
Hoelter 0.01	293.000	256.000

Refer to Appendix H for a complete list of results from the final model test.

5.3 Summary of Findings

A PCA provided the necessary foundation of proxies that support BI-enabled competitive advantage. However, the model fit fell short of broadly accepted thresholds. The application of Modification Model Search for SEM proved to be a valuable guide to significantly improve the model fit. The two key steps to this approach, MI and RM, proved successful at improving model fit. Modification Indices provided a means for incorporating the new construct, financial commitment, into the model hypothesized. Residual Moments provided the guidance to remove a proxy that potentially impacted the model fit. In the research, although Capital Investment was significant in PCA, its presence degraded the model fit which was demonstrated by its removal.

In a methodical approach, the base model born from the PCA effort evolved into a final model that meets all measures of good model fit. This statistically significant model now serves

as the basis for future research and provides guidance to factors that can improve the competitive advantage of BI programs.

CHAPTER 6. CONCLUSION

This initial phase of the research provides three significant findings. First, BI/DW is being widely adopted both in the academic community and in practice. To quantify the level of diffusion of BI/DW extends the body of knowledge for this space in four significant ways: (1) The study results suggest a stable investment environment for BI/DW that will not change significantly in trends of relevant technology, industry best practices, or resources. (2) Findings demonstrate that academic research in BI/DW is conducted in a closed community of peers, which may mean research is less relevant or even disconnected from practice. (3) Practitioners seem to be more influenced by external factors, and organizations must guard against being swayed by vendors, industry analysts, and consultants. And (4) the academic and practitioner communities may be isolated from each other, resulting in confusion and limited growth of the space.

As outlined in Table 14, the three hypotheses regarding BI leadership and BI infrastructure were supported by this research. Two hypotheses are considered undetermined due to a lack of data to reject or validate the BI skill construct.

Table 14. Hypotheses Supported or Rejected

Hypothesis	Description	Result
$H1_{Factors}$	BI skill will positively impact the competitive advantage of the firm.	Inconclusive
$H2_{Factors}$	BI infrastructure will positively impact the competitive advantage of the firm.	Supported
$H3_{Factors}$	BI leadership will positively impact the competitive advantage of the firm.	Supported
$H4_{Factors}$	BI leadership will positively impact BI skill.	Inconclusive
$H5_{Factors}$	BI leadership will positively impact BI infrastructure.	Supported

Second, support seems to exist for two of the three constructs of the BI-enabled competitive advantage model, BI infrastructure and BI leadership. Validating the importance of

these two constructs for the BI/DW space not only extends the body of knowledge, but also provides statistically significant evidence that can guide practice. For example, the research found that over 26% of the variance of BI-enabled competitive advantage can be explained by the proxies associated with BI infrastructure such as Standards in Technology, Standards for Development, and Adherence to those Standards. Moreover, empirical data validates existing research that leadership is a critical factor of success, with one exception, Accountability. This is an important dimension to leadership that, while discussed, has not been quantified for the BI/DW space.

A third major finding of this phase of research is the empirical evidence that points to a potentially new construct of competitive advantage that this researcher has labeled financial commitment. This construct includes proxies such as Funding, Annual Budget, and Maintenance Budget. While researchers have discussed the financial issues of BI/DW, this finding has not materialized as a formal construct on the level of leadership, infrastructure, or skill.

Finally, the data set did not support the BI skill construct as offering competitive advantage. However, this researcher believes that BI skill demands further examination before any conclusions can be made regarding its validation or rejection as a contributor to BI-enabled competitive advantage.

These findings provide evidence and guidance regarding the BI contribution to competitive advantage for an organization. For the private sector, these initial results provide guidance to better focus firms' investments and resources toward factors with the greatest impact. As this research evolved, the observed variables validated as statistically significant and their related constructs provide a robust framework for practitioners to leverage for making better investment decisions.

For the academic researcher, the outcome of this research substantiates, or rejects, proxies that serve to measure BI maturity and success. At a higher level, this research substantiates or rejects popular constructs used to measure competitive advantage enabled by technology.

CHAPTER 7. FUTURE RESEARCH

Demanding immediate investigation is the potentially new construct BI financial commitment. Figure 10 illustrates an updated model on which to base future research.

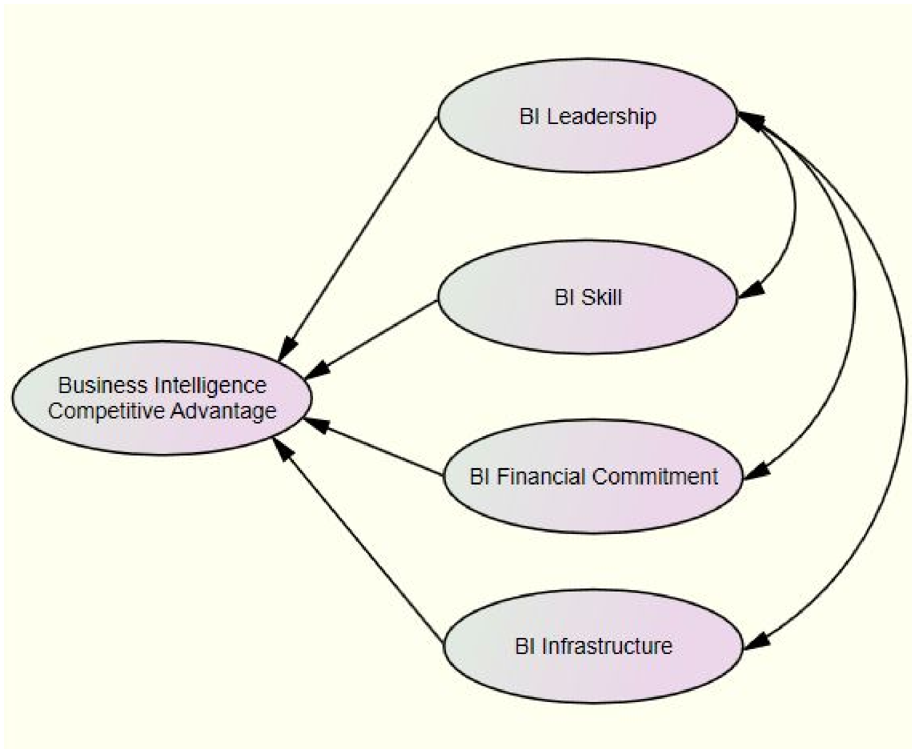

Figure 10. Future Model

Additionally, it is important that the considerable research in support of this construct be treated with deference. Sufficient evidence must be gathered to validate or reject BI financial commitment as a contributor to BI competitive advantage.

Other research tangents are available, specifically: (1) the diffusion of multi-innovation and multi-adoption, (2) global research, and (3) applicability to different technologies. Future research can be more specific about the relationship between BI and DW. In this study, the two areas were examined together because significant synergy arguably exists between the two. But

doing so masks the underlying and potentially significant differences between BI and DW. Studying multi-innovation diffusion models may expose important insights. For instance, because BI is a more recent innovation, does it serve as a substitute for DW, or is it complementary to or contingent on DW (Mahajan & Peterson, 1985)? Understanding the relationship between BI and DW diffusion potentially provides insight for organizations' investment strategies, among other benefits.

Multi-adoption diffusion models examine the possibility of adopters' repurchases of technical innovations. For the BI/DW community, successive investments in technology to support the BI/DW initiatives, as well as the iterative nature of implementation, present an excellent opportunity for research. From a product innovation perspective, how do first-time buyers and repeat buyers impact the adoption rate (Mahajan & Peterson, 1985; Dodson and Muller, 1978)?

Global research is an important extension to this study. A fundamental research question is whether the diffusion of BI/DW in the U.S. is similar to that in other areas. Is BI/DW diffusion similar, for instance, between the U.S. and Western Europe? A global variation of this question would be whether diffusion for BI/DW is similar between developed and developing countries. Insight into the global diffusion of BI/DW does provide potential guidance for investments, not only from a prospective adopter, but also for external influencers such as product vendors and consulting firms.

This paper presents the results of the first phase of this research leveraging diffusion models, principal component analysis, and structured equation modeling. This phase provides a strong foundation for future analysis and guidance on those areas that demand immediate attention.

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APPENDIX A: ACADEMIC PAPERS SELECTED AND REJECTED

The academic journals selected for the diffusion study include *MIS Quarterly* (MISQ), *Information Systems Research* (ISR), *Journal of Management Information Systems* (JMIS), *Management Science* (MS), and *Information & Management* (IM).

Table 15 lists the number of papers selected and rejected by journal designated for this research.

Table 15. Selected and Rejected Papers by Academic Journal

	MISQ		MS		ISR		JMIS		IM	
Year	S	R	S	R	S	R	S	R	S	R
1990	0	1	0	1	0	0	0	0	0	0
1991	0	2	0	0	0	0	0	2	0	0
1992	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	0	0	0	0	0	0
1994	0	1	0	1	0	0	0	0	0	0
1995	0	1	0	0	0	0	1	0	0	0
1996	0	0	0	1	0	0	0	0	0	1
1997	2	0	0	0	0	0	3	1	1	1
1998	0	1	0	0	0	1	0	4	1	1
1999	3	0	2	0	1	0	2	3	4	1
2000	1	2	0	0	3	0	4	1	3	1
2001	2	1	0	2	1	0	3	4	2	5
2002	0	2	1	0	0	1	3	0	9	4
2003	3	0	2	0	1	0	3	1	7	8
2004	3	0	1	0	0	0	2	1	6	3
2005	2	1	3	1	1	0	7	3	9	2
2006	4	1	3	0	2	0	4	3	3	4
2007	8	2	2	0	1	0	7	0	5	3
2008	4	1	0	0	0	0	1	2	3	9
2009	2	0	1	0	0	0	0	3	6	2
	34	16	15	6	10	2	40	28	59	45

S = Selected
R = Rejected

For a total of selected and rejected academic papers across the 15 years of this study refer to Table 16.

Table 16. Total Academic Papers Selected and Rejected

	Total Papers	
Year	Selected	Rejected
1995	1	1
1996	0	2
1997	6	2
1998	1	7
1999	12	4
2000	11	4
2001	8	12
2002	13	7
2003	16	9
2004	12	4
2005	22	7
2006	16	8
2007	23	5
2008	8	12
2009	9	5
	158	89

APPENDIX B: PRACTICE ARTICLES SELECTED AND REJECTED

Table 17 shows the number of selected and rejected articles per quarter, per year, for both publications targeted for the diffusion study. Additionally, the cumulative articles selected are shown by data point (60 quarters across 15 years).

Table 17. Practice Articles Selected and Rejected

		ComputerWorld		InfoWorld			Diffusion Values	
Year	Quarter	Selected	Rejected	Selected	Rejected		Data Point	Cumulative
1995	Q1	13	6	4	2		1	17
	Q2	23	10	7	4		2	47
	Q3	29	13	23	7		3	99
	Q4	10	7	22	8		4	131
1996	Q1	13	13	12	12		5	156
	Q2	46	15	27	7		6	229
	Q3	33	19	35	14		7	297
	Q4	24	11	29	4		8	350
1997	Q1	42	19	24	8		9	416
	Q2	43	30	35	14		10	494
	Q3	33	30	25	14		11	552
	Q4	36	30	29	6		12	617
1998	Q1	35	28	26	16		13	678
	Q2	33	24	35	19		14	746
	Q3	34	16	30	12		15	810
	Q4	47	39	30	12		16	887
1999	Q1	30	33	38	6		17	955
	Q2	30	35	33	2		18	1018
	Q3	29	28	25	2		19	1072
	Q4	20	19	29	3		20	1121
2000	Q1	20	25	23	1		21	1164
	Q2	20	18	30	3		22	1214
	Q3	11	7	25	1		23	1250
	Q4	15	16	11	3		24	1276
2001	Q1	15	9	23	0		25	1314
	Q2	18	6	23	3		26	1355
	Q3	11	8	12	1		27	1378
	Q4	13	7	21	1		28	1412

2002	Q1	8	11	19	2		29	1439
	Q2	11	9	8	2		30	1458
	Q3	7	12	15	0		31	1480
	Q4	18	16	14	1		32	1512
2003	Q1	19	16	13	0		33	1544
	Q2	27	17	10	1		34	1581
	Q3	13	19	11	2		35	1605
	Q4	13	13	9	3		36	1627
2004	Q1	20	8	4	1		37	1651
	Q2	18	11	9	3		38	1678
	Q3	11	8	5	2		39	1694
	Q4	32	8	5	1		40	1731
2005	Q1	21	2	10	1		41	1762
	Q2	31	3	9	2		42	1802
	Q3	32	8	11	13		43	1845
	Q4	34	6	6	2		44	1885
2006	Q1	34	22	11	0		45	1930
	Q2	24	6	12	2		46	1966
	Q3	50	17	6	1		47	2022
	Q4	22	19	10	3		48	2054
2007	Q1	25	11	2	1		49	2081
	Q2	14	17	1	0		50	2096
	Q3	19	4	0	0		51	2115
	Q4	17	7	0	0		52	2132
2008	Q1	23	1	0	0		53	2155
	Q2	6	1	0	0		54	2161
	Q3	18	1	0	0		55	2179
	Q4	14	2	0	0		56	2193
2009	Q1	10	0	0	0		57	2203
	Q2	4	0	0	0		58	2207
	Q3	5	0	0	0		59	2212
	Q4	3	1	0	0		60	2215
TOTALS		1329	797	886	228			

APPENDIX C: COMPLETE ROTATED COMPONENT MATRIX

Rotated Component Matrix[a]

	Component					
	1	2	3	4	5	6
STANDARDS TECHNOLOGY	.736	.024	.232	.177	.093	.041
STANDARDS for DEVELOPING	.730	.090	.175	.187	.057	.112
ADHERENCE	.669	.031	.199	.105	.214	.016
DEFINITIONS and RULES	.662	.179	.121	.027	-.002	.234
DEVELOPING SOLUTIONS	.640	.150	.187	.136	.181	-.023
DATA MODELS	.589	.062	.097	-.079	.174	.163
PREDOMINANT ARCHITECTURE	.574	.069	.173	.096	.253	-.003
BUSINESS METADATA	.549	.227	-.056	.021	-.069	.338
USER ACCESS	.548	.050	.151	.090	.390	.169
TRUST the DATA	.502	.098	.114	.006	.438	.155
REPORTING for CASUAL USERS	.483	.206	-.060	.122	.212	.126
PROJECT MANAGERS	.472	.253	.131	.089	.052	.048
PROCESSES	.442	.389	.396	.092	.028	.163
SUCCESS	.433	.139	.254	.176	.381	.292
EXECUTIVE	.123	.644	.091	.026	.070	.165
COMMITTED	.106	.644	.417	-.062	.185	.048
ACCOUNTABLE	.113	.606	.408	-.085	.060	.168
SPONSOR	.179	.515	.036	.243	-.005	-.029
BI FUNDING	.217	.266	.610	-.050	.126	.075
ANNUAL BUDGET	.106	.098	.609	.154	.035	.138
MAINTENANCE BUDGET	.336	.136	.606	.206	.082	.111
CAPITAL INVESTMENT	.409	.057	.507	.195	.150	.069
ALLOCATES	.217	.311	.318	.189	.005	-.092
APPS	.117	.011	.103	.754	.149	.128
DATA SOURCES	.078	.103	.036	.741	-.082	.102
PROJECTS 90 DAYS	.214	.044	.167	.649	-.023	.118
ROLE	.077	.056	.080	.597	.277	-.078
POWER USERS	.157	.355	.000	.123	.559	.147
SUBJECT AREA	.161	-.021	.092	-.134	.545	.136
DATA REFRESHED	.196	-.068	.188	.067	.525	-.093
RATIO of USERS	.059	.052	-.029	.236	.444	-.222
BUSINESS VALUE	.228	.228	-.091	.138	.428	.381
CASUAL USERS	.171	.355	.063	.092	.414	.319
CUSTOMERS or SUPPLIERS	.046	.007	.123	.116	.062	.657
UNSTRUCTURED DATA	.296	.087	.035	-.090	-.161	.601
EMPLOYEES	.033	-.001	.244	.245	.284	.497
BI PURPOSE	.389	.367	-.057	.049	.001	.419
INTANGIBLE BENEFITS	.175	.239	.120	.046	.132	.399

Extraction Method: Principal Component Analysis

Rotation Method: Varimax with Kaiser Normalization

a. Rotation converged in 9 iterations

APPENDIX D: INTRACLASS CORRELATION COEFFICIENTS

BI Infrastructure Intraclass Correlation Coefficient

	Intraclass Correlation[a]	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	F Test with True Value 0 Value	F Test with True Value 0 df1	F Test with True Value 0 df2	F Test with True Value 0 Sig
Single Measures	.413[b]	.398	.427	8.022	3057	27513	.000
Average Measures	.875[c]	.869	.882	8.022	3057	27513	.000

BI Leadership Intraclass Correlation Coefficient

	Intraclass Correlation[a]	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	F Test with True Value 0 Value	F Test with True Value 0 df1	F Test with True Value 0 df2	F Test with True Value 0 Sig
Single Measures	.342[b]	.323	.361	3.076	3057	9171	.000
Average Measures	.675[c]	.656	.693	3.076	3057	9171	.000

BI Financial Commitment Intraclass Correlation Coefficient

	Intraclass Correlation[a]	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	F Test with True Value 0 Value	F Test with True Value 0 df1	F Test with True Value 0 df2	F Test with True Value 0 Sig
Single Measures	.351[b]	.332	.371	3.165	3057	9171	.000
Average Measures	.684[c]	.665	.702	3.165	3057	9171	.000

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. Type C intraclass correlation coefficients using a consistency definition—the between-measure variance is excluded from the denominator variance.

b. The estimator is the same, whether the interaction effect is present or not.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

APPENDIX E: BASE MODEL FIT

1. CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	46	3402.077	144	.000	23.626
Saturated model	190	.000	0		
Independence model	19	25675.532	171	.000	150.149

2. RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.283	.905	.874	.686
Saturated model	.000	1.000		
Independence model	.610	.301	.223	.271

3. Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.867	.843	.872	.848	.872
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

4. Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.842	.731	.735
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

5. NCP

Model	NCP	LO 90	HI 90
Default model	3258.077	3071.829	3451.639
Saturated model	.000	.000	.000
Independence model	25504.532	24981.432	26033.922

6. FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	1.113	1.066	1.005	1.129
Saturated model	.000	.000	.000	.000
Independence model	8.399	8.343	8.172	8.516

7. RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.086	.084	.089	.000
Independence model	.221	.219	.223	.000

8. AIC

Model	AIC	BCC	BIC	CAIC
Default model	3494.077	3494.683	3771.251	3817.251
Saturated model	380.000	382.502	1524.848	1714.848
Independence model	25713.532	25713.783	25828.017	25847.017

9. ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	1.143	1.082	1.206	1.143
Saturated model	.124	.124	.124	.125
Independence model	8.411	8.240	8.585	8.411

10. HOELTER

Model	HOELTER .05	HOELTER .01
Default model	156	168
Independence model	25	26

APPENDIX F: MODIFICATION INDEX ADJUSTED MODEL MEASUREMENTS

1. CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	47	975.063	143	.000	6.819
Saturated model	190	.000	0		
Independence model	19	13053.374	171	.000	76.336

2. RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.050	.934	.913	.703
Saturated model	.000	1.000		
Independence model	.617	.295	.217	.266

3. Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.925	.911	.936	.923	.935
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

4. Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.836	.774	.782
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

5. NCP

Model	NCP	LO 90	HI 90
Default model	832.063	736.876	934.724
Saturated model	.000	.000	.000
Independence model	12882.374	12510.913	13260.139

6. FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.636	.542	.480	.609
Saturated model	.000	.000	.000	.000
Independence model	8.509	8.398	8.156	8.644

7. RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.062	.058	.065	.000
Independence model	.222	.218	.225	.000

8. AIC

Model	AIC	BCC	BIC	CAIC
Default model	1069.063	1070.305	1319.868	1366.868
Saturated model	380.000	385.020	1393.894	1583.894
Independence model	13091.374	13091.876	13192.763	13211.763

9. ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.697	.635	.764	.698
Saturated model	.248	.248	.248	.251
Independence model	8.534	8.292	8.780	8.534

10. HOELTER

Model	HOELTER .05	HOELTER .01
Default model	271	292
Independence model	24	26

APPENDIX G: RESIDUAL MOMENTS ADJUSTED MODEL MEASUREMENTS

1. CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	45	868.617	126	.000	6.894
Saturated model	171	.000	0		
Independence model	18	12265.635	153	.000	80.168

2. RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.046	.939	.917	.692
Saturated model	.000	1.000		
Independence model	.620	.307	.225	.275

3. Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.929	.914	.939	.926	.939
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

4. Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.824	.765	.773
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

5. NCP

Model	NCP	LO 90	HI 90
Default model	742.617	652.944	839.766
Saturated model	.000	.000	.000
Independence model	12112.635	11752.596	12478.976

6. FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.566	.484	.426	.547
Saturated model	.000	.000	.000	.000
Independence model	7.996	7.896	7.661	8.135

7. RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.062	.058	.066	.000
Independence model	.227	.224	.231	.000

8. AIC

Model	AIC	BCC	BIC	CAIC
Default model	958.617	959.746	1198.750	1243.750
Saturated model	342.000	346.289	1254.505	1425.505
Independence model	12301.635	12302.086	12397.688	12415.688

9. ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.625	.566	.688	.626
Saturated model	.223	.223	.223	.226
Independence model	8.019	7.785	8.258	8.020

10. HOELTER

Model	HOELTER .05	HOELTER .01
Default model	271	293
Independence model	23	25

APPENDIX H: FINAL MODEL TEST

1. CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	45	988.495	126	.000	7.845
Saturated model	171	.000	0		
Independence model	18	11984.937	153	.000	78.333

2. RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.048	.930	.905	.685
Saturated model	.000	1.000		
Independence model	.604	.319	.238	.285

3. Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.918	.900	.927	.911	.927
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

4. Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.824	.756	.763
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

5. NCP

Model	NCP	LO 90	HI 90
Default model	862.495	766.110	966.342
Saturated model	.000	.000	.000
Independence model	11831.937	11476.105	12194.073

6. FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.649	.567	.503	.635
Saturated model	.000	.000	.000	.000
Independence model	7.874	7.774	7.540	8.012

7. RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.067	.063	.071	.000
Independence model	.225	.222	.229	.000

8. AIC

Model	AIC	BCC	BIC	CAIC
Default model	1078.495	1079.633	1318.275	1363.275
Saturated model	342.000	346.323	1253.163	1424.163
Independence model	12020.937	12021.392	12116.849	12134.849

9. ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	.709	.645	.777	.709
Saturated model	.225	.225	.225	.228
Independence model	7.898	7.664	8.136	7.898

10. HOELTER

Model	HOELTER .05	HOELTER .01
Default model	236	256
Independence model	24	25

CURRICULUM VITA

Michael L. Gonzales, Ph.D., is an active practitioner in the IT space serving in roles of chief architect and solutions strategist. He specializes in the formulation of business analytics for competitive advantage and conducts research into exploratory and predictive analytics against extremely large data.

Dr. Gonzales holds a Ph.D. from the University of Texas at El Paso and has presented and published his research at international conferences, including: Decision Sciences Institute in 2009 and 2011 (nominated one of the best conference papers), Americans Conference on Information Systems in 2009, and Hawaii International Conference on Systems Science in 2011 (nominated one of the best conference papers). His dissertation is titled, "Competitive Advantage Factors and Diffusion of Business Intelligence and Data Warehousing."

Dr. Gonzales is a successful author, industry speaker and is currently the Director of Research and Advanced Analytics for a leading IT consulting firm.

MICHAEL L. GONZALES, PH.D. (ABD)

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CHIEF ARCHITECT, SENIOR SOLUTION STRATEGIST AND INDUSTRY ANALYST

A determined problem-solver impassioned about success, discovery, and innovation

- An accomplished solution strategist with a strong record of delivering business and technical results across multiple industries and in notable organizations.
- Sought out for ability to create the structures and standards that make analysis and design repeatable, implementation components reusable, and change manageable.
- Practical knowledge of the challenges and critical success factors involved in building and managing large databases, data warehouses, and enterprise-wide business intelligence (BI).

- A highly-credentialed individual who brings effective research methodologies into a corporate environment.

ROLES AND ACCOMPLISHMENTS HIGHLIGHTS

As a Business Intelligence/Data Warehouse Architect

- Developed multidimensional strategies, including five core views: Business, Analytic Architecture, Data Architecture, Technical Architecture, and Implementation (Roadmap).
- Developed statistical models for complex, multi-criteria, unbiased decision making and risk mitigation.
- Evaluated current and future needs to design technical platforms that enable growth and are resilient to change.
- Discovered unique business requirements and assimilated those requirements into the architecture.
- Optimized current technology for maximum return on investment by leveraging existing contracts, licenses, training, and experience.

As a Researcher

- Initiated the International Business Analytics Center of Excellence at the University of Texas at El Paso. Selected as one of its first information scientists researching the optimum data and technical architecture for large scale, in-database, advanced analytics.
- Applied the disciplines and practices of rigorous academic research in practical ways to drive clarity and confidence in business and technical decision making processes while reducing risk.
- Applied best-fit methods and models to requirements gathering, priority setting, and problem solving.

As a Business Owner

- Conceived and built HandsOn-BI, developing a new, interactive approach to experience-based learning.
- Successfully grew the business, becoming a favored instructor who continuously received high performance scores and had the most "sold out" courses of any conference offerings.
- Negotiated sale of successful business to fulfill exit strategy.

As an Educator

- Authored numerous books and articles, covering multiple dimensions of IT and BI.
- Designed a comprehensive data warehousing and BI curriculum, developing courses ranging from fundamental concepts to advanced analytics.
- Taught data warehouse and BI courses internationally through leading training and conference providers.

EDUCATION

Ph.D. (ABD), Information and Decision Science, University of Texas at El Paso, 2010
Post Graduate Work, Software Engineering, Southern Methodist University, 2005
M.A. Computer Resource and Information Management, Webster University, 1993
B.B.A. Market Research, New Mexico State University, 1980

WORK EXPERIENCE

Independent Consultant 2009–present
Claraview, A division of Teradata 2007–2009
HandsOn-BI, LLC 2001–2006
The Focus Group, LLC 1994–2006
Independent Consultant 1985–1993

Key Clients: Unilever, Disney, Goodyear, EMC, Toyota, United States Postal Service, The Gap, U.S. Mint, T-Mobile, The Mayo Clinic, IBM, Boeing, Hyperion, Oracle, Capital One, General Motors, BMW Financial, OnStar Corporation, Motorola Computer Group, Discover Financial

TECHNOLOGY PROFILE

Databases Teradata, IBM DB2 UDB, Microsoft SQL, Informix, Oracle, SAS Data Sets

Development Tools SAS PROC Programming, SAS Enterprise Miner, SPSS, Teradata Miner, Teradata SQL, IBM Intelligent Miner, Microsoft Analytics, CA Erwin, Microsoft Visio, MicroStrategy, Cognos PowerPlay, IBM DataStage, Microsoft SSIS, Oracle Essbase, ESRI Business Analytics, Provalis WordStat Text Miner

PROJECT SUMMARY

$38B Entertainment (Current)

Job Role: BI Consultant

Need: In-depth analysis of large scale development effort.

Actions: A study was conducted that covered a broad spectrum of BI/DW development, including: 1) identified best-practices to support target technical architectures such as Teradata warehouse, Business Objects (BOBJ) front-end, and SAS, 2) analyzed physical and logical data models of the existing semantic layers for adherence to existing standards and extending the standards as required, 3) examine development processes of both onsite and off-shore teams to ensure key partners are delivering according to agreement, and 4) evaluate if what the client is developing is the right direction necessary.

Instruments/Methodologies: Teradata SQL, Embarcadero ERStudio, Business Objects Information Design, Provalis WordStat Text Miner, and SPSS

Value:

- Formal semantic layer design standards guide all development to ensure enterprise consistency and BI delivery across business requirements
- Impartial project review
- BI/DW project adjustments to ensure effective solutions

$18B Manufacturer (2011)

Job Role: BI Consultant

Need: Establish global enterprise semantic layer standards.

Actions: Research included three dimensions: 1) identified best-practices to support target technical architecture with a Teradata warehouse and Cognos front-end, 2) analyzed physical and logical data models for the warehouse, 3) examined front-end reporting requirements.

Instruments/Methodologies: Teradata SQL, Teradata SQL Assistant/, Teradata Administrator, Provalis WordStat, and Cognos

Value:

- Formal semantic layer design standards to guide all development and ensure enterprise consistency and BI delivery across the globe
- Optimize current semantic layers for performance and data stability.

$65B Consumer Products (2011)

Job Role: BI Consultant

Need: Establish global enterprise semantic layer standards.

Actions: Research included three dimensions: 1) identified best-practices to support target technical architecture with a Teradata warehouse and Microsoft front-end, 2) analyzed physical and logical data models for the warehouse, 3) examined front-end reporting requirements via Microsoft including OLAP, reporting and SharePoint.

Instruments/Methodologies: Teradata SQL, Teradata BI Optimizer, and MS Analysis Services

Value:

- Formal semantic layer design standards guide all development to ensure enterprise consistency and BI delivery across the globe.

$60B Logistics Provider (2010)

Job Role: BI Consultant / Chief Architect

Need: Identify short and long-term opportunities for advanced decision support services.

Actions: Examined current technical architecture, data architecture, database and reporting activity, and user decision processes. These findings were evaluated against formal requirements to expose opportunities for improvement.

Instruments/Methodologies: SQL Performance Monitoring and Analysis, SPSS Pattern Search and Statistical Analysis, User Sentiment Surveys, Gap and Best-Practice Analysis, Infrastructure Analysis, Process Analysis, and Governance Assessment.

Value:

- Short-term opportunities were identified for immediate improvement of the BI/DW program value.
- Quantified analysis and discovery of previously unknown or misunderstand usage patterns.

$4B Logistics Provider (2010)

Job Role: BI Consultant / Chief Architect

Need: Establish a multiyear BI/DW strategy and implementation roadmap that addresses global requirements and drives business value.

Actions: Formal, in depth requirements gathering process was initiated. Thorough and methodical examination of current technology, data, and skill assessment was conducted. All findings were evaluated against industry best-practices and competitive analysis.

Instruments/Methodologies: Structure Executive Interviews, User Sentiment Surveys, Gap and Best-Practice Analysis, Infrastructure Analysis, Process Analysis, Governance Analysis, and Diffusion and Adoption Capacity.

Value:

- Effective and feasible implementation roadmap was established for a BI-enabled, global competitive initiative that supports the business strategy.

$15B Manufacturer (2009–2010)

Job Role: Executive Mentor / BI Expert & Advisor

Need: Define enterprise metrics and Key Performance Indicators (KPIs).

Actions: Identify consultancy to define strategy; monitor development to ensure robustness and compliance with project requirements; plan implementation processes and service providers.

Instruments/Methodologies: Linear Regression, Principle Component and Factor Analysis, KPI Value Map Assessment.

Value:

- Improve business effectiveness and efficiency through measures-based performance management.
- Align enterprise KPIs with the strategic direction of the organization.

$230B manufacturer (2009–2010)

Job Role: Executive Mentor and Coach

Need: Obtain enterprise level buy-in for proposed BI information system.

Actions: Develop enterprise metrics, value statements, and value maps for presentation and expectation management. Coach the Director of Information Management Systems who will serve as the catalyst to influence buy-in from upper management.

Instruments/Methodologies: Gap and Best-Practice Analysis, BI Maturity Assessment, KPI Value Map Analysis

Value:

- Achieve the right level of buy-in and sponsorship for the right reasons.
- Improve capability to plan, predict, solve problems, and make decisions, resulting in increased marketplace competitiveness.

$15B Retailer (2008–2009)

Job Role: BI Consultant / Chief Architect

Need: BI technology architecture and technical roadmap that centers on key technologies, builds for the future, and sunsets unnecessary tools.

Actions: Re-scoped technology assessment to include Microsoft which was originally out of scope despite large MS footprint. Quantitative research methods were used to develop the optimum technology roadmap.

Instruments/Methodologies: Structure Executive Interviews, User Sentiment Surveys, Gap and Best-Practice Analysis, Infrastructure Analysis, Process Analysis

Value:

- Created sustainable technology architecture for BI program.
- Delivered consensus on technology direction.
- Narrowed the gap between leading and trailing edge technologies that reduced Total Cost of Ownership (TCO).

HandsOn-BI (2001–2007)

Job Role: Business Owner / Educator / Technologist

Need: Conference industry need to overcome barriers to hands-on technical training.

Actions: Pioneered 'live laboratory' training in a conference setting by removing hands-on obstacles such as mobile lab logistics, cost effectiveness, volatile technologies, conflicting technologies, computer lab security, failsafe computer labs, etc.

Value:

- Intensified learning by combining high-energy lectures with hands-on labs; changing the experience from passive to active, from listening to doing.
- Earned high interest and repeat customers, increasing revenues for The Data Warehousing Institute (TDWI) by differentiating it from other events.
- Established core line of business that became the major force behind the success of HandsOn-BI.

$2B US Government DOD Contractor (2006)

Job Role: Solutions Strategist

Need: Objectively determine and prioritize BI user requirements across the organization for the largest private contractor of engineers and scientists to the US government**;** select best-fit technology.

Actions and Value:

- The right requirements—Combined traditional interview techniques with independent (and anonymous) user community surveys to create a unique requirements gathering approach.
- The right priorities—Designed, developed, and implemented a statistical model using Analytic Hierarchical Processing (AHP) to analyze and evaluate data about BI requirements.
- The right technology—Researched, evaluated, and selected best-fit BI technology.

$7B Financial Service Provider (2006)

Need: Resolve significant reporting performance and accuracy problems caused by conversion to new vendor tool.

Actions: Assembled a top-notch technical team; examined all participating systems; identified and specified essential changes to data architecture, data model, and query code.

Value:

- Made a smooth transition to technology supported by upper management.
- Implemented recommendations, improving performance to expected levels.

$66B Manufacturer (2005)

Job Role: Solutions Strategist

Need: Replace legacy technology architecture for crucial project costing system.

Actions: Created a short list of technology alternatives based on research and industry knowledge. Quantified evaluation criteria and developed a statistical model to evaluate submitted prototypes using comprehensive and unbiased analytical reasoning. Made final technology recommendation based on data.

Value:

- Made confident decision to implement best-fit technology architecture.
- Implemented highly effective analysis and decision process as an organization standard.

Service Division of $178B Manufacturer (2001–2002)

Job Role: Senior Technical and Data Architect

Need: Develop strategy and architecture for an Enterprise Reporting System for DW and BI environments.

Actions: Crafted strategy; led team to analyze, plan and design the data architecture. Conducted a maturity assessment and a gap analysis (current versus future states) to determine needs. Identified absence of spatial data in the analysis process for an organization rich in GPS related data; demonstrated type of spatial analysis possible.

Value:

- Implemented adaptable and scalable data architecture.
- Expanded the vision to leverage abundant resource of spatial data.

Healthcare Chain (1998–1999)

Job Role: Technical Architect

Need: Resolve long-term medical records systems failures that led to massive data losses for a national health care chain.

Actions: Conducted comprehensive analysis of entire platform (not just applications), identifying unusual cause of failures.

Value:

- Resolved problem within 6 weeks that had eluded such major players as HP and Informix.
- Identified root cause of systems failures and devised a permanent solution.

Job Role: Interim CIO

Need: Facilitate an acquisition growth strategy to monitor revenue and costs on a near real-time basis during a period of rapid acquisitions.

Actions: Developed and implemented a data integration hub that reflected current economic status of acquired clinics using an intra-day review

Value:

- Established Information Technology infrastructure to collect and manage immediate information needs.

- Analyzed current acquisition information in a dynamically changing environment.

PROFESSIONAL DEVELOPMENT

- American Mensa Member
- IBM Certified BI Solutions Expert
- Certified Business Intelligence Profession (CBIP), Mastery Level in Data Management
- Data Warehouse, Iterations Lifecycle (Inmon)
- Advanced Dimensional Modeling (Kimball),
- Advanced Data Warehouse Development (IBM)
- SAS Programming

SEMINAR AND SPEAKING ENGAGEMENTS

- Faculty Member, University of Texas at El Paso
- Faculty Member and Instructor, TDWI
- Guest Speaker, Teradata User Groups
- Conference Speaker, IBM's Developers User Group
- Guest Speaker, Data Management International (DAMA)

PUBLICATIONS

Technical Books

- BI Strategy: How to Create and Document, HandsOn-BI, 2005
- IBM Data Warehousing, Wiley Publications, 2003
- Informix Handbook, Prentice Hall, 2000 (contributing author)
- Informix Stored Procedure Programming, Prentice Hall, 1996
- CPM Software Review, Reston Publishing, NJ, 1984

Articles or Academic Papers

- BI Factors for Competitive Advantage, Decision Sciences Institute, November 2011. Selected as one of the best conference papers.

- Success Factors for Business Intelligence and Data Warehousing Maturity and Competitive Advantage, BI Journal, March 2011

- Diffusion of Business Intelligence and Data Warehousing: An Exploratory Investigation of Research and Practice, Hawaii International Conference on Systems Science, January 2011. Selected as one of the best conference papers.
- Risk and IT Factors that Contribute to Competitive Advantage and Corporate Performance, Americas Conference on Information Systems, August 2009
- Technology-enabled Competitive Advantage: Leadership, Skill and Infrastructure, Decision Sciences Institute, November 2009
- Strategic Intelligence Framework, Teradata Magazine, Q2 2008
- BI Framework, The BI Journal, Q3 2007
- What's Your BI Environment IQ?, DM Review, August 2005
- Insight Beyond The Obvious, DB2 Magazine, Q2, 2005
- Components of a BI Dashboard, DM Review, March, 2005
- How To Make BI Less of a Gamble, Intelligent Enterprise, February 1, 2005
- Get Active, DB2 Magazine, Quarter 1, 2005
- More Than Pie Charts, Intelligent Enterprise, November 14, 2004
- Creating a BI Strategy Document, DM Review, November 2004
- The No-Sacrifice, Affordable Data Warehouse APP, Intelligent Enterprise, October 2004
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