Understanding the Nature of
Business Intelligence Systems Use and Outcomes

Felix Lizama
BBusEco, Universidad de Chile
MBA, Universidad de Chile

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Caulfield School of Information Technology, Faculty of Information Technology
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ABSTRACT

Decision support systems (DSS) have evolved in terms of philosophy of support, system scale, level of investment, and potential organizational impact. Since the inception of the DSS in the early 1980s, several terms and systems have emerged to describe systems that support decisions in organizations. Currently, the umbrella term “business intelligence” (BI) is used widely to describe IT-based analytic and report tools that support managerial decision-making. The powerful improvements in capacity and analytic power of BI permit organizations to achieve a broader community of users than its predecessors.

Industry surveys have shown that senior managers from worldwide companies view BI as a top priority for enhancing their organization’s performance. Nonetheless, the BI industry has reported continually that BI systems are underused with usage rates as low as 8 percent. The “BI utilization problem” has captured the attention of trade seminars, conferences, and the media. It is mentioned currently as one of the main factors behind high BI project failure rates.

The first stage of this research analyzed the reported BI utilization rates in industry and consultants’ and vendors’ opinions about the BI utilization problem. The results of this analysis showed that industry surveys lacked rigor. Moreover, they conceptualized BI use and success via perceptual metrics of “number of users” and “frequency of use.” In addition to suggesting explanations for the reported low utilization rates, industry commentators were critical of the value that using these metrics to measure success offered to the BI industry. The lack of understanding of how BI systems are used and what drives more effective use makes it important to evaluate BI system project success or failure.

Despite its relevance for practice, research on BI systems is one of the least-published types of DSS research in prestigious academic journals. BI systems research has not developed models
that account for the nature of BI systems use and outcomes. Thus, the aim of this research is to
develop models that explain BI systems use and outcomes.

The research approach employed in this thesis comprises the development of a conceptual
framework based on (1) richer conceptualizations of systems’ use, (2) task–technology fit elements,
and (3) representation theory components and principles. The conceptual framework guided an
exploratory case study conducted in a large government authority in Australia. As a result of the
analysis of documentation and interviews with 25 BI users in the exploratory case study, two
models were developed. The first model accounts for a direct method of use of a BI system, where
the decision maker directly accesses the BI system. The second model accounts for an indirect
method of use of a BI system, where a “chauffeur” accesses the BI system to support a decision
maker.

The two models were evaluated and refined using a follow-up case study in a large insurance
company in Australia. Using semi-structured interview protocols, seven direct users (decision
makers) and seven pairs of decision makers and intermediaries were interviewed. While the analysis
of the follow-up case study data supported the propositions arising from the two models, it also
provided insights into the nature of the associations among the models’ constructs. As a result, a
new construct emerged and two existing constructs were clarified.

The main contributions of this research are the clarification of the nature of BI system use
and outcomes constructs and a proposal for an alternative model for effective and efficient use of
a BI system. The research results also (1) support the usefulness of representation theory to help
account for BI system use, (2) contribute to practice by providing BI professionals with models to
help to evaluate their BI system implementations, and (3) assist BI practitioners determine how to
improve BI use and outcomes. Future research might extend and validate the models this research
has developed. The findings of this thesis can also motivate research on some of the aspects
covered by the models in greater detail or in different contexts.
DECLARATION

This thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Signature: …………………….

Print Name: ……………………

Date: ……………………………
PUBLICATIONS DURING ENROLMENT

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Last but not least, I would like to dedicate this thesis to my grandparents who passed away during the course of this PhD. Thank you for all those old stories and for keeping me conscious about my origins. Forever and always, your memory lives with me and all of us.
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<table>
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<th>Abbreviation</th>
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<tbody>
<tr>
<td>BI</td>
<td>Business Intelligence</td>
</tr>
<tr>
<td>BIC</td>
<td>Big Insurance Company (Follow-up Case Study Site)</td>
</tr>
<tr>
<td>DSS</td>
<td>Decision Support System</td>
</tr>
<tr>
<td>DW</td>
<td>Data Warehouse</td>
</tr>
<tr>
<td>EIS</td>
<td>Executive Information System</td>
</tr>
<tr>
<td>ETL</td>
<td>Extract Transform and Load</td>
</tr>
<tr>
<td>IS</td>
<td>Information System</td>
</tr>
<tr>
<td>LGA</td>
<td>Large Government Organization (Exploratory Case Study Site)</td>
</tr>
<tr>
<td>OLAP</td>
<td>Online Analytical Processing</td>
</tr>
<tr>
<td>PEU</td>
<td>Perceived Ease of Use</td>
</tr>
<tr>
<td>PU</td>
<td>Perceived Usefulness</td>
</tr>
<tr>
<td>TAM</td>
<td>Technology Acceptance Model</td>
</tr>
<tr>
<td>TPC</td>
<td>Technology-to-Performance Chain Model</td>
</tr>
<tr>
<td>TTF</td>
<td>Task-Technology Fit</td>
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CHAPTER 1: INTRODUCTION

Chapter Overview

This chapter introduces the research aim of this thesis by reviewing industry opinions about Business Intelligence (BI) systems use and outcomes. The industry perspective is obtained through an exploratory background study that analyzes what is known in industry as the “BI utilization problem.” The chapter concludes with the formulation of the research aim of this thesis based on the insights provided by the exploratory background study.

Background Study
Critical Analysis of the “BI utilization problem”: BI industry consultant and vendor’s views on the extent in which BI systems are used by organizations

Literature Review & Conceptual Framework
Analysis of the existing BI (including its predecessors) use and outcomes literature. Review of the existing IS use and outcomes theories. Development of conceptual framework

Exploratory Case Study
Analysis of how individuals use BI systems in a large government organization (LGA), and the outcomes obtained by their use

Initial Models Development
Design of direct and indirect BI system use and outcomes models

Follow-up Case Study
Evaluation of the proposed BI system use and outcomes modes in a big insurance company (BIC). Refinement of constructs and associations

Final Models of Direct and Indirect Use of BI Systems
Reflection on research findings and definition of final models
1.1 INTRODUCTION

Following the development of transaction-processing and operational information technology (IT) applications, decision support systems (DSS) emerged during the 1970s to support managerial decision-making (Keen, 1980b). Over time, several names have been used to define approaches that support managers’ decision-making including management information systems (MIS), personal decision support systems (PDSS), executive information systems (EIS), and online analytical processing (OLAP) (Alter, 2004; Arnott & Pervan, 2005; Clark, Jones, & Armstrong, 2007). DSS have evolved in terms of philosophy of support, system scale, level of investment, and potential organizational impact (Arnott & Pervan, 2005). Currently, the umbrella term “business intelligence” (BI) is used widely to describe IT-based analytics and reporting tools that support managerial decision-making (Watson & Wixom, 2007; Wixom et al., 2011a). The powerful improvements in capacity and analytic power of BI permit organizations to achieve a broader community of users than its predecessors.

Surveys by industry analysts and vendors consistently find that BI development and deployment is one of the highest priorities for CIOs and will remain so at least until 2018 (Gartner Inc, 2013). BI industry surveys have shown that C-level\(^ 1\) managers from worldwide companies view BI as a high priority for enhancing their organization’s performance (Gartner Inc, 2007, 2008, 2009; McKinsey, 2011). Kappelman, McLean, Johnson, and Torres (2016) in the annual *SIM IT Issues and Trends Study* reported that BI was the largest organizational IT investment in 2015 and has been the largest since 2009. Put simply, BI is one of the most important IT applications in an organization and is expected to remain so for some time.

Despite the prominence of BI in the IT market, the academic study of the adoption and effective use of BI substantially lags industry practice (Arnott & Dodson, 2008). Furthermore, once

\(^1\) C stands for Chief. It is used to describe top-level executive titles. Examples are CEO (chief executive officer), CFO (chief financial officer), CIO (chief information officer)
a BI platform is implemented in an organization, a new issue seemingly arises, namely, “the BI utilization problem.” The BI utilization problem has captured the attention of trade seminars, conferences, and the media (Dresner, 2010). It is currently mentioned as one of the main factors behind high BI project failure rates. One industry survey shows that organizations that have adopted a BI system perceive the typical usage rate of their system is around 7-8 percent (Pendse, 2009). Vendors and users appear to agree that BI systems are significantly underused.

To properly identify and define the problem addressed by this research, this introductory chapter critically analyzes the existing industry literature about the BI utilization problem and reports industry adoption rates available at the time of this project. Furthermore, the research objectives for the thesis are provided based on the conclusions of the analysis of the problem. Finally, the structure of the thesis is presented.

1.2 BACKGROUND STUDY

As the first stage in the research approach used in this project (described in Chapter 2), this section analyzes the nature of the problem. To do this, an exploratory approach was adopted. Exploratory studies attempt to determine whether a phenomenon exists (Neuman, 2011). Due to the lack of academic studies on this topic, it is important to establish whether the BI utilization problem is a real phenomenon before undertaking expensive and rigorous field research on how to alleviate the problem. Because little published research on the nature of BI usage exists in peer-reviewed journals, the focus of the exploratory study was industry white papers, blogs, industry surveys, and opinion and news articles. This industry material is the data that underpins the narrative in the exploratory study.
1.2.1 DATA COLLECTION

Secondary data were gathered from specialist portals, vendors’ websites, and consultants’ blogs. These sources offered a rich media repository for the problem, concentrating opinions about low BI usage rates and its relationship with BI success and failure. Nonetheless, despite the ease of data gathering, the extent and mutability of the Internet complicates the development of scientifically random samples (Weare & Lin, 2000). Hence, in this study, data were extracted sequentially from three different sources. The examination of the texts was approached using thematic analysis that follows the Braun and Clarke (2006) guidelines presented in Table 1.1. Thematic analysis is a systematic technique for coding non-numerical data by looking for semantic patterns or themes. In this case, an iterative process between data collection and the development of codes was undertaken. This means that in each data-collection cycle the emerging codes were contrasted and compared to the previous coding. Consequently, the outcomes that can be gained from this iterative data collection approach hopefully ensure an in-depth analysis of the extant BI industry literature. The three cycles of data gathering are discussed in turn.

<table>
<thead>
<tr>
<th>#</th>
<th>Phase</th>
<th>Description of the process</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Sampling and Data Collection</td>
<td>Define and collect the data. If necessary, use more than one source. Search for new data until saturation in coding is reached.</td>
</tr>
<tr>
<td>1</td>
<td>Familiarizing yourself with your data</td>
<td>Transcribing data (if necessary), reading and re-reading the data, noting down initial ideas.</td>
</tr>
<tr>
<td>2</td>
<td>Generating initial codes</td>
<td>Coding interesting features of the data in a systemic fashion across the entire data set, collating data relevant to each code.</td>
</tr>
<tr>
<td>3</td>
<td>Searching for themes</td>
<td>Collating codes into potential themes, gathering all data relevant to each potential code.</td>
</tr>
<tr>
<td>4</td>
<td>Reviewing themes</td>
<td>Checking if the themes work in relation to the coded extracts (Level 1) and the entire data set (Level 2), generating a thematic ‘map’ of the analysis.</td>
</tr>
<tr>
<td>5</td>
<td>Defining and naming themes</td>
<td>Ongoing analysis to refine the specifics of each theme and the overall story the analysis tells. Generating clear definitions and names for each theme.</td>
</tr>
<tr>
<td>6</td>
<td>Producing the report</td>
<td>The final opportunity for analysis. Selection of vivid, compelling extract examples, final analysis of selected extracts, relating back of the analysis to the research question and literature, producing a scholarly report of the analysis.</td>
</tr>
</tbody>
</table>
1.2.1.1 BI News Portals (First Cycle)

TechTarget is a web portal that publishes a significant number of integrated media (news, podcasts, and white papers) that “enable technology providers to reach targeted communities of technology professionals and executives in all phases of their decision making and purchase process” (TechTarget, 2010). In particular, the portal claims it publishes vendor-independent news and analysis. Data were gathered from two different sources within the portal.

The first source (Source A) was a specific news channel named “Enterprise Business Intelligence Software.” This repository contains 87 news items from March 2003 to July 2010. In accordance with Braun and Clark’s Phase 2 (familiarizing), every post within the channel was read; the complete texts of the 14 most-relevant posts for this project were stored using software for qualitative analysis (QSR International NVivo). Phase 3 (generating initial codes) was undertaken using the coding features of NVivo.

The result was a list of codes that formed the basis of data analysis. The second data collection source (Source B) was another TechTarget channel named “Business Intelligence Software.” Although, the total number of items contained in the dataset (187 articles) was larger than Source A, its focus was more technical, so only five items were relevant to the BI utilization problem. During Phase 3 (searching for themes) with this data source, the previously compiled list of codes was reconsidered. Where appropriate, they were updated. Table 1.2 presents a summary of the first data collection cycle. After the first data collection cycle was completed, an initial identification of potential themes was undertaken (Braun and Clarke’s Phase 4).
Table 1.2 Data Collection from TechTarget.com Channels (First Cycle)

<table>
<thead>
<tr>
<th>Source A</th>
<th>Source B</th>
</tr>
</thead>
<tbody>
<tr>
<td>News Channel</td>
<td>Enterprise business intelligence software</td>
</tr>
<tr>
<td>Domain</td>
<td><a href="http://searchcio.techtarget.com">http://searchcio.techtarget.com</a></td>
</tr>
<tr>
<td>Number of news items</td>
<td>87</td>
</tr>
<tr>
<td>Number of relevant news items coded</td>
<td>14</td>
</tr>
</tbody>
</table>

1.2.1.2 Vendors’ and Consultants’ White Papers (Second Cycle)

The second data collection cycle was aimed at a different type of research data. White papers are commercial reports or guides that are oriented toward specific business problems. Software vendors use them as major marketing and sales tools. The third data collection source (Source C) comprised white papers that had a direct relationship to the BI utilization problem. The websites of ten vendors were scanned for relevant white papers. As shown in Table 1.3, only six vendors had relevant papers. Eight white papers were coded using the codes created during the first data collection cycle. Some new codes were added, and some existing codes were modified.

The fourth data collection (Source D) was from publications available on the relevant professional association’s website, The Data Warehouse Institute (TDWI). TDWI was founded in 1995 to “provide education, training, certification, news, and research for executives and information technology” (TDWI, 2010). The Information Management online magazine was the fifth data collection source (Source E). The magazine’s website claims it is “the educated reader’s choice for the latest news, commentary and feature content serving the information technology and business community” (Information Management, 2010). Documents were gathered from each source and then stored and coded using NVivo. Table 1.3 presents a summary of this collection cycle. To complete this data gathering cycle, the list of potential themes was updated.
Table 1.3 Data Collection – White Papers (Second Cycle)

<table>
<thead>
<tr>
<th>Organization Type</th>
<th>Source C</th>
<th>Source D</th>
<th>Source E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Website Owner</td>
<td>Apesoft, EMC, IBM Cognos, Information Builders, SAS, Tableau</td>
<td>The Data Warehouse Institute</td>
<td>Information Management magazine (formerly DM Review)</td>
</tr>
<tr>
<td>Date Interval</td>
<td>2007 - 2010</td>
<td>2008 - 2010</td>
<td>2007 - 2010</td>
</tr>
<tr>
<td>Documents coded</td>
<td>8</td>
<td>5</td>
<td>4</td>
</tr>
</tbody>
</table>

1.2.1.3 Google Search (Third Cycle)

The final data collection cycle involved a Google search. Using the keywords BI “usage,” “utilization,” “adoption,” “failures,” and “rates,” a dataset was constructed (Source F). Several documents from the first and second data collection cycle were also retrieved in this search, but only new documents were stored, coded, and analyzed. In this cycle, very little modification of codes and themes was required. Braun and Clarke’s Phase 4 (reviewing themes) was undertaken during this cycle. Subsequently, a final definition and specification of each theme was undertaken (Braun & Clarke’s Phase 5). Table 1.4 presents a summary of this collection cycle.

Table 1.4 Data Collection - Google Search (Third Cycle)

<table>
<thead>
<tr>
<th>Author Type</th>
<th>Source F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Website Owner</td>
<td>Computerworld, Datamartist, Information-Management, InfoWorld, Intelligence Enterprise, Noetix, TDWI, Teradata, Tableau</td>
</tr>
<tr>
<td>Date Interval</td>
<td>2004 - 2010</td>
</tr>
<tr>
<td>Documents coded</td>
<td>11</td>
</tr>
</tbody>
</table>
1.2.2 Analysis

The resultant dataset included a broad diversity of industry opinions that related to the adoption and use of BI applications. It included the opinions of consultants, analysts, CIOs, project managers, and academics, as well as vendors, managers, sales personnel, and market researchers. The analysis of this data was also undertaken using the thematic analysis guidelines indicated by Braun and Clarke (2006; see Table 1.1). As a result, the 47 articles were finally coded and grouped into three themes: (1) understanding usage rates, (2) barriers between potential and actual BI use, and (3) dealing with organizational conflict. These themes are discussed below. Quotations that appear in italics are taken from items in the collected dataset.

1.2.2.1 Theme 1: Understanding Usage Rates

This theme focuses on how the industry conceptualizes the utilization of BI systems and measures usage. First, it is important to clarify how analysts, consultants, and vendors define BI utilization. Although “utilization” and “usage” are the terms most used to define the phenomena under study, from the analysis of the content of the articles and the context in which they were written, it is clear the BI industry also uses the terms “adoption” and “acceptance” to refer to BI utilization. When a BI news headline indicates that “Business intelligence software adoption lags BI vendors' perception,” the use of the word “adoption” does not refer to the decision to implement a BI solution. Rather, it is making reference to how many individuals use BI software in an organization: in the reporter’s words, “only a small fraction of workers actually use them.”

The most common industry measure of BI utilization is a simple usage rate. In Equation 1.1, \( U \) is the number of users actually using a BI application, and \( P \) is the potential number of users of the BI application.
Equation 1.1 BI System Use Ratio

\[ BI\_usage = \frac{U}{P} \]

Although the ratio seems straightforward, there is considerable variation in how the two constructs are measured. Most vendors and consultants have their own methodology for collecting and measuring user numbers. From the data available in the sample, they follow three identifiable strategies to measure the number of users that use a BI application:

\( U_1 \): Surveying business and IT managers and asking them to estimate the number of active users of a BI application (perception).

\( U_2 \): Surveying a community of potential users and asking if they actually use a BI system (quantification).

\( U_3 \): Analyzing system log files to determine usage (behavior).

A similar situation occurs with the denominator of the usage-rate equation. Here, industry analysts attempt to estimate the number of potential users that a particular BI application might have. From analyzing the sample, three strategies for measuring the potential number of users were discovered:

\( P_1 \): Surveying business and IT managers and asking them to estimate the population of possible users for a BI application (perception).

\( P_2 \): Counting the total number of knowledge workers in an organization that are relevant to the BI application (quantification).

\( P_3 \): Counting the total number of BI software licenses installed (behavior).
These findings mean that nine possible combinations for measuring BI usage exist in the sample. To further understand the industry view of the BI utilization problem, usage rates that were explicitly mentioned in the sample were gathered. Table 1.5 provides a summary of surveys conducted by IT research and advisory firms that report usage rates. When the data collection method was unclear, the indicator was categorized as ‘ND’ (no data).

<table>
<thead>
<tr>
<th>Year</th>
<th>Source</th>
<th>Claimed usage rate</th>
<th>Type of BI utilization rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>TDWI</td>
<td>39%</td>
<td>ND/P₁</td>
</tr>
<tr>
<td>2008</td>
<td>TDWI</td>
<td>24%</td>
<td>U₁/ P₂</td>
</tr>
<tr>
<td>2009</td>
<td>TDWI</td>
<td>25%</td>
<td>U₁/ P₂</td>
</tr>
<tr>
<td>2010</td>
<td>TDWI</td>
<td>22%</td>
<td>U₁/ P₂</td>
</tr>
<tr>
<td>2007</td>
<td>BARC</td>
<td>8.7%</td>
<td>U₁/ P₃</td>
</tr>
<tr>
<td>2008</td>
<td>BARC</td>
<td>8.2%</td>
<td>U₁/ P₃</td>
</tr>
<tr>
<td>2007</td>
<td>BI Scorecard</td>
<td>25%</td>
<td>U₁/ P₁</td>
</tr>
<tr>
<td>2009</td>
<td>BI Scorecard</td>
<td>24%</td>
<td>U₁/ P₁</td>
</tr>
<tr>
<td>2009</td>
<td>Gartner</td>
<td>28%</td>
<td>ND/ P₂</td>
</tr>
</tbody>
</table>

Consultants and vendors use the surveys listed in Table 1.5 to articulate reasons for purchasing their services and products. For instance, a common practice seen in the collected dataset is to cite a usage rate from a survey and then promote a specific vendor’s solution that claims the prospect of a more successful implementation. Usage rates in the sample were categorized in a 4x4 matrix, as shown in Table 1.6. Based on the matrix, it is clear that industry has no consistent or reliable measure of usage. In several cases, industry surveys actually measure different things. This means it is impossible to compare ratios over time or between firms. While the number of users actually using a BI application is operationalized mainly by P₃, which is the
total number of BI software licenses installed, the strategy for measuring the potential number of BI users of the application often is unreported or unclear.

<table>
<thead>
<tr>
<th>UR ( (n, m) = \frac{U_n}{P_m} )</th>
<th>ND</th>
<th>( U_1 )</th>
<th>( U_2 )</th>
<th>( U_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>ND</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( P_1 )</td>
<td>-</td>
<td>BI Scorecard (2007, 2009)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( P_3 )</td>
<td>TDWI (2006)</td>
<td>BARC (2007, 2008)</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Although significant variance exists among surveys, the consistent interpretation of industry analysts, vendors, and consultants is that a considerable number of BI systems are underused. A common statement among the articles gathered in the sample is that BI systems are not performing to their full potential.

Another finding in this theme is the importance of measuring BI usage. A consultant from the sample states, “The most tangible success measure of business intelligence technology is usage.” A low usage rate indicates that the BI program has failed. One article recognizes this specific feature of BI systems “…they are primary intended to be support in decision making process. That means that users are not forced to use this system, as they have to use transactional systems…” The consultant also forecasts problems for a BI project when its usage rate is low “…the fact that business intelligence systems can be expensive… if users don’t use it, eventually the solution will be terminated.” Although the cost of BI software licenses can be high, one consultant argues, “the real costs are the time and complexity to configure the tools and integrate them.” For that reason, BI teams are encouraged to demonstrate tangible benefits of BI in order to maintain the project. Furthermore, one consultant recommends, “BI managers need to continuously monitor query and report activity. When activity appears to slow down, they need to investigate the reason.” The uncertainty that emerges from the user’s freedom to use or not use a BI system can be a challenge for IT managers who are used to enterprise systems with involuntary users.
In addition to the problem of questionable construct validity in measuring BI usage rates in the sample, one analyst discussed another dimension of the meaning and validity of utilization rates:

*On the other hand, maybe the "right" number of people using business intelligence is 5%.*

*Maybe in some industries it's three people at head office and that's it. In other cases, it might be that the target should be every single employee using BI every single day.*

There are two underlying assumptions exposed in the quotation. First, the nature of the task or decision that is supported could be relevant for the patterns of use of BI. Second, BI is a broad term, and considering a single pattern of use overlooks the suitability of the choice of a specific BI tool for a specific organization. As a result, one organization could successfully implement an enterprise BI system where every employee has access to the system, whereas another organization could form a group of power users who have the mission to act as intermediaries between business managers and the BI system. The current operationalization of the BI usage construct in industry literature does not seem to take account of this type of indirect use, and it is probably aimed at the “everyone uses” type of usage patterns.

### 1.2.2.2 Theme 2: The Barriers Between Potential and Actual BI Use

The second theme that emerged from the analysis of the sample concerns factors that impede using a BI system at its full potential. In the discussion of this theme, the term “user” was operationalized as an individual within an organization who could be supported by a particular BI application. The articles in the sample divide BI users into two distinctive groups. One group of users, defined as “*a handful of users who have the technical and business literacy to exploit BI tools,*” are called power users. The other group, termed casual users, are considered to be “*inexperienced users or consumers of reports and analytics tools.*” The BI industry is currently promoting “pervasive BI,” where every decision is supported by the BI system. The idea of targeting a larger population of users, and specifically
casual users, is in the marketing plan of every major vendor: “…talk to any major business intelligence (BI) vendor these days and there’s one person they’re clearly targeting – the casual users of their technologies…” Nevertheless, while power users are often eager and early adopters, casual users can be reluctant to change the way they work and can be resistant to a BI implementation.

The industry literature in the sample is rich in pessimistic comments about the difficulties for broader BI utilization. Examples of these comments are, “What I do believe, however, is that big business intelligence is broken,” or “I do not expect the percentage of employees using BI tools and software to grow significantly in subsequent surveys.” This idea of a problem without a solution is interpreted by the industry literature into two sub-themes: BI applications and user understanding of BI.

**Issues about BI interfaces**

In general, industry analysts argue that many users tend to view BI technology as too complex. One industry research company states “45 percent of respondents said that BI applications are difficult to learn and navigate.” Linked to those estimates, several industry analysts claim the focus of BI vendors and developers has been the technology of BI rather than the development of efficient interfaces. For example, “One of the reasons for poor utilization rate is there hasn’t been enough focus on employing developers that have advanced interface skills.” Making BI interfaces intuitive through the effective use of visualization and usability techniques could lead to a broader use of BI. Nonetheless, industry analysts consider that the current state of BI falls short of this aim. “For the average business user, even a point-and-click interface is not enough. All our studies show that it is not the Nirvana of intuitiveness.” Furthermore, a group of industry analysts has noticed that BI vendors tend to offer similar tools. This promotion of standardized BI tools has led to overlooking differences in the way individual users acquire and interact with data: “Pretty or fast doesn’t matter, if it is not what the business wants or uses.”
**Users’ understanding of BI**

Finally, in this theme, BI analysts, consultants, and vendors view users’ skills as one the main problems for BI utilization. In response, the industry intensively promotes user training and education for BI systems. A clear example of this thinking is, “Lack of training was listed as the biggest obstacle to making better use of BI.” Furthermore, despite the necessity of training in particular BI tools, BI commentators recognize that not every user in the organization will have appropriate knowledge in data and statistical analysis. One article reports that the factor that “had the most impact on BI pervasiveness was the degree of training, not in the BI tools, but in the meaning of the data.” Moreover, industry analysts in the sample assert that BI will achieve its full potential when a new generation of managers takes executive positions. They believe the next generation of managers will have more technology knowledge and superior analytical skills.

Familiarity, or rather the lack of familiarity, with BI tools is the second factor in this sub-theme. The industry data recognizes that users who are familiar with spreadsheets are reluctant to replace them with BI applications. As mentioned in the first theme, most users are not forced to use a specific BI application. Moreover, many business users are unwilling to replace their spreadsheets with a BI tool because they do not see the benefits of the change. Nevertheless, industry writers persistently criticize the use of spreadsheets, stating “to enter data into spreadsheets is an inefficient and error-prone process.” This concern is often articulated as a principal rationale in the business case for the implementation of a BI application. BI vendors recognize the importance of spreadsheet experience in the product design. In the data sample, there was widespread acceptance of interfaces with a spreadsheet appearance.

**1.2.2.3 Theme 3: Dealing With Organizational Conflict**

The third and final theme identified in the thematic analysis is illustrated by the following extracts:

*The technology has been around for a long time. It’s the people that often get in the way.*
“I kept hearing: Just tell me what to build, from the technology team, and: I don’t know what I don’t know [as far as information they wanted access to], from users.

IT was confused and out of their comfort zone.

The environment in which BI systems are developed and implemented is perhaps the most complex in business IT. As mentioned in the second theme, users do not normally understand what BI means. The IT department often leads BI projects, but unfortunately it often has little detailed knowledge about the business or about BI systems. This issue can affect the adoption and further utilization of BI systems because users can reject a project even before the system is implemented and before the IT department knows it has been rejected. Thus, the relationship between the IT department and business users is a critical success factor in the adoption of BI systems. Within the sample, industry analysts suggest that an internal marketing communication plan for BI, sponsorship of business involvement via C-level commitment, and including business users in the BI team are critical for BI utilization.

The second major issue within this theme is the culture shock that the implementation of BI can produce in an organization. An organization needs to be prepared for the impact of a BI project; in particular, the focus on analytics and evidence-based decision-making can be confronting for many managers. The reality, as mentioned in the sampled articles, is that “they still rely more on experience rather than analytics.” In addition, business analysts can feel threatened by the implementation of a system that “can do the work for you” or they can react by complaining the “BI application can create more work.” It was clear that the authors believed that organizational social issues affect the adoption and successful utilization of BI.
1.2.3 DISCUSSION

1.2.3.1 Calculating BI Usage Rates

As mentioned above, the “BI utilization problem” has captured the attention of trade seminars, conferences, and the press. It is currently posited as one of the major reasons for BI project failure. It is clear from the first theme of the thematic analysis, however, that the industry lacks a valid and reliable understanding of the BI utilization phenomenon. Industry surveys conceptualize BI utilization as a measure of the “presence of use”; this is the most simplistic and leanest type of measure of system usage (Burton-Jones & Straub, 2006). Moreover, industry surveys operationalize the constructs using methods that are likely to be inaccurate, such as the respondents’ perceptions of what the usage rate is in their organizations.

In addition, most surveys reported in the first theme are from companies that sell their findings to organizations that are evaluating their BI requirements and considering purchasing a BI application. While the gross usage rates are publicly available through short articles that are published in web portals, they are usually summaries that offer little detail about research methodology and sampling. This makes it difficult for potential buyers to assess their validity and reliability. After analyzing the methodology employed in the eight surveys gathered in the sample, it became clear that none used a valid and reliable method of measuring BI usage. This means that organizations, which rely on surveys conducted by industry analysts, can easily misunderstand the current and potential use of their BI systems. This in turn can lead to significant errors in decision-making with regard to BI strategy, development, and governance. It is important for the industry to evaluate BI usage through objective metrics, such as $U_3/P_3$, rather than subjective or undefined metrics. In the absence of rigorous measurement practices, currently available surveys and reports are problematic as a basis for concluding that a BI usage problem exists.
1.2.3.2 Contextualizing BI Usage

Another important finding in the first theme is that the industry surveys tend to simplify the patterns of use of BI systems in organizations. For instance, indirect use is mentioned as one of the problems in calculating the number of personnel using the BI system. BI users can directly interact with the system or they can use the system through others. A common indirect-use scenario is where a senior executive asks a subordinate to provide information to help with a decision task. The subordinate in turn sources the information from a BI system.

The analysis also highlighted that several BI system instantiations have a short life span. Managers can use BI systems for supporting a specific decision task that has a particular timeline. After the decision has been made, these managers will not use the system further. Using a usage rate approach to assess the utility or worth of a BI system would indicate that such a system is a failure. In its short life, however, the system may have had a profoundly positive effect on the organization and thus should be regarded as successful. As a consequence, none of the eight measures of BI usage rates that industry analysts employ address the complexity of BI systems in practice. Richer measures of system usage need to be developed to represent the patterns of use of BI in a more accurate manner. Extending the Burton-Jones and Straub (2006) approach of measuring information system (IS) use to BI may provide richer insights into the phenomenon.

1.2.3.3 Characteristics of the BI User

The methods that industry surveys use to measure BI usage do not account for differences between BI users. The assumption is that BI systems are similar to transaction-processing applications and operational IT applications. As a result, their users are to a large extent homogeneous. However, according to the academic literature (for example, Arnott, 2010; Clark et al., 2007; Watson & Wixom, 2007) and the industry literature gathered in the sample, BI systems differ significantly from transactional systems in their nature of use and their purpose. In the analysis of the second
theme, industry analysts argued that the current BI vendor tools are not intuitive enough and do not accommodate the different ways in which they are used. Consequently, understanding the ways users acquire data and the ways they interact with BI interfaces are important factors in achieving broader utilization of BI tools. Thus, it is crucial for the understanding of BI system usage success that rigorous research be carried out in the area of the usability of BI tools. In addition, the common belief in the sample that every employee in the organization should use a BI system is unrealistic.

Another common view is that users often do not have sufficient analytical skills and do not sufficiently understand the meaning of the data available to effectively use BI. Users who have problems understanding analytical BI tools prefer to rely on their own experience. This is inconsistent with Davenport’s (2006) assertion of the widespread use of modelling and optimization tools by managers. According to industry analysts in the sample, this position will only be reached when a new generation of managers with superior analytical skills assume executive positions. Nevertheless, there is no research evidence that this trend to superior analytic skills exists. In addition, current business school curricula do not guarantee that students will graduate with “deep statistics and quantitative skills required for descriptive and predictive analytics” (Wixom et al., 2011a, p. 302). Unless this generational change has actually occurred, organizations may base their BI strategies on invalid assumptions.

1.2.3.4 Organizational Issues

Poor leadership and lack of communication among project teams are mentioned by the academic literature as some of the factors that may lead to BI project failure (Marks & Frolick, 2001). The articles in the sample also argued that the conflict between IT departments and BI users is one of the main obstacles to broader use of BI systems within organizations. Significant issues arise from this argument. First, there is a need to understand how a BI system should be implemented and governed. It seems that significant tension could exist between the dominant governance strategies
of enterprise IT and the way BI systems should be governed. Second, the articles in the sample argue that BI users do not necessarily know what they want from the system. This means that traditional development methodologies that IT departments have in place can be inappropriate for developing rapidly evolving BI systems requirements. Finally, articles in the sample argued that BI systems might require a change in the way managers perform their work. This might cause significant resistance to change and lead to managers rejecting BI systems. It is then suggested that further research is necessary in order to understand the social issues that constrain or encourage the implementation of BI systems, especially in the context of organizational cultures.

1.2.4 Concluding Comments on the Study of the BI Utilization Problem

Despite the potential limitations of using articles and white papers available on web portal and vendors’ websites, this analysis has shown that what is widely discussed in industry conferences, seminars, and web portals as the “BI utilization problem” is more a misunderstanding of the way that BI systems are actually used. The BI usage rates reported in BI industry surveys employ inappropriate and invalid metrics. They misrepresent the manner in which BI systems are actually used. The eight industry surveys analyzed lack rigor, particularly with regard to their sampling and methodology. As a result, it could be dangerous for an organization to use them as basis for their decision-making on BI adoption, or as a way to evaluate the success of their BI programs once they are implemented. Falsely believing that the BI utilization problem exists could lead organizations to prematurely cancel a significantly beneficial BI project. Moreover, they might overlook the real impact that a BI project has on their organization. A rigorous reconceptualization of the patterns of use of BI systems needs to be undertaken. Moreover, while the understanding of BI utilization is important for practitioners and researchers, using lean measures of use is not adequate as a surrogate for BI success or failure. As Goodhue (2007) has pointed out, more utilization of a technology is not always better. Therefore, if the purpose of BI systems is to
improve management decision-making, having valid and reliable conceptualizations and models of effective BI system use and outcomes are a research priority.

1.3 **Research Aim and Expected Contributions**

BI development and deployment is one of the highest priorities for CIOs and will remain so at least until 2018 (Gartner Inc, 2013). Senior managers rate BI as the top priority technology investment for enhancing decision-making in their organizations. Nonetheless, the BI industry has reported continuously that BI systems are underused with usage rates as low as 8 percent. The exploratory background study presented in Section 1.2 has revealed that the BI industry (1) lacks understanding of the BI outcomes construct, and (2) oversimplifies the nature of BI use. The lack of understanding of how BI systems are used and what drives more effective use makes it difficult to evaluate BI system project success or failure. Research on BI systems is one of the least-published types of DSS in prestigious academic journals. Thus, BI systems research has not developed models that account for the nature of BI system use and outcomes.

The expected contribution of this research is clarification of the BI system use and outcomes constructs. In particular, the exploration and analysis of the patterns of use of BI systems in practice will permit better understanding of the nature of BI systems use in different contexts. The clarification and understanding of the BI systems use and outcomes constructs will provide a systematic way to conceptualize and measure BI systems outcomes. In practice, it will provide organizations with a conceptual framework for measuring the current state of a particular BI system implementation. The primary aim of this research project is: **The development of models that explain the nature of BI system use and outcomes.** These models will be based on richer conceptualization of information systems use, and they will acknowledge the multidimensionality of measuring outcomes.
1.4 Thesis Outline

This section outlines the structure of this thesis. While the sequence followed by the chapters is presented in a linear manner, several iterations between existing theories and empirical evidence took place during the development of this thesis. Chapter 2 presents a more detailed specification of the research approach used to satisfy the research aim of this thesis. In the following paragraphs, each chapter is described by a title and a short summary of its contents:

Chapter 1 – Introduction

This chapter introduces the research problem. Industry surveys and industry commentators’ articles related to BI systems utilization issues are summarized and analyzed critically. The chapter also defines the object of study, namely, BI systems, based on industry and academic definitions of the phenomenon. The chapter concludes with the research aims and scope, and it provides an outline of the structure of the thesis.

Chapter 2 – Plan of Research

The chapter describes the research strategy used in this research. It also discusses the data collection strategies used in the different phases of the project.

Chapter 3 – Literature Review and Conceptual Framework

This chapter reviews the existing literature in the information systems field about BI system use, adoption, success, and outcomes. It also covers the same set of constructs in the existing DSS literature, particularly in relation to the types of decision support systems that are considered predecessors of BI systems. Using the existing literature as a foundation, the final section of the chapter describes the initial theoretical assumptions that guide the exploratory phase of this research.
Chapter 4 – Exploratory Case Study

This chapter describes and analyzes the data collected during an in-depth exploratory case study carried out in a large government authority in Australia. A better understanding of how BI systems are used in practice is obtained through semi-structured interviews with the users of the centralized BI system that the organization implemented four years before this study. The chapter includes the context in which the centralized BI system was implemented, the description of the data collection approach, a thematic analysis of the interview transcripts, and a discussion of the main findings and limitations of the case.

Chapter 5 – Models Development

This chapter presents two models developed as a result of the exploratory empirical phase of this research. It combines the prior theories and models reviewed in Chapter 3 with the analysis of the data collected during the exploratory case study and the existing IS and DSS theories in which the findings described in the previous chapter can be sustained.

Chapter 6 – Follow-Up Case Study

This chapter describes and analyzes the data collected during a follow-up case study carried out in a big insurance company in Australia. A confirmatory analysis is performed validating the propositions presented in Chapter 5. Each proposition is analyzed for its validity. In addition, each proposition and contrast is analyzed in terms of whether it might potentially refine the models. The chapter findings are a set of requirements to be implemented in the final models of BI system use and outcomes, which are presented in the subsequent chapter.
Chapter 7 – Models Refinement

This chapter presents the final and final models of BI system use and outcomes. Each proposition presented in Chapter 5 and evaluated in Chapter 6 is discussed based on the findings of the follow-up case study and enfolding literature presented in Chapter 3 and existing DSS and IS theories that helps to explain the nature of BI system use and outcomes in more detail.

Chapter 8 – Conclusion

This concluding chapter discusses the findings obtained across the research, the strengths and limitations of the thesis, the contribution to research and practice, and the implications for further research, and it presents a final conclusion.
CHAPTER 2: PLAN OF RESEARCH

Chapter Overview

This chapter presents the research approach used to satisfy the research aim of this thesis: “to develop models that explain the nature of business intelligence systems use and outcomes.” It describes each stage of the research process undertaken.

1. **Background Study**
   - Critical Analysis of the “BI utilization problem”: BI industry consultant and vendor’s views on the extent in which BI systems are used by organizations

2. **Literature Review & Conceptual Framework**
   - Analysis of the existing BI (including its predecessors) use and outcomes literature.
   - Review of the existing IS use and outcomes theories.
   - Development of conceptual framework

3. **Exploratory Case Study**
   - Analysis of how individuals use BI systems in a large government organization (LGA), and the outcomes obtained by their use

4. **Initial Models Development**
   - Design of direct and indirect BI system use and outcomes models

5. **Follow-up Case Study**
   - Evaluation of the proposed BI system use and outcomes modes in a big insurance company (BIC). Refinement of constructs and associations

6. **Final Models of Direct and Indirect Use of BI Systems**
   - Reflection on research findings and definition of final models
2.1 INTRODUCTION

The previous chapter provided an extensive background study of the research problem this thesis aims to address. It also explained that the research aim of this thesis is to develop models that account for BI systems use and outcomes. This chapter explains and describes the approach used in this research to develop these models.

As recommended by Creswell (2003), the first part of the chapter presents the purpose statement of this research. Then, the chapter briefly discusses theory development and its relation to the desired models of this thesis. The second part introduces the structure of the research design, including the purpose and methods employed in each phase.

2.2 PURPOSE STATEMENT

The purpose of this two-phase, sequential case-study research design is to explore the nature of BI systems use and outcomes in one case study and then follow up with a second case study to evaluate and refine the research models. In the first phase, a comprehensive conceptual framework based on existing information system (IS) theories is employed as a theoretical lens (Creswell, 2003; Neuman, 2011) to guide the data collection in a large government authority. In the second phase, research models derived from the first-phase work are evaluated and refined by a follow-up case study conducted in a large insurance company.

2.3 THEORY DEVELOPMENT

Many researchers view the development of theory as the main goal (Eisenhardt, 1989; Shapira, 2011) and the most rewarding activity in science (Glaser & Strauss, 1967; Zmud, 1998). Thus, it is common practice to evaluate the quality of a research paper by its theoretical contribution (Colquitt & Zapata-Phelan, 2007; Straub, Ang, & Evaristo, 1994; Sutton & Staw, 1995). As a result, senior
IS researchers have continually made calls for the development of “good theory” (Watson, 2001), arguing that the field is at an early stage of theory development (Webster & Watson, 2002).

A common criticism about IS research is that the field has borrowed theories from other disciplines (Benbasat & Weber, 1996; Keen, 1980c). To attain a disciplinary status, it is necessary to develop our own theories (Benbasat & Weber, 1996). This problem is what Benbasat and Zmud (2003, p. 183) have called “the identity crisis within the IS discipline,” arguing that the lack of focus on the phenomena associated with IT-based systems creates an ambiguous disciplinary identity. To avoid this issue, Benbasat and Zmud (2003) recommend that theories in IS include conceptualizations of the IT artefact and its immediate nomological net. By IT artefact they refer to the “structures, routines, norms, and values implicit in the rich contexts within which the artefact in embedded” Benbasat and Zmud (2003, p. 186). The immediate nomological net of the IT artefact comprises the understanding of “(1) how IT artifacts are conceived, constructed and implemented, (2) how IT artifacts are used, supported, and evolved, and (3) how IT artifacts impact (and are impacted by) the contexts in which they are embedded” (Benbasat & Zmud, 2003, p. 186). Although research that excludes constructs relating to the IT artefact can contribute to knowledge, it might not be considered to be IS research. In this sense, IS researchers must avoid excluding constructs about the IT artefact and its nomological net properties and including constructs that lie outside this scope.

Following Benbasat and Zmud’s (2003) considerations of what constitutes IS research, this research project considers BI systems as a particular type of IT artefact that supports decision-making (a complete definition of “BI systems” is given in Chapter 3). Further, the models developed in this thesis specifically account for the use of BI systems, which is the phenomenon of interest in this research.
2.4 Theory and Models

The meaning of “theory” differs across different research fields and paradigms. The existing multiple definitions of theory in the literature cause confusion about how to differentiate between weak and strong theories (Sutton & Staw, 1995). Furthermore, as Gregor (2006, p. 612) notes, “researchers who use the word theory repeatedly in their work fail to give any explicit definition of their own view of theory.”

To provide guidance to the IS field, Gregor (2006) developed a classification of theories based on a complete examination of the structure of theory in IS. As a result of her analysis, five types of theories are distinguished: Type I—theories for analysis; Type II—theories for explanation; Type III—theories for prediction; Type IV—theories for explanation and prediction; and Type V—theories for design and action.

According to Gregor (2006), while Type I theories go beyond description of a phenomenon by analyzing its attributes and relationships, they do not explicitly specify causality. These theories are known as frameworks, taxonomies, or typologies. Type II theories are employed to explain how and why a particular phenomenon occurs. These theories fall into the views of the interpretivist paradigm (Klein & Myers, 1999). Interpretivists assume that our knowledge of reality can only be obtained via social constructions. Thus, Type II theories do not provide any testable propositions. Although Type III theories for prediction employ testable propositions, they do so to predict an outcome without explaining why that particular outcome is achieved.

From the five type of theories proposed in Gregor (2006) taxonomy, Type IV, theory for explaining and predicting, is what it is most commonly understood by theory in science. It provides descriptions of the constructs and the relationships among them in the form of testable propositions that are used describe causal explanations and predict outcomes. Finally, Type V theories, theories of design and action, are developed to describe how to do something. This type
of theory is associated with what is being denominated as the design science paradigm (Hevner, March, Park, & Ram, 2004; March & Smith, 1995).

An alternative view on the nature of theory is proposed by Weber (2012). According to Weber (2012), while Type I theories can provide precise definitions of the constructs that could form a theory, they lack other necessary parts to fall into that category. Type II and Type III theories may or may not constitute a theory, depending on how rigorously the parts have been articulated. The key argument of Weber (2012) is that the Gregor (2006) Type I, II, III, and V theories can be considered models but they are not actually theories. A model is an “abstracted, simplified, concise representation of something else (phenomena) in the world” (Weber, 2012, p. 5). According to this view, models provide an approximated explanation for the complexity of the phenomena, compromising “precision to achieve cognitive economy” (Weber, 2012, p. 5). While the terms “models” and “theory” are sometimes used interchangeably in the literature (March & Smith, 1995), not all models can be considered theories. Weber (2012, p. 5) explains that for a model to be considered a theory, a rigorous specification of its parts (constructs, associations, and states), and particular qualities of the whole (parsimony, novelty, importance, and level) need to be satisfied. This is better aligned with the Gregor (2006) Type IV theory – theories for explanation and prediction. Weber (2012) does not aim to denigrate the contribution to knowledge that the other types of “theories” can offer; rather he aims to clarify the parts that need to be rigorously specified to develop theories for the IS field.

The purpose statement (section 2.2) explained that this research aims to “develop models.” In using the term “models,” this research follows the Weber (2012) notion of theory. In particular, the approach undertaken is designed to explore the phenomenon of BI system use, identifying in both empirics and existing IS literature the parts of the model (constructs, associations, and states). In this sense, this research models aim to fall in the Gregor (2006) Type IV. The term “models” is consciously employed because it depicts more accurately the emerging nature of the research
process followed in this thesis. The research commences with very broad conceptualizations of the models. These definitions are then progressively improved during each research phase to form a resultant model that accounts for the nature of BI system use and outcomes.

2.5 Research Approach

Empirical research makes theoretical contributions by testing or building theory (Colquitt & Zapata-Phelan, 2007). Typically, theory testing is performed via the hypothetico-deductive model using prior theory to formulate hypotheses before refuting or corroborating those hypotheses with empirical observation. Theory building generally is performed via an inductive reasoning approach, where observations are used to generate theory.

Dul and Hak (2007) distinguish three types of research activities that form what they called the empirical cycle of theory development: (1) exploration, (2) theory-building research, and (3) theory-testing research. They propose that exploration of prior literature and practice is needed to evaluate whether propositions are available on the phenomena of interest and whether those propositions have been tested. This initial step helps to decide which type of research is more adequate to conduct. If the exploration of the prior literature and practice in the search for propositions is not conclusive, then a theory-building approach can be used to formulate propositions. If the exploration is successful, then the research project may follow a theory-testing approach. While initial theory-testing must be used if the proposition has not been tested before, replication theory-testing is used to enhance a proposition’s generalizability. Figure 2.1 shows Dul and Hak’s (2007) empirical cycle for developing theory.
As the purpose statement indicates, this research adopts a two-phase research approach. The first phase has an exploratory focus that aims to understand the phenomena of BI systems use and outcomes. As Chapter 1 indicated, there is a lack of understanding of how BI systems are used and what drives more effective use. Therefore, the focal phenomenon must first be understood with the objective of discovering relevant constructs and propositions based on the evidence drawn from individuals who use BI systems in a particular organizational setting. Nonetheless, this empirical phase is not approached without any prior theory and definitions. Both the exploratory background study described in Chapter 1 and the conceptual framework developed in Chapter 3 provide the bases for the first phase of the research.

The second phase aims to evaluate the proposed BI system use and outcomes models by obtaining the views of individuals who use BI systems in different organizations. The goal is to refine the model’s constructs and associations. Although this thesis is written in a unidirectional way, literature and empirical observations were contrasted continually during the research.

### 2.6 Research Process

This research follows a six-step process (Figure 2.2). The first two steps are the exploration of the phenomena under study and a review of existing literature (Dul & Hak, 2007). These initial two steps help clarify the object of study and identify the type of research to be conducted. The third
and fourth steps comprise an exploratory case study aimed at building models. The final two steps serve to evaluate and refine the models’ constructs and propositions via a follow-up case study.
2.6.1 BACKGROUND STUDY

The first step in this research examined the problem to be addressed. A thematic content analysis of the BI industry literature was performed to identify and define the phenomenon under study and to analyze existing beliefs about BI system use and outcomes (see Chapter 1). The outcomes of this step are that there is (a) lack of understanding of BI use in the BI industry and (b) little academic literature on the topic. Furthermore, this step highlighted the need for conducting rigorous research to better understand the nature of more efficient and more effective use of BI systems.

2.6.2 LITERATURE REVIEW

This second step in the research sought to define the object of study by examining the existing literature on BI systems and its predecessors. The outcome of this step was a conceptual framework that guided the subsequent empirical phases.

IS use and outcomes theories were examined as a basis for formulating a conceptual framework. The approach employed was to seek elements and properties of elements used in IS use and outcomes research. Furthermore, the framework considered existing conceptualizations of BI systems and their differences with IS in general. The framework provided the starting point for the design of an instrument used to collect data.

Miles and Huberman (1994) argue that conceptual frameworks have a focusing and bounding function. Therefore, the framework used in this research states the things, the key elements, and constructs to be studied. In this sense, the framework differs from the models that this research aims to build because no causal relationships exist between constructs in the framework. These relationships are structured later in this research.
2.6.3 **EXPLORATORY CASE STUDY**

The third step in this research was an exploratory case study. This research method was selected for three reasons. First, the phenomena of BI systems use and outcomes are difficult to understand outside the context in which they occur. Case studies are preferred when the research focuses on contemporary events (Benbasat, Goldstein, & Mead, 1987) or when variables can only be measured in their natural context (Yin, 2018). Second, case studies are appropriate when researchers cannot manipulate the behavioral events of the phenomenon (Yin, 2018), and where the actor’s experiences are important (Benbasat et al., 1987). Third, an exploratory case study is appropriate as the research method because at this stage of the research process little is known about the phenomena under study (Eisenhardt, 1989).

The outcome of the exploratory case study was an improved understanding of how BI systems are used in practice. This understanding was built via analysis of BI systems users’ views about the ways in which BI systems are used and the outcomes obtained from their use. The study also examined alternative patterns of BI system use and refined prior conceptualizations of BI systems outcomes by identifying different outcomes measures.

The findings of this step were the foundations for the development of research models. The empirical data collected were contrasted with the existing literature as a means of shaping the constructs and associations used in the models (Eisenhardt, 1989).

2.6.4 **MODELS DEVELOPMENT**

This step aimed to develop the models that account for BI system use and outcomes. The findings of the exploratory case study and related IS literature were reviewed as a basis for developing the models. The models incorporate both constructs and associations that underpin a set of propositions that are evaluated in subsequent steps of this research.
The specification of the models’ components was guided by the principles suggested in Weber’s (2012) framework for theory evaluation. Remember that the main objective of Weber’s framework is to provide criteria for evaluating the usefulness of a theory. Nevertheless, using the framework for the development of the models in this research provided a foundation not only for the models to account faithfully for the phenomena of BI system use and outcomes but also for the development of high quality theory in due course.

2.6.5 Follow-Up Case Study

The fifth step in the research evaluated and refined the models proposed in the previous step. A follow-up case study was conducted in a different organization. Since the models and propositions had not been tested before, an initial evaluation was needed to confirm whether propositions based on the models were supported by at least one more case. The follow-up case study was also used to refine the propositions. As Figure 2.2 shows, during this step data from the exploratory case study and existing literature were revisited to improve the extent to which the models accounted for the phenomena.

The outcomes of the follow-up case study were the confirmation and refutation of certain propositions and a more precise specification of constructs and associations in the models. In particular, the nature of the associations between constructs was described in more detail. The analysis of the data collected not only suggested the existence of some different associations among constructs but also provided insights into the nature of the associations.

2.6.6 Resultant Models of BI System Use and Outcomes

The last step of the research method aimed to define the final models. Using the accumulated understanding achieved via the initial exploration of the industry literature, the existing IS use and outcomes literature, and the results of the exploratory and follow-up case studies, the final models were articulated.
A reflection was also part of this step. It aimed to summarize the main findings of this research and to identify the strengths and limitations of the research and the models proposed. It also focused on the contributions of this research to practice and knowledge. Finally, a set of implications for future research were derived.

2.7 Research Method

Because this study seeks to explore the phenomena that are still poorly understood, an exploratory method is required. According to Yin (2018), the selection of the appropriate research method depends on (1) the form of research question, (2) whether control of behavioral events is required, and (3) whether a focus on contemporary events is needed.

This research aims to understand the nature of the BI system use and outcomes, developing models that account for the phenomena under study. This aim can be translated to the following research questions: “How are BI systems used? Why are they used in the ways they are used?” These questions motive additional research questions: “How do BI system users conceptualize BI systems? Why do they conceptualize them in these ways?” Yin (2018) argues that “how” and “why” questions can be answered using experiments, histories, or case studies.

Yin’s (2018) next step is to determine the extent of control of behavioral events and the degree of focus on contemporary events that are necessary for the study. Because this research is focused on contemporary events and no control is required, Yin argues only histories and case studies are suitable methods. Nevertheless, he contends that case studies are preferable over histories when (a) the researcher has access to direct observation of the phenomena under study, and (b) it is possible to interview subjects that are part of the phenomena. For the study proposed, the latter is possible and also desirable.
Case study research is suitable for the studies that aim to obtain a deep understanding of the phenomena under investigation (Eisenhardt, 1989). Obtaining such an understanding is the reason for the exploratory phase of this research described in section 2.5.3. Nevertheless, the second phase aims to evaluate the propositions developed from the findings of the exploratory phase. Case studies are also suitable for testing propositions (Dul & Hak, 2007). In particular, a multiple case study approach makes comparisons among cases possible (Eisenhardt, 1989). Therefore, the selected method for this study is case study research.

2.7.1 Unit of Analysis

The unit of analysis is the focus of measurement in an investigation (Neuman, 2011). The main unit of analysis of both empirical phases of this research is the process of using a BI system in large organizations. In particular, the research focuses on the ways individuals from two different organizations use their BI system and their perceptions of the outcomes they had achieved from using their BI system.

2.7.2 Selection of the Cases

According to Eisenhardt (1989), in a multiple-case design the cases may be chosen to replicate previous cases or extend emergent theory. In order to select the right cases, this study conducted the first case in a large government organization where the researcher was sufficiently familiar with the business context in which organization operated.

The selection of the second case considered the set of propositions that needed to be evaluated as the main criteria. A large organization was also required for the second case. Nevertheless, the business context of the second case organization differed substantially from the business context of the first case. However, the most important factor that influenced the selection of the second case organization was to find patterns of indirect use of BI systems. A matched pairs approach was needed to obtain responses from decision makers and the individuals who supported
them in the use of the BI system. This approach is explained in detailed in the section about the research approach employed in the second case study.

### 2.7.3 Data Collection and Analysis

Three main data collection techniques were used in each case study:

(1) **Documentation**: Documents such as implementation proposals, business cases, progress reports, and system documentation that describe any element of the purpose, functionality, and current state of the BI system were obtained. This dataset was used to gain an initial understanding of the business context and the current status of the BI system project in the organization.

(2) **Coordination meetings**: Several meetings took place with the leader of the BI system project of each case study site. During these meetings, informal and formal interviews occurred to explain the project and recruit participants. Moreover, these meetings served as an opportunity to clarify the responses provided in interviews.

(3) **Semi-structured interviews**: In these interviews the researcher guides a conversation with the interviewee using a protocol. Nonetheless, the researcher can improvise in order to gain richer detail about the case. Interviews were audiotaped and transcribed for analysis. This dataset comprises the main empirical data for exploring the phenomena and evaluating propositions.

Triangulation is an approach that uses multiple sources of evidence to achieve convergence. Thus, the case study research involves analyzing the data using at least two data collection techniques. Furthermore, the data gathered were analyzed using the technique of content analysis.
(Krippendorff, 2003). In this regard, software for qualitative analysis (QSR International NVivo 10) was used for data coding and analysis. The analysis of each case was performed via tables as proposed by Miles, Huberman, and Saldaña (2014).

2.8 Conclusion

This chapter has described the research approach employed in this research. It outlined the steps followed in this research to develop models of BI system use and outcomes. In particular, each step was described with a focus on their outcomes and the relationships among them.

The following chapter defines the object of study of this thesis, namely, BI systems. It also reviews existing IS theories and conceptualizations about use and outcomes to provide a conceptual framework for the first empirical phase.
CHAPTER 3: LITERATURE REVIEW & CONCEPTUAL FRAMEWORK

Chapter Overview

The purpose of this chapter is to define BI systems and explore the academic literature that relates to their use and outcomes. With the aim of building a conceptual framework for this thesis, this chapter examines existing IS theories and conceptualizations of use and outcomes. The final section of this chapter presents the conceptual framework to be employed in the empirical phases of this research.

![Diagram of research process]

- **Background Study**: Critical Analysis of the “BI utilization problem”: BI industry consultant and vendor’s views on the extent in which BI systems are used by organisations.

- **Literature Review & Conceptual Framework**: Analysis of the existing BI (including its predecessors) use and outcomes literature. Review of the existing IS use and outcomes theories. Development of conceptual framework.

- **Exploratory Case Study**: Analysis of how individuals use BI systems in a large government organization (LGA), and the outcomes obtained by their use.

- **Initial Models Development**: Design of direct and indirect BI system use and outcomes models.

- **Follow-up Case Study**: Evaluation of the proposed BI system use and outcomes modes in a big insurance company (BIC). Refinement of constructs and associations.

- **Final Models of Direct and Indirect Use of BI Systems**: Reflection on research findings and definition of final models.
3.1 Brief History of Business Intelligence Systems

During the last five decades, the IT industry has offered different tools and methods aimed at supporting managerial decision-making. In the early 1970s, in part because of the decentralization of computer power, decision support systems (DSS) were developed to provide managers with direct access to information (Keen, 1980b). Although this first generation of DSS required some level of consolidation of data from the existing transactional systems and external sources into a data repository, it had an application-centric approach (Watson, Wixom, Hoffer, Anderson-Lehman, & Reynolds, 2006). DSS eventually evolved to become a solution to address a specific decision task where the underlying data structure supported the application or decision task specified.

While DSS included executives in their target audience, in practice they were employed mainly by middle managers and highly trained staff in specific problem domains (Watson, Rainer, & Koh, 1991). Executive information systems (EIS) emerged during the 1980s with the aim of supporting top-level managers and executives. The main characteristics of EIS were the integration of internal and external information and the existence of a user-friendly interface to monitor the performance of the organization (Millet & Mawhinney, 1992). An important development that facilitated the evolution of EIS was the use of customized data repositories for decision support known as data warehouses (DW). The concept of DW was first introduced by Devlin and Murphy (1988) as a read-only database that integrates and accumulates historical data from diverse transactional systems to support management decision-making. DW permitted EIS to support varied decision tasks where the data stored in the data warehouse could be used by multiple applications.

The first generation of EIS introduced graphical interfaces and coincided with the widespread proliferation of spreadsheets. EIS interfaces and spreadsheets did not handle large amounts of data well, however. In the early 1990s, Codd, Codd, and Salley (1993) specified
standards for online analytical processing (OLAP) tools. OLAP is considered as the IT-based decision support tool with the highest level of functionality for analyzing large data sets (Power, 2008). The main characteristic of OLAP is the adoption of a multidimensional structure that can be navigated using “slicing and dicing” capabilities. In contrast to the static reports that were previously available in versions of EIS and DSS, navigation through different pre-defined hierarchical levels allows OLAP users to query and analyze information in a more flexible manner. By the late 1990s, most EIS had OLAP web browser interfaces that facilitated access to and exploration of data (Singh, Watson, & Watson, 2002).

In addition to the emerging decision support tools described above, a new movement toward use of methods for measuring the performance of the organizations was being promoted. For instance, Kaplan and Norton’s (1996) balanced scorecard makes use of performance dashboards (Eckerson, 2006) to allow executives to have continuing access to pre-selected key performance indicators. In this way, IT-based tools were linked to business performance management as a means to facilitate the adoption of an organization culture of measurement. The line between the management measurement methods and IT solutions became thinner. Thus, by the end of the 1990s, several new buzzwords with their corresponding acronyms appeared in the market. Among them, business intelligence or simply the acronym BI was the one that perhaps had the major penetration and acceptance by industry. By 2006, the main vendors of IT-based management support solutions started to use BI as part of their branding strategy.

Although several authors claim that the term “business intelligence” dates from an article by Hans Luhn published in 1958 in an IBM journal and titled “A Business Intelligence System” (Shollo & Kautz, 2010), the term was not widely used by the industry until the late 1990s (Watson & Wixom, 2007). Anecdotal sources report that an industry consultant from Gartner Inc., Howard Dresner, coined the term in 1989 (Buchanan & O’Connell, 2006). Regardless of its origin, IT
vendors and businesses appropriated and disseminated the term. As a consequence, organizations started to implement and develop their BI solutions, and a buoyant market emerged.

### 3.1.1 BUSINESS INTELLIGENCE SYSTEMS DEFINITION

BI systems need to incorporate technologies and applications to integrate and deliver data for their users. Integration of data can be achieved by using software that facilitates the extraction, transformation, and loading of data (ETL) from different sources into a data mart or data warehouse. Delivering data to users can be done via reports. Common forms of these reports are dashboards, OLAP structures, and pivot-tables (Watson, 2009).

BI systems extend the scope of their predecessors by engaging a broader set of users and decision-making tasks (Clark et al., 2007). BI initiatives can be implemented not only at the level of a department or division but also at the level of an organization (Watson, 2009). Organization-wide BI initiatives generally require integrating data from a larger variety of source systems. They tend to be developed in a centralized manner. BI vendors push for enterprise-wide adoption of BI applications and promote their large software packages or BI platforms. Thus, terms such as “pervasive BI,” “operational BI,” or “BI-based organizations” are touted as describing the next trends in BI. Nonetheless, the current definitions of BI systems include more than the technological aspects. Table 3.1 shows three definitions of BI selected from three influential sources.
Table 3.1 Definitions of Business Intelligence

<table>
<thead>
<tr>
<th>SOURCE</th>
<th>DEFINITION</th>
<th>REFERENCE</th>
</tr>
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<tbody>
<tr>
<td>IT advisory firm</td>
<td>“Business intelligence is an umbrella term that includes the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance.”</td>
<td>Gartner Inc (2012a)</td>
</tr>
<tr>
<td>A-ranked journal paper</td>
<td>“Business Intelligence is a broad category of applications, technologies, and processes for gathering, storing, and analyzing data to help business users make better decisions.”</td>
<td>Watson (2009, p. 39)</td>
</tr>
</tbody>
</table>

The target audiences of the different definitions in Table 3.1 are different. While Davenport’s *Harvard Business Review* article and the book he co-authored with Harris mainly target the business community, Gartner (an IT advisory firm) targets IT practitioners and managers. Nonetheless, these definitions are similar. Watson’s BI definition published in an academic IS journal also uses a similar approach as the other two definitions. Thus, it is possible to combine and analyze these definitions and to identify their main underlying concepts:

1. **Helping users make better decisions:** All the definitions describe the main goal of BI as improving decision-making, thereby impacting the performance and survival of an organization.

2. **BI processes:** BI supports decision-making by a set of processes that can be grouped into two stages. The first is getting the data into a database. In this regard, the definitions use the terms “gathering,” “collecting,” and “storing” data. The second one is getting the data out of the database. This stage is done for reasons of “enabling access for analysis” and “dissemination” of information.
3. BI systems: The definitions use the terms “software,” “applications,” “infrastructure,” and “tools.” Therefore, there will be an IT artefact that will facilitate the processes detailed in (2) that are required for the outcomes in (1).

It is important to distinguish between the general IS movement of BI/Analytics/Big Data and the IT artefacts that are used in organizations. This thesis focuses on the IT artefacts that are BI systems. Davenport's definition is used to guide the research: a BI system is “a wide array of process and software used to collect, analyze, and disseminate data, all in the interests of better decision making” Davenport (2006, p. 106).

3.1.2 BUSINESS INTELLIGENCE SYSTEM COMPONENTS

In order to guide the inclusion of cases in the empirical phases of this research and to circumscribe the review of the BI literature, it is necessary to describe the components of BI systems. Figure 3.1 shows an example of a typical BI architecture. The operational systems in the left box are the data sources that are integrated to create a representation that is stored in the data warehouse (DW). The left-hand oval is the integration environment where the technical team “capture, clean, model, transform, transfer, and load transactional data from one or more operational systems into the DW” (Eckerson, 2006, p. 52). The right-hand oval represents the analysis environment in which business users access the DW using a variety of tools to query, analyze, and prepare reports and dashboards.
BI vendors provide organizations with tools to perform the activities described above. The current vendor offerings consist of platforms which Gartner Inc (2012b) describe as large package software with capabilities for integration, delivery, and analysis that help organizations to understand their business. BI vendors offer platform packages promoting the potential benefits of enterprise-wide solutions. In practice, however, BI initiatives differ. For instance, an organization can develop a single or a few related BI applications for specific departments that use data from only one data source. They might also develop an enterprise data warehouse that will support future BI needs (Watson, 2009).

BI systems can be defined by their organizational scope. The most complex systems that support management decision-making, enterprise BI systems, are usually developed by the central IT department to support as many managers in an organization as possible. At a minimum, they have users from more than one division. The data available to an enterprise BI system is organization-wide in scope and interest and often comes from a data warehouse (DW) or a federation of data marts. A second type of BI system, functional BI, is where development is restricted to one division, department, or function, and the governance of the system is the responsibility of that business unit rather than the IT department. Most commonly, functional BI systems have their data provided by a specialized data mart. When vendors, consultants, and
researchers talk about BI, they usually mean enterprise BI systems rather than functional BI systems.

3.2 BUSINESS INTELLIGENCE SYSTEMS USE AND OUTCOMES

With the aim to create a firm foundation for this research and to facilitate the development of BI systems use and outcomes, this chapter reviews the existing academic literature on BI systems. While BI systems are used widely in industry, which has resulted in a significant number of media articles, blogs, and white papers, academic research on BI systems is limited. In their assessment of the DSS literature, Arnott and Pervan (2008) found that BI is one of the least published topics in the DSS literature in peer-reviewed academic journals. The existing academic BI literature consists of literature reviews (Jourdan, Rainer, & Marshall, 2008; Negash, 2004), tutorials (Watson, 2009), and reports of the current state of BI in industry (Watson & Wixom, 2007) and academia (Wixom et al., 2011a). The only available empirical work published in top-ranked academic journals is specific BI application developments and evaluations (Rouibah & Ould-ali, 2002) and descriptive case studies (Watson et al., 2006; Wixom, Watson, & Werner, 2011b). As a consequence, this section draws on the broader DSS literature, extending the review to cover literature the use and outcomes of EIS and DW.

Prior research about the outcomes of BI systems and their predecessors has been undertaken from two perspectives. The first perspective attempts to examine the factors that need to be considered to ensure the implementation of a BI system project is successful. Because the implementation of a BI system in an organization requires significant resources and commitment, researchers have proposed a set of factors that are likely to facilitate and ensure a successful implementation and start-up of BI. The second perspective focuses on the necessary characteristics that a BI system must offer in order to have a positive impact on the work of individuals in an organization. This perspective concerns not only the BI system’s functions and interface but also
the underlying characteristics of the data it provides. These two perspectives are not separate streams of research. Rather, a common practice is to include some desirable characteristics of the BI system as key factors for a BI project to be successful.

Another matter to be considered is how measures of BI outcomes have been conceptualized. The literature has employed alternative measures and operationalization of successful outcomes. Among the most-used metrics are “decision performance,” “user satisfaction,” “economic return,” and “frequency of use.” Because of the multidimensional nature of use and outcomes, the above-mentioned measures are frequently employed simultaneously. An issue that arises from employing multidimensional constructs is that they often reflect multiple levels of assessment (Burton-Jones & Gallivan, 2007). On the one hand, some of the outcomes described in the literature correspond to the organization as a whole. For instance, a higher “profit” is an outcome that the organization can obtain through using a BI system. On the other hand, “satisfaction” is a measure about the fulfilment of an individual’s expectations in relating to use of the BI system.

To examine the different approaches used in the BI literature, articles were gathered using the structured approach recommended by Webster and Watson (2002). Four steps were followed: (1) scanning of leading journals in IS, (2) searching in journal databases, (3) going backward by reviewing citations, and (4) going forward using the Web of Science.

### 3.2.1 Critical Success Factors in the BI Literature

Several studies have attempted to identify ways that increase the likelihood the implementation of BI systems will be considered successful. The critical success factor approach is a method proposed by Rockart (1979) that is aimed at determining executive information needs. Rockart’s method is based on the concept of critical success factors (CSF) developed by Daniel (1961) in the
management field. His CSF method attempts to determine only “critical” factors for decision makers, as a way of focusing on their significant information needs.

The CSF method has also proved useful as a way of identifying the factors that are important for the successful development of information systems. Thus, in the late 1980s, Rockart and DeLong (1988) published an influential book in which eight critical success factors were proposed for EIS: (1) a commitment and informed executive sponsor, (2) an operating sponsor, (3) an appropriate IS staff, (4) an appropriate technology, (5) management of data, (6) a clear link to business objectives, (7) management of organizational resistance, and (8) management of system evolution and spread.

The CSF method has had a significant impact on the study of IS success and in particular BI success. Studies in the field have extended and reorganized the list of factors (Poon & Wagner, 2001) in differentiated phases of development and use (Rainer & Watson, 1995a). The method has also been useful when academics have reviewed and made recommendations about the issues practitioners should consider when implementing BI systems in their organizations (Watson & Wixom, 2007). Finally, the original and successive extensions and adaptations of the CSF list have permitted the development of causal models for EIS and DW success (Poon & Wagner, 2001; Wixom & Watson, 2001). Table 3.2 offers a snapshot of the EIS, DW, and BI literature that has adopted and extended the CSF method.
## Table 3.2 Critical Success Factors in the BI Literature

<table>
<thead>
<tr>
<th>Article</th>
<th>System</th>
<th>Description &amp; Constructs</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barrow (1990)</td>
<td>EIS</td>
<td>Seven Steps for EIS Success: (1) Find an executive champion, (2) Maintain simplicity, (3) Use MIS expertise, (4) Ensure feasibility of data availability, (5) Develop a small but significant prototype, (6) Communicate to overcome resistance, (7) Plan for the future</td>
<td>Conceptual</td>
</tr>
<tr>
<td>Rai and Bajwa (1997)</td>
<td>EIS</td>
<td>Adoption of EIS Variables: Independent: Environmental uncertainty, Top management support, IS support, Organization size, Information system department size. Dependent: Adoption status (adopter vs non-adopter), Adoption level</td>
<td>Survey</td>
</tr>
<tr>
<td>Poon and Wagner (2001)</td>
<td>EIS</td>
<td>Eight of Rockart and Delong’s (1988) CSFs plus two new CSFs: (9) Evolutionary development methodology, (10) Carefully defined information and system requirements EIS Success: (1) Access, (2) Use, (3) Satisfaction, (4) Positive impact, (5) Diffusion.</td>
<td>Case Study</td>
</tr>
<tr>
<td>Salmeron (2003)</td>
<td>EIS</td>
<td>Keys to EIS Success (no definition given). Human Resources: (1) Users’ interest, (2) Competent and balanced EIS staff, (3) Executive sponsor’s support Technical and Information Resources: (1) Right information needs, (2) Suitable soft/hard. System Operation: (1) Flexible and sensitive system, (2) Speedy development of a prototype.</td>
<td>Survey</td>
</tr>
<tr>
<td>Watson and Wixom (2007)</td>
<td>BI</td>
<td>Contents: Definitions, Benefits, CSFs, New Trends. Success Factors: (1) Senior management believes in and drives the use of BI, (2) Use of information and analytics is part of the organization’s culture, (3) There is alignment between the business and BI strategies, (4) There is effective BI governance, (5) There is a strong decision support data Infrastructure, (6) Users have the necessary tools, training, and support to be successful.</td>
<td>Commentary</td>
</tr>
</tbody>
</table>

Despite its popularity, the CSF method has been criticized. For instance, Poon and Wagner (2001) revisited the eight factors proposed by Rockart and Delong (1988) and added two specific EIS factors. With the aim of validating how critical the factors were for EIS success, Poon and...
Wagner (2001) studied the correlation of the 10 factors with five measures of success (access, use, satisfaction, positive impact, diffusion). Their results suggested that only three of the 10 factors were really “critical.” Another CSF study conducted by Rainer and Watson (1995b) compared CSF for three different groups of EIS stakeholders and found significant differences in the CSF that were important for each group. Additional criticisms have arisen from the fact that the method does not provide the means for discovering inter-relationships among the factors (Nandhakumar, 1996). Furthermore, the CSF method does not account for the variation of the importance that each factor will have across the different stages of the implementation process (Larsen & Myers, 1999). This can be a problem when studying BI use and outcomes, because IT-based supporting systems can evolve quickly through an iterative process during systems design and use (Keen, 1980a). Thus, researchers have adapted previous CSF approaches to assess implementation success as a dynamic process. For instance, Bajwa, Rai, and Brennan (1998) conceptualized EIS success by differencing success factors associated with the phases of development, implementation, maintenance, and enhancement activities.

3.2.2 System Characteristics in the BI Literature

While the CSF method has been useful in guiding the implementation of BI systems, its application to a particular BI system instantiation does not inform managers of the necessary characteristics of effective BI systems. Several studies have focused their attention to the BI system to understand the characteristics that enable its effective use.

Two aspects of the systems have been studied in the BI literature on effective use: information quality and system quality. Information and system quality have been fundamental not only for the study of BI systems but also for the study of IS effectiveness. DeLone and McLean’s Model of IS Success (1992), which is perhaps one of most influential models in the IS field, presents constructs affecting use and user satisfaction. The articulation of two separate constructs for determining the level of use and satisfaction that an individual user has with a particular system
comes from the assumption that information quality refers to the “content” and system quality to the “delivery.” The distinction offers a useful clarification for IS researchers and a theory about IS effectiveness. Nonetheless, the researchers have had several issues with operationalizing the constructs. Among the articles reviewed for this research, the same variables could be employed for system quality or information quality. For instance, Khalil and Elkordy (2005) used “ease of use” and “format,” two variables that are more frequently used under “system quality,” as variables to measure information quality in their study about EIS success.

Another example is “access to external data,” which some researchers have conceptualized as information completeness, a component of information quality (Bergeron & Raymond, 1992; Salmeron, 2002; Wixom & Watson, 2001). Other researchers, however, have employed “access to external data” as a component of “system quality” (Rainer & Watson, 1995a). Table 3.3 shows the different ways in which information quality and system quality have been operationalized in the BI literature.
Table 3.3 Characteristics of the System in the BI Literature

<table>
<thead>
<tr>
<th>Article</th>
<th>System</th>
<th>Information/Data Constructs</th>
<th>System Constructs</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bergeron and Raymond (1992)</td>
<td>EIS</td>
<td>Quality of Information [IndVar]: Flexible, Correct, Timely, Relevant, Complete, and Validated</td>
<td>User Interface [IndVar]: Easy-to-use, Secure and confidential access, Short response time, Accessible at home, Reliable access procedure, Produces information quickly, Minimizes keyboard use, Quick retrieval of desired information, Dedicated printer</td>
<td>Survey</td>
</tr>
<tr>
<td>Nord and Nord (1995)</td>
<td>EIS</td>
<td>-</td>
<td>Information accessibility, Ease of use, Decision tools, Graphics, Minimum number of keystrokes, Mouse &amp; touch screen</td>
<td>Survey</td>
</tr>
<tr>
<td>Wixom and Watson (2001)</td>
<td>DW</td>
<td>Data Quality [DepVar]: Accuracy, Comprehensiveness, Consistency, and Completeness of the data provided by the DW</td>
<td>System Quality [DepVar]: Flexibility and integration of the DW</td>
<td>Survey</td>
</tr>
<tr>
<td>Salmeron (2002)</td>
<td>EIS</td>
<td>Information timeliness, Information accuracy, Briefer information, Information relevance, Competitor’s information, Access to external information, Access to informal information</td>
<td>Speedier access to information, Data presentation</td>
<td>Survey</td>
</tr>
<tr>
<td>Salmeron (2003)</td>
<td>EIS</td>
<td>Right information</td>
<td>Flexible and sensitive system</td>
<td>Survey</td>
</tr>
<tr>
<td>Watson, Fuller, and Ariyachandra (2004)</td>
<td>DW</td>
<td>Consensus in data definitions Data accuracy</td>
<td>-</td>
<td>Case Study</td>
</tr>
<tr>
<td>Khalil and Elkordy (2005)</td>
<td>EIS</td>
<td>Information quality [DepVar]: Content, Accuracy, Format, Ease of use, Timeliness</td>
<td>Ease of use</td>
<td>Survey</td>
</tr>
<tr>
<td>Popović, Hackney, Simões Coelho, and Jaklić (2012)</td>
<td>BI</td>
<td>Data integration, Information content quality</td>
<td>Information access quality, Analytical capabilities</td>
<td>Survey</td>
</tr>
<tr>
<td>Isik, Jones, and Sidorova (2013)</td>
<td>BI</td>
<td>Data quality (Reliability)</td>
<td>User access, System flexibility, Integration with other systems, Level of risk the system supports</td>
<td>Survey</td>
</tr>
<tr>
<td>Bischoff, Aier, Haki, and Winter (2015)</td>
<td>BI</td>
<td>Information quality, Trust</td>
<td>Continuous use [DepVar], Usefulness, Ease of use</td>
<td>Survey</td>
</tr>
<tr>
<td>Shollo and Galliers (2016)</td>
<td>BI</td>
<td>Data selection practices: Data on demand, turning data into evidence.</td>
<td>Organizational knowing [DepVar] capabilities, Articulation practices: articulating new distinctions (i.e., identification that something requires further investigation), articulating different perspectives, articulating organizational actions (i.e., comparison across different units, identification of common patterns).</td>
<td>Case Study</td>
</tr>
</tbody>
</table>

[DepVar]= Dependent Variable, [IndVar]= Independent Variable
Eleven of the twelve articles shown in Table 3.3 used information quality in their models. Among the articles, information quality was found to be a necessary condition for a BI system to be used and to ensure positive outcomes. In this sense, achieving valuable BI system outcomes can be hindered by poor information quality and inappropriate politics around data ownership (Watson & Wixom, 2007).

The BI literature has mainly modelled information quality and system quality as factors for success or independent variables. Studies of the successful implementation of DW, however, have used information quality as a dependent variable and adapted the measurement of system quality. For instance, in their study, Wixom and Watson (2001) proposed flexibility and integration capabilities of the DW as factors that affect the perceived benefits of the using a DW. On the other hand, ease of use, presentation, and accessibility are the most common variables used to measure system quality.

In summary, with the current BI systems available in the market that offer support for all phases of making the data available to decision makers, building models of BI use and outcomes that employ only one of the perspectives – information quality or system quality – would be inappropriate. Both concepts should be incorporated to allow an examination of which part of the BI process each of them has a more preponderant role.

3.2.3 Measuring Outcomes in the BI Literature

3.2.3.1 Use as a Measure of Positive BI Outcome

BI research has frequently measured the impact of BI systems simply via a user’s acceptance of the system. Researchers have argued that system usage is a good surrogate of system success when usage is not mandatory. However, BI systems differ fundamentally from traditional transaction-oriented systems because BI users are in the main discretionary users (Singh et al., 2002). Thus, studies have operationalized diverse system usage measures, such as number of users (Salmeron, 2002), frequency of use, and length of time of use (Leidner & Elam, 1993).
Although researchers and practitioners frequently rely on system usage as a valid measure of system success, there are circumstances in which system usage is not a good surrogate of system success. Goodhue (2007), for instance, argues that more usage is not always better. That could be the case when individuals are forced to use a particular system that decreases their performance. Moreover, some situations exist where the low use of a system may not indicate failure. O’Keefe gives three examples: “(a) the nature of the system may be such that use of the system is only expected in rare instances, (b) occasional use of the system in complex situations may produce a high payoff, and (c) initial use of the system may produce a worthwhile shift in management perceptions and decision making, so that the system is management perceptions and decision making, so that the system is effective but then falls into disuse.” (O’Keefe, 1989, p. 281)

While O’Keefe’s (1989) examples seem intuitively correct for the use of BI systems in practice, the BI literature has not taken into consideration these various possible system usage contexts. Instead, researchers have focused their studies on using user satisfaction (Bergeron & Raymond, 1992; Bergeron, Raymond, Rivard, & Gara, 1995; Poon & Wagner, 2001; Salmeron, 2002; Singh et al., 2002) and decision performance (Green & Hughes, 1986; Hung, Ku, Liang, & Lee, 2007) as replacements for or additions to the vague definitions of the system usage construct.

3.2.3.2 Individual and Organizational Impact

“The purpose of the development of a DSS is an attempt to improve the effectiveness of the decision maker” (Arnott & Pervan, 2005, p. 68). Hence, it makes sense that the BI literature measures the benefits of BI by measuring decision outcomes, such as the quality of the decision (measured, for example, as decision speed or number of alternatives considered) and/or user satisfaction. Using a framework of decision styles, Elam and Leidner (1995) articulated two performance variables: problem identification speed and decision making speed. Another example is the study conducted by Hung et al. (2007). They proposed a model where the use of a DSS causes three effects in individuals: increased user satisfaction, increased decision performance and reduced regret.
Defining and measuring the outcomes of BI, as in IS in general, involves dealing with some intangible outcomes. For instance, Nord and Nord (1995) defined the benefits of EIS and proposed outcomes such as better communications and increased confidence in decision-making. Others BI outcomes have a more tangible nature; nonetheless, they are difficult to measure in practice. Generally, BI systems will not be evaluated by an organization unless the cost of measurement is less than the benefits of knowing the impact of using a BI system. Perhaps the more compelling framework for BI benefits is the one developed over the years by Hugh Watson, Barbara Wixom, and their collaborators (Watson, 2009; Watson, Goodhue, & Wixom, 2002; Watson & Haley, 1998; Watson & Wixom, 2007) illustrated in Figure 3.2. The right-hand vertical axis of the framework represents the scale of the outcome, while the left-hand vertical axis represents the ease of measurement. As BI utilization matures in an organization, the benefits become more global and simultaneously become more difficult to measure. The idea that underlies the trade-off between the two vertical axes is that the outcomes provided by a BI system can be tangible (e.g., cost savings and time savings) or intangible (e.g., better decisions and support for the accomplishment of strategic business objectives).

![Figure 3.2 BI Benefits Framework (Watson & Wixom, 2007)](image)

While some of the measures of BI outcomes mentioned above refer mainly to outcomes that can be conceptualized at the individual level, the multilevel nature of use and outcomes
complicates the elaboration of models for outcomes. The multilevel nature of use leads to the articulation of collective constructs (Burton-Jones & Gallivan, 2007). According to Burton-Jones and Gallivan (2007, p. 661), the structure of a collective construct refers to “the actions among individuals that generate collective phenomena that a collective construct is used to reflect.” The main issue with collective constructs is that individuals’ evaluation of a system can differ from the evaluation at the group or organizational level. In addition, in certain circumstances a researcher may be more interested in understanding a high level of variance in the individual evaluations of a particular system. Thus, managing multilevel measures for evaluating use and outcomes of BI seems problematic and difficult to implement.

When researchers have measured the impact of BI system at the organizational level, the approach has been the measurement of an organization’s economic return for the investment in BI. For instance, Devaraj and Kohli (2003) studied the impact of a DSS in eight hospitals using revenue per admission and revenue per day. Elbashir, Collier, and Davern (2008) measured the extent of BI usage through business process performance and the relationship of business process performance to organizational performance. Nonetheless, some researchers have argued that the economic return approach is incomplete when measuring decision support systems because most benefits are intangible (O'Keefe, 1989).

While the academic and industry literatures claim the purpose of BI systems is to improve management decision-making across a broad range of business activities (Dresner, 2010; Elbashir et al., 2008), the current assessment is that the area of BI benefits is poorly researched (Jourdan et al., 2008). According to these authors, the difficulties in the quantification of improvements in decision-making make this topic unattractive for researchers. However, this present literature review has shown several useful approaches employed for precursors of BI systems that can be used as a theoretical foundation for the development of models of BI use and outcomes.
3.3 Managers as BI System End-Clients

Users of BI systems can be mapped into two categories: (1) information producers, “who create reports and views for others to view,” and (2) information consumers, “who consume those reports and views” (Eckerson, 2006, p. 64). Information consumers of BI systems include executives, managers, and external users (Eckerson, 2006), whereas information producers include the developers inside the BI team and business analysts who sit between IT and the business. Nevertheless, as mentioned earlier in this chapter, BI systems aim to support decision-making and such activity belongs to managers and executives. Thus, this section reviews the literature that defines the concept of managers to describe the characteristic of the end-users of BI systems.

Defining what managers do has captured the attention of scholars since the inception of management as a subject of study and research. Most of the definitions and frameworks developed can be found in textbooks that either cite classic definitions introduced during the last century or attempt to reintroduce a new trend in management such as leadership or entrepreneurship. Despite the abundance of literature, the definitions are particularly vague. For example, Simon (1959, 1987) defines a manager as a decision maker, and Mintzberg (1973) as someone who mostly performs management. A similar approach is used by management books such as Robbins, Judge, and Breward (2003) who define managers by differentiating them from non-managerial employees. Surprisingly, the lack of a formal definition in the literature has been somewhat accepted in practice. The concept has almost been accepted as self-explanatory and not requiring a formal definition to be understood in practice.

Among the existing frameworks about managers are the functional frameworks. Most management textbooks base their definition of the managerial activity on Fayol’s functions of the manager (Miner, 1982). The classical management functions are planning, organizing, commanding, and controlling (Fayol, 1949). These functions have been extended and re-conceptualized by several authors. Hemphill (1959) proposed 10 dimensions that he calls “position
elements” of managerial work: providing a staff service in nonoperational areas; supervision of work; internal business control; technical aspects of products and markets; human, community, and social affairs; long-range planning; exercise of broad power and authority; business reputation; personal demands; and preservation of assets. Mahoney, Jerdee, and Carroll (1965) extended the subset of key management functions to seven: planning, investigating, coordinating, evaluating, supervising, negotiating, and representing. Horne and Lupton (1965) classified activities into four activities: formulating, organizing, unifying, and regulating. Finally, Koontz and O'Donnell (1972) extended Fayol’s framework to planning, organizing, staffing, directing, and controlling. As can be observed in the list of functions presented by the different authors, four functions seem to reappear: communicating, coordinating, planning, and organizing.

The frameworks mentioned above are mainly conceptual and lack empirical evidence. There are two authors who have attempted to describe managers after following and observing them. Mintzberg (1973) and Kotter (1982a, 1982b) followed a sample of top-level managers (also called senior managers or executives in their books) and explored what they do in practice. Mintzberg (1973) presented a typology of managerial roles that comprises three interpersonal roles, three informational roles, and four decision-making roles. Mintzberg also specified that the roles vary in relative importance across different managerial levels. Kotter (1982a, 1982b) introduced the concept of leadership in management. For Kotter, managing is about coping with complexity, and leadership is about coping with change. Thus, both functions involve “deciding what needs to be done, creating networks of people and relationships that can accomplish an agenda, and then trying to ensure that those people actually do the job” (Kotter, 1990, p. 104). Kotter also specified a different set of activities for management (planning and budgeting, organizing and staffing, controlling, and problem solving) and leadership (setting direction, aligning people, and motivating and inspiring).
This research will use the conceptualization of the management functions proposed by Kotter (1982a, 1982b, 1990) for two reasons: First, Kotter’s management functions appear to summarize prior conceptualizations (Carroll & Gillen, 1987; Lamond, 2003). Second, the idea that managing is “getting the work done by others” permits the identification of potential participants during the empirical phases of this research.

3.4 INFORMATION SYSTEMS SUCCESS THEORIES

Organizations develop and implement information systems (IS) with the aim of improving their efficiency and effectiveness (Hevner et al., 2004). Nonetheless, in some cases, information systems are not implemented successfully, and the expected benefits are not always achieved (Markus & Keil, 1994). Unfortunately, measurement of information system use and outcomes is a complex, difficult process (Rockart & DeLong, 1988). Despite this, IS success research is essential for the field, because a well-defined dependent variable or (variables) can have a positive impact on practice (DeLone & McLean, 1992). For this reason, researchers have conceptualized varied definitions of IS outcomes and operationalized diverse surrogates to measure it (Guimaraes, Igbaria, & Lu, 1992). This section reviews three main IS outcomes research streams: (1) information systems success (DeLone & McLean, 1992, 2003), (2) technology acceptance (Davis, 1989), and task-technology fit (Goodhue & Thompson, 1995).

3.4.1 INFORMATION SYSTEMS SUCCESS

With the aim of organizing prior research on IS success, DeLone and McLean (1992) built an IS success taxonomy. Their work was based on Shannon and Weaver’s (1949) communication theory and Mason’s (1978) information influence theory. The taxonomy was used to categorize empirical work in MIS research from 1981-1987. The result was a six-dimension taxonomy that flows from a technical and a semantic level to an effectiveness or influence level. The first level, defined as the technical level, measures the accuracy and efficiency of the IT artefact itself. The second level,
called the semantic level, is defined as “the success of the information in conveying the intended meaning” (DeLone & McLean, 2003, p. 10). The last level, which is defined as “the effect of the information on the receiver” (DeLone & McLean, 2003, p. 10), is the effectiveness or influence level. These levels underpin the six dimensions of the DeLone and McLean’s IS success taxonomy: systems quality (technical level), information quality (semantic level), use, user satisfaction, individual impact, and organizational impact (effectiveness/influence level). DeLone and McLean also theorize that these six dimensions of success are interrelated, resulting in a model that specifies that causality flows in the same direction as the information process. Figure 3.3 presents the resultant model.

The impact of the DeLone and McLean’s (1992) IS success model has been significant for system success research. This model was the first to address the IS success construct and offer a framework with which researchers could articulate their research designs. The authors’ call for “further development and validation” have been heeded by IS researchers. As a result, the model has been subject to critical evaluations. For instance, Seddon (1997) argued DeLone and McLean’s model is not only a process model but also a variance model. In this light, the model is confusing because the boxes and arrows can be interpreted in alternative ways. It also makes difficult the application of statistically valid tests because the nature of the constructs is not clear.

Retaining the characteristics of the original model, Seddon (1997) splits the model into two variance sub-models and eliminates the process model interpretation. The major difference between the models is the definition of IS use. For Seddon, IS use is not a measure of IS success,
but a resulting behavior of IS success. Although he recognizes that usage precedes benefits, he argues that it does not cause them. Therefore, usage is a consequence of IS success. In this light, the two variance sub-models contain system and information quality and perceptions of net benefits of IS use, and the process model contains the IS usage variables. Figure 3.4 shows the resultant model.

![Figure 3.4 Seddon's (1997) Respecified Version of D&M's (1992) Model of IS Success.](image)

DeLone and McLean (2003) published an updated model based on a decade of contributions to the application of, validation of, and challenges to their model. In particular, they addressed three main issues that had been discussed widely in the IS success literature. As mentioned above, Seddon (1997) argued IS usage should be removed from the causal success model. DeLone and McLean (2003) retained IS usage in their updated model, but they clarified the construct using two definitions of IS usage. The first definition is that “use must precede ‘user
satisfaction’ in a process sense, but positive experience with ‘use’ will lead to greater ‘user satisfaction’ in a causal sense” (DeLone & McLean, 2003, p. 10). The second definition of IS usage was proposed on the basis that “increased user satisfaction” will lead to a higher “intention to use,” which in turn will affect use. Therefore, the updated model of IS success conceptualizes IS usage as an attitude (intention to use) and a behavior (use).

SERVQUAL is an instrument from the marketing literature (Parasuraman, Zeithaml, & Berry, 1985) that can be used to measure the service quality of IT departments (Jiang, Klein, & Carr, 2002). For an organizational level analysis, several researchers have argued that the service quality construct could be more important than system and information quality. To resolve this issue, DeLone and McLean (2003) decided to include service quality as part of the success model because “the changes in the role of IS over the last decade argue for a separate variable” (DeLone & McLean, 2003, p. 18).

The original model included two levels of impact: the individual and the organizational level. During the decade since the publication of the original model, researchers had proposed the extension of the model to measure different impact levels. One example is Seddon’s (1997) model in which “society benefits” are included as part of the success model. DeLone and McLean’s (2003) updated model replaces the impact variables with net benefits. The “net benefits” construct accounts for benefits using a multilevel approach. Figure 3.5 shows DeLone and McLean’s updated model.
Finally, DeLone and McLean (2003) argued that their model is more complete and parsimonious when both process and variance considerations are combined in the model. In their opinion, Seddon’s (1997) changes and separation into sub-models only complicate the model, thereby diminishing its impact.

3.4.2 Acceptance of Information Systems

Users’ acceptance of IS has been a key element of various definition of IS success (e.g., Markus & Mao, 2004; Wixom & Todd, 2005). Davis’s (1989) technology acceptance model (TAM) is the most influential and commonly employed theory in IS (Lee, Kozar, & Larsen, 2003). Some consider TAM to be the only well-recognized theory in IS (Benbasat & Barki, 2007).

In TAM, user acceptance is determined by two constructs. First, Davis (1989, p. 320) argues that “people tend to use or not use an application to the extent they believe it will help them perform their job better.” In his model, Davis used perceived usefulness (PU) as a construct to represent a user’s belief. The second construct was perceived ease of use (PEU), which refers to “the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989, p. 320). Davis (1989) found PU and PEU were correlated with usage. PU had a significantly stronger link to use, however, and it also mediated the effect that PEU had on usage.
The dependent variable for Davis’s (1989) theory is a surrogate measure of attitude (intention to use) or behavior (level of usage). As mentioned before, IS usage has also been conceptualized as a measure of success, in particular, when the focus is on the implementation process (Larsen, 2003). Therefore, the underlying assumption is that increased use will lead to positive outcomes (DeLone & McLean, 1992; Goodhue, 2007; Goodhue & Thompson, 1995; Lucas, 1975). Unfortunately, some evidence shows that more usage of a system does not always lead to better performance and positive outcomes (Pentland, 1989).

Usage is a construct that has long taken the attention of the field. Barkin and Dickson’s (1977, p. 36) early study in MIS utilization recognized the relevance of the construct as “one of the ‘key’ variables associated with the success or desirability of the system.” Nonetheless, they also point out that “MIS professionals have not adequately defined this seemingly elusive variable” (Barkin & Dickson, 1977, p. 36). TAM’s intensive focus on the prediction and explanation of usage as a single measure of IS adoption, however, has led to researchers neglecting the study of other important behaviors (Benbasat & Barki, 2007) or larger contexts of IT phenomena (Goodhue, 2007). As a result, unfortunately, the theoretical assessment of the IS usage construct has received limited attention (Burton-Jones & Straub, 2006).

To overcome this deficit, Burton-Jones and Straub (2006) intensively studied the system usage construct. They reconceptualized the construct and identified various contexts in which dimensions of system usage will vary. They proposed that system usage is “an activity that involves three elements: (1) a user, i.e., the subject using the IS, (2) a system, i.e., the object being used, and (3) a task, i.e., a function being performed” (Burton-Jones & Straub, 2006, p. 231). Using these three elements, they suggested one could use lean or rich measures of the context in which system usage is studied. Rich measures incorporate the nature of the usage activity, whereas lean measures fail to measure the context in which an information system is used (Burton-Jones & Straub, 2006). Table 3.4 shows the spectrum from leaner to richer measures of system usage.
### Table 3.4 Richness of Usage Measures (Burton-Jones & Straub, 2006)

<table>
<thead>
<tr>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Presence of use</td>
<td>Extent of use (omnibus)</td>
<td>Extent to which the system is used</td>
<td>Extent to which the user employs the system</td>
<td>Extent to which the system is used to carry out the task</td>
<td>Extent to which the user employs the system to carry out the task</td>
</tr>
<tr>
<td>Domain of content measured *</td>
<td>Usage</td>
<td>Usage</td>
<td>Usage</td>
<td>Usage</td>
<td>Usage</td>
<td>Usage</td>
</tr>
<tr>
<td>Example</td>
<td>Use/nonuse</td>
<td>Duration; extent of use</td>
<td>Breadth of use (number of features)</td>
<td>Cognitive absorption</td>
<td>Variety of use (number of subtasks)</td>
<td>None to date (difficult to capture via a reflective construct)</td>
</tr>
</tbody>
</table>

* Lean measures reflect usage alone; rich measures reflect its nature, involving the system, user, and/or task.
Finally, another issue that affects system usage as an appropriate dependent variable of IS success is that use is often not voluntary (Guimaraes et al., 1992; Petter & McLean, 2009). It is clear that actual use, as a measure of IS success, only makes sense for voluntary or discretionary users (DeLone & McLean, 2003). Nonetheless, it is important to notice that the validity of the usage construct in systems success models will depend on the definition and context in which system usage has been conceptualized.

3.4.3 TASK-TECHNOLOGY FIT

The third stream in the IS success literature is the task-technology fit approach proposed by Goodhue and Thompson (1995). The model is consistent with DeLone and McLean’s (1992, 2003) models in that utilization is an important variable in the determination of IS success. Nonetheless, Goodhue and Thompson (1995) noticed that the direct application of TAM, which measures IS acceptance using system usage as a dependent variable, on IS success research is insufficient as means of measuring the impact of a particular technology on user performance. A high level of use of a system does not necessary provides positive outcomes (Goodhue, 2007; Goodhue & Thompson, 1995). In addition, TAM does not consider the nature of the task as part of the model. To resolve these concerns, the technology-to-performance chain model (TPC) combines theories focusing on utilization and task-technology fit. The rationale is that “for an information technology to have a positive impact on individual performance, the technology must be utilized, and the technology must be a good fit with the tasks it supports” (Goodhue & Thompson, 1995, p. 213).

Task-technology fit (TTF) is the degree to which a technology assists individuals in performing their portfolio of tasks. This outcome is achieved when the technology is suitable for the targeted application and users are competent to use it. Although Goodhue and Thompson (1995) argued that a fit between technology and task must be established before use of a system can lead to individual performance impact, they also found that both utilization and TTF predicted performance impact. Figure 3.6 shows the resultant model.
The contribution of the Goodhue & Thompson's (1995) TPC model is that it provides the necessary context in which richer theories can be framed. In accordance with Burton-Jones and Straub's (2006) reconceptualization of richer system usage measures, the TPC model combines users, technologies, and tasks. It also proposes an interaction between the three elements through task-technology fit. Finally, the TPC model recognizes the importance of the utilization research stream, incorporating the elements of theories of attitudes and behavior.

3.5 A REPRESENTATIONAL PERSPECTIVE OF INFORMATION

As discussed earlier in this chapter, BI systems facilitate the delivery and analysis of information and the extraction of value from it. In this light, it is important to determine the perspective about the term *information* that this present study will be based on.

Most literature in information systems treats information “as a ubiquitous label whose meaning is almost never specified” (McKinney & Yoos, 2010, p. 329). Often, the terms data, information, and knowledge are used interchangeably in the literature (Boisot & Canals, 2004; Spiegler, 2003). In practice, managers intuitively differentiate data from information: they define
the latter as data that has been processed in some way (Wang, 1998). The area of knowledge management has also attempted to differentiate information from knowledge, suggesting that knowledge is information processed in the mind of individuals (Alavi & Leidner, 1999, 2001).

The literature of information use and outcomes has treated information in different ways. McKinney and Yoos’s (2010) taxonomy of information views is a normative classification scheme that attempts to provide a coherent theoretical foundation around the concept of information. The taxonomy provides four information views: token, syntax, representation, and adaptation. The token view is similar to what is understood as data where no meaning is given. McKinney and Yoos (2010, p. 331) describe the token view as “both inputs and outputs of the processes, in minds, machines, or organizations.” The syntax view allows the measurement of the relationship between tokens. In this view two tokens, can be compared by their equivalence. For instance, in the syntax view, “day of birth” of two different customers can be compared or distinguished.

The representation view, which is the selected view used in the research that underpins this thesis, is a “model to something to someone” (McKinney & Yoos, 2010, p. 334). With this view, an observer, an object, and a status or change of status (sign) is required. The observer must interpret the information and give a meaning based on prior knowledge. Representations aim to simplify reality. Better representations are the ones that more closely inform observers about reality. The following section describes representation theory, which accounts for the nature of use of information systems.

### 3.5.1 Representation Theory

Because all the definitions of BI listed in the previous section recognize an IT artefact as a central component of the BI environment, this research assumes that the IT artefact is what in practice organizations identify as the BI system. In this light, one theory that is useful because it intends to define the unique nature of IS is Wand and Weber’s (1988, 1995) representation theory. The theory
provides assumptions about the nature and purpose of any IS. Thus, an adaptation of this model for BI systems' use and outcomes is proposed at the end of this section.

Representation theory is considered one of the native theories in the IS discipline (Burton-Jones, Recker, Indulska, Green, & Weber, 2017). While representation theory was initially mainly used in conceptual modelling research, it has been later use in diverse areas of IS research such as data quality (Wang & Strong, 1996) and effective system use (Burton-Jones & Grange, 2013). Nevertheless, the theory has not yet used in DSS and BI research. This research employs representation theory to articulate a conceptual framework that will guide the empirical phases of this project.

3.5.1.1 Representation Theory Foundations

Weber (1997) argues that information systems exist as a consequence of the human condition of always seeking to find better and richer ways to understand and represent the world. A functional (task-oriented) perspective of the purpose and use of a particular IS can be conceptualized using the task that the IS is intended to support (Goodhue & Thompson, 1995). For example, an inventory system will be used effectively if it allows its users to manage products. Representation theory argues that the basic function of all information systems is to provide a representation of some real-world phenomena. In this manner, users can obtain a representation of the state of a thing through the IS. This is particularly valuable when the states of the thing we want to know about are not easily observable in a direct manner. For instance, share prices in the stock market can fluctuate at a speed that would make them difficult to track through direct observation. In consequence, according to representation theory, the purpose of any IS is to provide a faithful representation of the real world.
3.5.2 Representation Theory Components

According to representation theory, information systems consist of three structures. The following paragraphs describe the three structures and use a BI system as an example. Figure 3.7 illustrates the components of the theory.

**Deep structure:** The deep structure is the essence of the IS. This structure is where the real-world system is represented. For instance, a BI system user will be interested in knowing the state of the sales of a particular set of products for a particular period of time.

**Surface structure:** The surface structure contains the facilities that are presented to users to allow them to interact with and obtain representations from the IS. The format of the screen, the icons that are displayed, and the buttons that invoke actions are part of this structure. For instance, often the layout of a BI system screen displays hyperlinks that allow users to drill down to the information they need. This allows users to move through hierarchies to obtain a more detailed representation of some underlying real-world phenomena.
**Physical structure:** The physical structure refers to the underlying hardware/software technology that is used to operate the IS. This structure consists of inputs devices such as a keyboard and mouse, output devices such as monitors and projectors, and networks and circuits. BI systems need servers in which the data marts are stored, networks in which the information is transmitted, and laptops and desktops that end-users can employ.

### 3.6 The Conceptual Framework of This Project

Based on the definitions of BI systems, the extended review of the BI use and outcomes literature, and the exploration of current IS theories, a conceptual framework was developed to provide a foundation for subsequent empirical phases.

Initially, the thesis explored the multidimensionality of the IS outcomes construct in the context of BI system usage. The aim was to understand the nature of BI systems use and develop models that explain and predict BI systems outcomes. The conceptual framework employed in this thesis is the conceptualization of system usage proposed by Burton-Jones and Straub (2006). Burton-Jones and Straub suggest that the first step for research about system usage is to “select the elements of usage that are most relevant for the research model and context” (Burton-Jones & Straub, 2006, p. 232). They also suggest that a very rich measure of system usage must cover the three elements of usage: a user, a system, and a task.

Among the IS success models that were evaluated in the literature review, Goodhue and Thompson’s TPC (1995) model appears to be the most suitable for the initial development of a model for BI system use and outcomes. Table 3.5 shows how Burton-Jones & Straub’s (2006) system usage elements link to Goodhue and Thompson’s TPC model. The third column of the table also shows how this research adapts and defines the elements of system usage.
As indicated earlier in this chapter, Goodhue and Thompson’s (1995) central idea in their model was task-technology fit (TTF). Drawing on representation theory (Weber, 1997), this thesis argues that when a high degree of correspondence between task requirements, individual abilities, and the functionality of the technology is present in the use of a BI system, a faithful representation of the decision task is provided by the BI system. Finally, the outcomes of a BI system that is capable and is being used effectively for the creation of faithful representations of the decision task will be of high value for the users and potentially their organizations.

Representation theory can be useful in the development of the models that this research aims to build. The tasks that BI systems are intended to support are information-oriented. This means that users will access the BI system to obtain a representation of particular real-world
phenomena (domains). The set of activities that a user of a BI system needs to perform to obtain a representation of the phenomena of interest is what this research conceptualizes as “system use.” In this light, BI system use incorporates both “information production” and “information consumption” (Eckerson, 2006). As discussed in Chapter 1, usage rates indicate and industry commentators state that BI systems are not used to their full potential. Hence, the models developed during the empirical phases of the current study would need to describe the necessary conditions for obtaining valuable and positive outcomes from using BI systems. Figure 3.8 provides a diagram of the conceptual framework for the first phase of this research project.

![Conceptual Framework - BI Systems Use and Outcomes](image)

### 3.6.1 The System Dimension

The literature shows a variety of BI implementation scales and scopes. Watson (2009) specifies that BI initiatives can vary from a focus on a single or a few applications to an enterprise-wide development. It can also be the case that the current BI applications within an organization do not have all the full range of functionalities that the vendor’s solution offers. Organizations also can
have competing BI systems with different functionalities or dedicated to different information
domains.

This research will focus on BI systems at the divisional or functional level and at the
enterprise level. The idea is to assess the outcomes of a particular BI system that has been used for
a significant period of time and that has a cohort of users that perform different tasks with the help
of the system.

### 3.6.2 The Task Dimension

Singh et al. (2002) found that IT-based support systems provide support for all phases of the
strategic management process (formulation, planning, and control). Although BI systems are often
aimed at individual users, Clark et al. (2007) explain that the scope of their decisions can be
departmental or enterprise wide. This argument is consistent with the influential framework
developed by Anthony (1964) in which planning and control systems are classified as different
“species.” According to Anthony (1964, p. 156), "Planning and control systems, although related
to one another, … have different purposes and different characteristics; different ways of thinking
about each of them are therefore required.” Accordingly, the task dimension for this research will
be first divided in three levels: (1) operational, (2) tactical, and (3) strategic. The levels vary in
impact, purpose, and complexity.

### 3.7 Conclusion

The objective for this chapter was to review the literature to build a conceptual framework that
will be used in the subsequent empirical phases of this research project. First, BI systems definitions
and components such as managers as end-users of these systems were reviewed to define the unit
of analysis. Second, the chapter reviewed the literature and theories about IS use and outcomes.
Task-technology fit, representation theory, and Burton-Jones and Straub’s conceptualization of IS
use and outcomes seemed to be appropriate for the objective of this study, i.e., to understand the nature of BI system use and outcomes. Finally, a conceptual framework was described that will be used in the first empirical phase of this research: an exploratory case study.

The next chapter will describe the exploratory case study in detail.
CHAPTER 4: INITIAL EXPLORATORY CASE STUDY

Chapter Overview

This chapter presents the first empirical phase of this research: an exploratory case study. Using the conceptual framework described in Chapter 3, this case study explores how individuals use BI systems and the outcomes obtained by their use in a large government organization.
4.1 INTRODUCTION

This chapter presents the first empirical phase of the thesis, which was an in-depth exploratory case study (Benbasat et al., 1987; McCutcheon & Meredith, 1993; Yin, 2018). Exploratory case studies are used when little is known about the phenomena under study (Eisenhardt, 1989). Therefore, they are suitable in the early stages of theory building (Benbasat et al., 1987; Yin, 2018). This approach was selected because, as explained in the previous chapters of this thesis, little established theory exists about the nature of business intelligence systems use and outcomes.

One extreme position in exploratory case studies is to generate theory only from the data collected (Glaser & Strauss, 1967; Strauss, 1987). However, the current study draws on previous IS theories—namely, representation theory, task-technology fit theory, and the richer conceptualizations of system usage. The selection of appropriate IS theories to be included in conceptual framework conceptualization was supported by an analysis of BI use in the industry literature (Chapter 1), an extensive review of the academic IS literature (Chapter 3), and a review of the documentation available in the organization where this case study was conducted. In this sense, the case study was conducted in a highly iterative manner, where the emergent conceptual frame and data were compared systematically on an ongoing basis (Eisenhardt, 1989).

4.2 LGA CASE BACKGROUND

Large Government Authority (LGA) is a semi-autonomous Australian federal government authority headquartered in Melbourne. It has branches around the state of Victoria and several locations overseas. LGA has 11,500 staff to support two central business activities (or portfolios): “core services” and “research and development.” The operational revenue of LGA is currently A$1.5 billion.
The senior management structure of LGA is comparable to the structure of other large organizations in Australia. It comprises six C-level executives or vice-presidents reporting to the CEO. At the next management level, 11 executive vice-presidents have specific functional responsibilities. LGA has a divisional organization structure. The top divisional executives of the 10 divisions of LGA are responsible for the efficient and effective delivery of their specific services. The divisional structure is controlled and supported by the central corporate level ensuring coordination and collaboration across the divisions.

Although LGA is an organization owned by the Australian government, it operates in a competitive market. LGA is part of a group of similar large government authorities that have to compete with each other for private and public funding. The Australian government has increased the mechanism for competition through a performance-based funding system that requires periodic submission of performance reports to the central government funding and controlling body. According to LGA’s managers, the current competitive scenario has created a high demand for information across the different units of the organization. The implementation of a BI system was seen as a tool that would contribute to the improvement of LGA’s performance, thereby helping to ensure it remained successful in the market.

4.3 LGA’s BUSINESS INTELLIGENCE SYSTEM PROJECT

LGA’s BI system project is ongoing. It had its inception in an LGA information management strategy meeting that took place during the last quarter of 2005. The outcome of this meeting was a recommendation for implementing a BI strategy by 2006. LGA initiated its BI strategy a year later during the third quarter of 2006. This plan emphasized strong governance structures to overcome data quality and data ownership issues.

As a way to ensure collaboration and senior management commitment to the project, during the second quarter of 2007 LGA created a BI steering committee that included the executive
owners of each information area as data stewards, C-level executives as sponsors, and key members of LGA as consultants. The BI steering committee appointed a project manager to lead a team of business analysts and system developers. It was also decided to deliver the BI solution in phases through a series of information releases aligned to portfolio areas.

The first stage of the project was the development of a solution for the research and development portfolio, which was one of the LGA’s two central business activities. After a year of development work, however, the BI team was still not able to deliver any usable outcome to users. As a result, the steering committee decided to replace the original project manager and appointed a new project manager who was the incumbent at the time of this study.

The new project manager had been the team leader of the BI team since the commencement of the project and had a good understanding of the state of the project. Under this new leadership and with the endorsement of the steering committee, the BI team was able to deliver the first BI solution in less than a month. The research and development portfolio project was then completed and improved during 2009.

Figure 4.1 presents a timeline of the LGA business intelligence project. The timeline not only shows the milestones toward the delivery of the first portfolio project but also the subsequent project releases that the BI team had delivered at the time of this study.
Figure 4.1 LGA’s Business Intelligence Project Timeline.
By the middle of 2009, the BI team had been able to deliver a functional solution for the research and development portfolio. The solution continued to be refined and extended, and more users were trained and given access to the system. Because positive results were achieved with the first project, the BI steering committee decided to initiate the second phase of development. This phase aimed to deliver a solution for the “core services” portfolio.

The lessons learned in the development and implementation of the first solution influenced the development approach used for the second solution. For instance, to engage users from the start, a group of potential users was continually consulted during the development. In addition, a decision was taken to deliver the portfolio incrementally. Finally, the system to support the core services portfolio was delivered in three releases in 2010 and 2011.

This case study was undertaken in 2012, which is the year in which the LGA BI project changed from the status of “project” to “ongoing internal organizational service.” The BI team was, at the time, working on a new interface software platform to replace the existing presentation layer platform. This case study was conducted based on the experiences of LGA BI users with the existing BI system presentation layer platform that accesses the main two portfolios of “core services” and “research and development.”

4.3.1 LGA’S CURRENT BI SOLUTION

Before the implementation of the BI strategy, several units had delivered solutions for cross-system reporting. These received enthusiastic support among users. Nonetheless, the efforts were not considered efficient, because they used not one but many technologies. The BI project was conceived as a means to overcome multiple views of data through a centralized approach to the development of a corporate data warehouse. The centralized source of data for reporting and analysis was viewed as a solution for the dissonant definitions of data and the discrepancies
between the different reporting systems available. The data warehouse was also to be used in subsequent BI applications and projects.

While the data warehouse was physically one central database on an Oracle server, the general architecture included an additional layer so that substructures of data known as data marts could be created. The data marts had the function of delivering data to the reporting tools that users could employ. Each data mart represented a defined scope of one of LGA’s business activities. It offered a set of measures and hierarchical structures that supported users preparing flexible reports.

The two portfolios systems described in the previous section, “research and development” and “core services,” were developed using the data architecture approach described above. The development of the data warehouse took most of the available resources and time of the BI team. To provide users with access to the portfolio systems, LGA needed a reporting tool. LGA decided to postpone the purchase of the presentation layer software. Instead, it opted to use licensed-software that was available in the organization as the BI presentation layer (Oracle Business Intelligence Discoverer). The use of the Oracle reporting tool allowed the BI team to deliver the systems needed to support the portfolios and to collect valuable feedback from users.

At the time of this study, LGA had acquired what will be the next BI presentation layer—namely, SAP Business Objects. All users interviewed in this study were using the current Oracle presentation solution. Only three users interviewed reported having seen demonstrations of the new BI presentation software.

### 4.3.2 Characteristics of the Current BI System

The BI presentation software used at the time of the case study was a web-enabled application that ran on a server physically located in the central IT datacenter of LGA. The software had a central menu that allowed users to select the portfolio of interest. The menu redirected users to a preloaded
report that offered a summarized view of the portfolio at the highest hierarchical level. The main functions available in the software were the options of slicing and dicing the report. Thus, users were able to drill down to lower hierarchies of interest. Users could also select some elements of interest under the hierarchies. For instance, users from one of LGA’s division could select specific activities that were relevant to that division. All users had to go through a training session where the functionalities of the tools were explained in detail. The project manager was personally involved in the training sessions, using them as a mechanism for obtaining valuable feedback about the data and the requirements for the future BI presentation software.

4.4 **CASE STUDY DATA COLLECTION**

The contact and liaison person for this study was the project manager of LGA’s BI system. A personal contact of the researcher, who was involved in the BI steering committee, approached the project manager to seek assistance with the research project. The researcher maintained contact with the project manager via email and face-to-face meetings. One of the LGA’s top executives, who had oversight responsibility for the BI project, gave approval to conduct the study. The project manager provided printed documentation on the project plan and progress reports. He also provided the researcher with a list of current users and their email addresses.

The case study received its ethics approval by the end of March 2012 (Appendix 1). Data were collected during the third quarter of 2012. By this time, the system to support both the “core services” and “research and development” portfolios had been used for more than a year and a half. Thus, users of the systems would have had time to form views about their usefulness.

Before entering the field and contacting potential participants, the researcher attended one of the training sessions that users who wanted to obtain access to the BI system had to attend. At the same time, the technical documents and progress reports provided by the project manager were analyzed. These documents provided the context and background story of the BI project. For
instance, the timeline presented in Figure 4.1 was developed from that analysis and informal correspondence with the project manager.

The second source of data for the case came from semi-structured interviews with LGA BI users. The selection criterion for LGA employees to be interviewed was whether they had accessed the BI system to perform a task. The project manager prepared a list of 42 users based on the criterion. Two potential participants were excluded from the list because they were based overseas. To facilitate the scheduling of the interviews, an invitation initially was sent to half of the 40 users on the list and, after three days, an invitation was sent to the other half. The invitation contained a formal exploratory statement of the research (Appendix 2), and the researcher’s email address and contact number.

Twenty-five users agreed to take part in the study. The interviews were conducted in all four branches of LGA in Melbourne, between April and July 2012. While an interview protocol was prepared and sent in advance to participants (see Appendix 4), new questions were introduced during the interviews with the aim of clarifying some of the participants’ answers. When participants agreed, interviews were audio-recorded and then transcribed. Only two participants did not agree to their interviews being audio-recorded. In these two cases, note taking was the main data collection approach. As best the researcher can tell, audio-recordings were not disruptive and participants freely answered the questions.

At the beginning of each interview, the researcher asked the interviewee to read and sign a consent form (Appendix 3). The researcher also explained to the interviewee that no information that could lead to the identification of any individual would be disclosed in any reports of the project or to any other party. Interviews lasted between 45 and 70 minutes. No interview was finished without completing the full interview protocol. Among those interviewed were LGA’s top divisional executives, senior analysts, middle managers, and business analysts (see Table 4.1).
## Table 4.1 LGA BI Users Position/Role and Tenure

<table>
<thead>
<tr>
<th>Position Level</th>
<th>Method of Use</th>
<th>Involvement in Decision Making</th>
<th>Code - Position/Role</th>
<th>Tenure (*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Divisional Executive [TopExe]</td>
<td>(Yes) As Decision Maker (Yes) As Decision Maker</td>
<td>High</td>
<td>TopExe-10 Division “Alpha” – General Manager</td>
<td>23 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>TopExe-18 Division “Iota” – General Manager</td>
<td>18.5 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>TopExe-22 Division “Epsilon” Director Core Services Portfolio</td>
<td>7 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>TopExe-23 Division “Kappa” Director Core Services Portfolio</td>
<td>13 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>TopExe-25 Division “Beta” Director Core Services Portfolio</td>
<td>22 years</td>
</tr>
<tr>
<td>Senior Analyst [SenAna]</td>
<td>(Yes) (No) As Intermediary</td>
<td>Medium - High</td>
<td>SenAna-02 Research Strategy Advisor</td>
<td>1 year</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>SenAna-06 Division “Zeta” - Research Information Systems Manager</td>
<td>6 years</td>
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<td></td>
<td></td>
<td></td>
<td>SenAna-20 Research Coordinator</td>
<td>2 years</td>
</tr>
<tr>
<td>Middle Manager [MidMan]</td>
<td>(Yes) As Intermediary (Yes) As Decision Maker</td>
<td>Low - Medium - High</td>
<td>MidMan-01 Division “Alpha” – Operations Manager</td>
<td>not reported</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>MidMan-04 Division “Delta” – Customer Manager</td>
<td>10 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>MidMan-07 Division “Delta” – Services Manager</td>
<td>3.5 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>MidMan-08 Division “Gamma” – Operations Manager</td>
<td>not reported</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>MidMan-11 Division “Eta” – Services Coordinator</td>
<td>6 years</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td>MidMan-13 Division “Theta” – Quality Manager</td>
<td>6.5 years</td>
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<td></td>
<td></td>
<td></td>
<td>MidMan-15 Project Officer</td>
<td>8 years</td>
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<td></td>
<td>MidMan-16 Division “Theta” – Unit Manager</td>
<td>18 years</td>
</tr>
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<td>MidMan-17 Division “Alpha” – Services Manager</td>
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<td></td>
<td>MidMan-19 Division “Theta” - Administrative Officer</td>
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<td></td>
<td></td>
<td></td>
<td>MidMan-24 Division “Beta” – Quality Manager</td>
<td>19 years</td>
</tr>
<tr>
<td>Business Analyst [BusAna]</td>
<td>(Yes) (No) As Intermediary</td>
<td>Low - Medium</td>
<td>BusAna-03 Division “Theta” - Project Manager</td>
<td>2.5 years</td>
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<td></td>
<td></td>
<td></td>
<td>BusAna-05 Division “Epsilon” Research and Operations Manager</td>
<td>8 years</td>
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<td></td>
<td>BusAna-09 Division “Beta” Assistant Research Manager</td>
<td>8 years</td>
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<td></td>
<td></td>
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<td>16 years</td>
</tr>
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<td></td>
<td></td>
<td>BusAna-14 Business Analyst</td>
<td>2.5 years</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>BusAna-21 Business Analysts</td>
<td>9 years</td>
</tr>
</tbody>
</table>

*Tenure: the length of time the participant had been in the exploratory case study’s organization.
The researcher kept a case study notebook that was used at the end of each day of interviews to make notes on emerging concepts and ideas. The researcher undertook the transcription of the recordings (see below), which was a second opportunity for the researcher to reflect on the data and the refinement of a set of codes that were used later in the analysis. The transcripts were emailed to all participants for their approval. Only three participants sent notes back with clarification of ideas expressed during the interviews.

The analysis of the data was conducted in three phases. The first phase was essential in producing a general understanding of the data collected. The researcher personally transcribed the recordings using specialized software that allowed synchronizing transcript and audio. The transcribed files were imported to software for qualitative analysis (QSR International NVivo). They were classified according to the organizational position of the interviewee and the role they performed in the use of the BI system. The classification was fundamental in the identification of various approaches in the use of the LGA BI system.

The second phase involved the coding of emerging concepts about the (a) obtained and desired outcomes of using BI in LGA, and (b) characteristics of the BI system that its users required for effective use. Initially, the researcher read the transcripts for a second time to familiarize himself with the whole data set. During the second reading of the transcripts, a decision was made about deciding which portion of texts were to be coded. Once finished with the coding, data was reorganized in tables and diagrams for condensation and analysis.

The third phase of the analysis was to produce a narrative for the case, which is presented in the following section.
4.5 **The Case Study Analysis**

This section presents the results of the analysis of the interviews with the LGA’s BI users. As the conceptual framework described in Chapter 3 illustrates, the analysis was structured around the elements of system use (users, system, and tasks) and outcomes. Therefore, this section will discuss LGA’s BI users, the tasks that they perform using the BI system, and the outcomes obtained. This is followed by an analysis of the characteristics of the elements of system use that affect the outcomes obtained by using LGA’s BI system.

4.5.1 **BI Users**

Early in the process of interviewing the 25 participants, the researcher observed significant differences in the way they described the tasks supported by the system. The initial protocol was designed to cover the decision-making dimension as a main goal to be achieved by using the system based on the existing BI system’s definitions (described in Chapter 3). While a number of BI users described their purpose in using the BI systems as supporting their decisions, other BI users claimed that the main purpose of their using the BI system was to deliver reports to a different individual in the organization.

*I don’t [participate] directly in the decision-making. Any data analysis that I do would go to my reporting supervisors… I just have to generate the data. I mean, I could interpret it, but I wouldn’t be responsible for making decisions on it.* (Bus.Anal-12)

*I have the sensation that I provide the scope… I mean I would make recommendations… but I don’t make decisions of where the direction of the [division] should go… I’m an advisor or a consultant.* (Bus.Anal-03)

The delegation of the use of the BI system was a common practice in LGA. Instead of accessing the BI system directly, several decision makers in LGA relied on subordinates to build
representations to support their decision tasks. This means that it was not possible to simply conceptualize BI users as a homogeneous group.

Two different methods of use were then clearly distinguished in the LGA case. The first method – the direct – occurred when decision makers accessed the BI system themselves to obtain a representation for the decision task they needed to undertake. The second method – the indirect – occurred when a decision maker had delegated the use of the system to an intermediary. In this case, the decision maker and the intermediary discussed a set of requirements to be considered for the production of a representation of the decision task, and in turn, support for the decision maker’s actions. Nonetheless, the role of intermediaries varied in the degree of involvement they had in the decision-making process they were supporting:

I advise the [manager]. Ultimately, he is the [manager], so those decisions rest with him.

But obviously a lot of what I say has a lot of weight. (MidMan-17)

The [manager] would ultimately make the decision… but I was there to explain the data and to filter it and sort it… and show what was more meaningful in the data, I guess. (MidMan-07)

At one extreme, an intermediary can just receive an instruction to retrieve a set of numbers from the BI system. In this situation, the intermediary acts as the interface for very basic queries that are answered directly by querying the BI system.

For example, sometimes our director… sometimes a request from Marketing… They ask me for numbers, how many [customers have we had] in the last past 5 years for [service X]… that’s when I go into BI and just quickly do a report. (MidMan-04)

At the opposite extreme, a capable individual will be needed to take a more complex intermediary role. In this role, the intermediary is required to understand the decision task and to use the BI system effectively to create a valid representation of the decision task to support the
decision maker. In several cases, chauffeurs would actively participate in the decision-making process and recommend a course of action for the decision maker to take (see section 5.3.1 for a discussion of chauffeurs). They also would be responsible for managing the agenda of the department or division. Decision makers not only delegated the production of responses of their queries but also expected that the intermediary would alert them to business activities that needed attention.

The discussion happens within the key three or four people within this office… I am the only person in this office who works with data. So, I would be the one responsible for raising the issues, and bringing this to the awareness, and suggesting we do something about it. Other times, I might be asked for a specific ad hoc task. (BusAna-14)

The predominance of the indirect method of using the BI system in LGA varied across interviewees’ different organizational positions. Interviewees were asked to describe their positions and role in the organization, not in terms of their use of the BI system but in terms of their everyday activities and responsibilities. The analysis of the interviewees’ responses allowed the researcher to classify the position held by the interviewees into four different groups. The classification distinguishes the interviewees by their role and hierarchical level in the organization.

The first two groups consisted of middle managers and top divisional executives. The second two groups were business analysts at the divisional level and senior business analysts at the corporate level. Table 4.1 presents the four organizational positions with the system usage methods and roles in decision-making.

4.5.1.1 Group 1: Top Divisional Executives

Top divisional executives in LGA were responsible for the services their divisions offered. For that reason, they had to deal with the decisions that had a direct relation with the division and services for which they were responsible. At the more strategic level, top divisional executives were
constantly requested by the LGA’s central corporate level to provide explanations and courses of action about the performance of their business activities. At the same time, this group of users also declared they were responsible for operational decisions about the service they were responsible. In both cases, top divisional executives explained they would use the BI system directly only if the perceived complexity of the task was not high. Where the perceived complexity of the task was high (based on the required number of queries and manipulation of the reports’ layout), they delegated the required report production to a subordinate who knew how to use the system and had business knowledge of the domain.

In a lot of situations, I could probably do all of this, well, most certainly could do all of this with BI and pivot tables. But if things become too complex, I need complex reports, I’m not doing them myself, I call someone to produce the report. (TopExe-23)

For top divisional executives, strategic decisions about the services provided by their divisions generally required a larger set of reports and queries than some of the operational decisions. For instance, if a division was going through a review of one of its services, it was necessary to obtain data from different sources in an iterative manner to obtain a sufficient understanding of issues that related to the provision of the service and actions that might be undertaken to improve the service. In such cases, the executive would most likely hand over the task to a subordinate.

If I require a lengthy report, so I require a report over the last five years history in all our [services]... I can write all of this down as a specification. It takes days to produce those reports. I’m not going to do that. So, I’ll ask someone here to do it. And these people will go away and do it with whatever system they are most familiar with. (TopExe-23)

Despite the trend of delegation of the BI system for strategic decision tasks, operational decisions are not necessarily supported by direct use of the BI system by top divisional executives. In any situation where executives perceive difficulties in the extraction of the representation of the
decision task required, they delegate the task to a subordinate. The exception is when executives believe the cost of delegation is higher than the cost of undertaking the task themselves. This situation could arise when time pressure exists to get a quick answer to a problem.

...because of the nature of my work, I more likely to ask someone else to do it... to come up with a report that doing it myself, but I could do it... I do know how to run a report using BI... and probably in a sense I'm more efficient that our data person here in the [division] because is my personal interest and sometimes I just want to get things done and I go and do it.... Yes... I am a very, very efficient user. (TopExe-22)

4.5.1.2 Groups 2 and 4: Senior Analysts and Business Analysts

The scope and size of the LGA divisions were diverse. The size of a division reflected the number and complexity of the services it provided. Larger divisions had more personnel at all levels and a more complex structure. In smaller divisions, middle managers sometimes had dual functions as managers and analysts. Larger divisions, however, were able to hire skilled individuals to take the role of business analysts. These analysts focused mainly on the analysis of data and the production of reports. In a similar manner, the corporate level of LGA had appointed experienced and skilled senior analysts who had a more advisory role to the LGA’s top-level executives. In both cases, the predominant method of use was indirect. In other words, the analysts were not making decisions for LGA, rather they were interpreting the information requirements of the decision makers they supported. They then made use of the BI system to obtain reports to facilitate the decision-making process of the executive they supported.

The senior analysts interviewed in this case showed a high level of understanding of the supported decisions and their outcomes. While business analysts in the divisions supported multiple users for a large spectrum of BI tasks, senior analysts worked on a one-to-one basis with the top executives of LGA.
Although senior analysts spent most of their time analyzing data and producing reports, they did not use the BI system to the extent they could have. Senior analysts declared that the BI system could not completely and directly support their tasks because they required a different structure of the data. The three senior analysts interviewed in the case declared that they had to execute manual processing of the data from differences sources to obtain the required report. While the BI team had attempted to deliver the report directly from the BI system, the senior analysts had already started the design and implementation of alternative BI applications that were oriented to the representation they required for the decision tasks supported.

To do their job, business analysts strongly relied on the BI systems. They spent more time using the BI system than the other groups of users. They often declared that the BI system provided too much information. An issue they faced was to know and select the right measures from a large set of options available in the system. They complained that little indication was given by the interface about the meaning of the measures. As a result, they had to guess about the meaning of the measures or seek assistance from the BI team.

How often I use it? It is actually project dependent, depending of the tasks that I have been assigned to. It's probably about 2-3 times a week. No more than 3, and no less than 2.

(BusAna-03)

Every week, every couple of days. I would say I'm very... I'm quite familiar with it… Sometimes I find it actually provides me with too much information. Like it’s kind of too clever. Like sometimes if you only want to know five categories but it spits out ten. I find I have to sort of cut a lot of information. (BusAna-17)

4.5.1.3 Group 3: Middle Managers

Middle managers were an important part of the LGA’s day-to-day operations. They were responsible for managing activities that supported the performance of their division. As a result,
they had their own decision tasks that required information from the BI system. They also used the BI system to monitor and control their business activities.

Middle managers used the BI system directly. Nonetheless, they also needed to report to their superiors about the performance of the services they managed. In this light, they acted as intermediaries for other individuals in their division. Because of their expertise with the BI system and the general perception of their knowledge of the business activity domain, other managers in their division approached them to request data and reports related to their business domain. Thus, the indirect method of usage was also identifiable among middle managers.

In LGA, the top divisional executive in charge of the particular area of interest was the person who would sign off the decision. Nevertheless, middle managers were responsible for the whole decision-making process for the day-to-day operations. When making a decision, middle managers would require approval and probably would discuss and negotiate the funding of their decision. Moreover, middle managers also had responsibility for implementing the decisions.

Middle managers’ level of independence in LGA was variable. It depended on their superior’s personality and the amount of resources involved. Often, middle managers performed most of the day-to-day operational decision-making process (providing significant resources were not involved). They also implemented decisions. Thus, a middle manager’s method of use was often direct.

If we are looking at significantly changing the way we do something, then the [top divisional executive] has to have the final sign… If we do it or we don’t do it. So, it depends on whether there are as well financial implications for the [division], in which case definitely has to be signed off because of its budget impact. (MidMan-08)

Because middle managers were directly using the BI system to support some of their managerial activities, they had a substantial understanding of the BI system interface and the
underlying data structure and definitions. As mentioned in the background of the LGA case, it was compulsory for any employee in LGA who wanted to obtain access to the BI system to attend a training session. Therefore, it was convenient for other managers to request data and reports from the middle manager rather than learn how to use the BI system themselves. The information requests generally required simple queries in the BI system and the selection of the right delivery format of the report. In addition to the convenience of accessing the BI system indirectly, the division managers could rely on the middle manager’s expertise for providing reports and data that had gone through a validation process that only someone with specific domain knowledge could understand.

*I think there is a mentality that anything with [clients] they just ask me… because a lot of them don’t have BI access… they just… it is a mental thing … it is a culture that was established before I started. My predecessor, she was always helpful, she just was here and every day she could work about two to three hours extra, on top of the normal hours, to provide customer service. So… I suppose that there is the expectation that anything about [clients] they just call me or send an email and ask me.* (MidMan-04)

As discussed earlier, LGA divisions differed in scope and size. The simpler organizational structures of the small divisions required that middle managers acted also as business analysts and therefore as intermediaries of the top divisional executives. In several cases, middle managers were in charge of periodical reports that were distributed and discussed by the division’s top executives and managers. In this regard, the services provided by LGA had a cyclical nature where repeating activities and milestones took place every year. Middle managers who were responsible for the business areas that concerned some of the predefined activities that took place during the year had to release reports before, during, and after the activity. At the strategic level, periodic reports helped with the analysis of annual trends and performance of the division. LGA organized committees to review the reports and to plan actions aimed at improving the activity in the next period.
4.5.2 BI OUTCOMES

Once the BI users in LGA had described and reflected on how the BI system had been used to support their tasks, the researcher asked them about the outcomes that had been achieved using the BI system. Instead of providing the interviewees with a list of generic outcomes, they were given time to list and explain as many positive and negative outcomes as they wanted. An open-ended questioning approach was employed to avoid restricting the answers to a pre-defined structure of BI outcomes. The open-ended approach was combined with psychometric scales aimed at classifying BI outcomes at different levels of effectiveness and relevance for the user.

4.5.2.1 LGA BI System – Outcomes Level

Overall, interviewees pointed out that the BI system in LGA had produced effective outcomes. More than two-thirds of the LGA employees who participated in this study indicated that the outcomes were somewhere in the range of “generally effective” to “very effective.” BI users also considered that BI system was an indispensable tool to support the management of LGA. At the same time, they had high expectations of future improvements in the quality of the BI system data and the functionalities of the BI system interface. LGA users indicated that more and better outcomes could be achieved by improving the BI system.

For the most part, LGA managers were in charge of only one of the LGA’s business activities. As a result, users such as top divisional executives, middle managers, and business analysts used only one of the system’s portfolios. The only exceptions were the executives with a finance role and the three senior analysts interviewed. In particular, the senior analysts were the group of users who classified the outcomes at a significantly lower level than the rest of the users. The BI system did not always provide the analysts with complete representations for the task they attempted to support. As a consequence, they had to access other sources of information to build usable reports.
Overall, LGA’s BI users expressed positive attitudes toward the BI system and the BI development team. In particular, users tended not to criticize the BI system directly. Instead, when the BI representations presented problems, BI users viewed the source systems in which the data was originally collected as the cause of the problems. The processes of integration and transformation of the source systems’ deep structures into the BI system’s deep structure went unnoticed by the users. In this sense, BI users were unaware of the data structures created directly in the BI system. For the BI users, all the data came from the transactional systems.

That is only because people are doing the wrong thing and not putting the information into the system in the first place. So that is not BI’s fault... So, where it is not right [BI] highlights in it a problem or somewhere else, which is really good... If it is getting the wrong answer is not because of BI, it is because of dirty data somewhere, or lack of data somewhere.

I think BI is so reliable and if it is not there is for a very good reason. (TopExe-10)

4.5.2.2 Defining the Outcomes of LGA’s BI System

At this point, it is important to note that LGA had gone through a significant transformation in the way in which its managers had access to relevant information for supporting their decisions. Only four of the 25 users who were interviewed had arrived at LGA before the release of the portfolio they were using. Employees who had been working for a long period at LGA remembered the difficulties they had experienced in gathering and validating information in the past.

Well there is no doubt that there has made far easier to produce statistical reports on historical performance. It wasn’t long ago that [LGA] simply relied on a little booklet on very basic statistical data, so in the time that I have been at [LGA], just 7 years, we have gone from the book to something like what we are seeing today, which is a huge change, we can’t complain too much... (BusAna-05)
The analysis of the responses given by the users interviewed in the case resulted in three hierarchical outcomes from using the BI system: (1) better information accessibility, (2) informed managers, and (3) informed decisions. In addition, two secondary outcomes were indicated as a result of using the BI system in LGA: (1) improvement of the organization’s information quality, and (2) facilitation of individuals’ learning about the business and organizational domain.

Figure 4.2 shows a hierarchy comprised of three conceptualizations of BI outcomes. Each level in the hierarchy establishes a necessary condition for the next level. In the case of a direct use of a BI system, a user must be able to access the representation (1st level) to obtain a faithful representation (2nd level), and they must be able to obtain that faithful representation to support and make an informed decision (3rd level). In the alternative case of indirect use of a BI system, an intermediary must be able to access the representation (1st level) to deliver a faithful representation to the manager (2nd level), and the manager must be able to obtain the representation delivered by the intermediary to support and make an informed decision (3rd level).
It is important to note that the achievement of a lower-level outcome does not guarantee the achievement of higher-level outcomes. For instance, a decision maker who is able to obtain a faithful representation from the BI system would not necessarily make decisions based on the representation. This would be the case if the decision maker chose to ignore the representation or misinterpret the representation. In either case, the outcomes would not be achieved. The three hierarchical conceptualizations are described below.

1. **Better Information Accessibility**: The BI system facilitated access to information that had been difficult to obtain in the past. During the years before the implementation of the BI system, decision makers and intermediaries spent excessive time collecting data from different sources. As a result, the cost of producing each report was high, and the report was likely to be delivered too late. The situation had changed with the implementation of the BI system. Thus, the improvement in access to relevant information was seen as the first-level BI system outcome.
I mean… it is good to have data there to be able to query things. I mean without that it would take a long time to gather information. (MidMan-24)

Well… there is no doubt that there has made far easier to produce statistical reports on historical performance. (BusAna-05)

Because of the BI system, LGA had improved the availability of relevant information for its managers. According to users, the BI system had not only opened opportunities for analysis that were not possible before its implementation, but also accelerated the process of information acquisition, facilitating the task and saving costs.

You’ve got information at your fingertips… I think it just speeds the process… Rather than having to go to multiple different peoples in different areas. (MidMan-17)

Because the access to information had been improved and expedited, LGA managers tended to require information from the BI system more frequently than in the past. As a result, managers believed that the general approach within the organization was to base their decision-making, actions, and plans on the evidence provided by the BI system representations.

2. **Informed Managers:** On the one hand, several users, and in particular the ones that had an intermediary role, argued that the outcome of the BI system was the delivery of truthful information to managers. Intermediaries relied on the BI system because they were told that the BI data had been checked and validated. On the other hand, top division executives who directly accessed the BI system argued that their beliefs about LGA business activities and the beliefs of other managers around the organization could be contrasted with the BI system as source of “truth.”
People say lots of things and make lots of claims… and some of them are justified and some of them are not. But the BI gives the truth. (TopExe-10)

Well it takes out the guess work. I mean I can… what it does is you get a feeling for things… And so I can go to BI and I can run a report and I go, yeah, it is. Okay, yeah, it is right. Or, oh, who knew? They’re actually doing better than I thought they were. (MidMan-16)

BI users also mentioned that the BI system could facilitate control and monitoring of the performance of staff and services. However, the current BI system interface did not allow the creation of dashboards. As a result, BI users had to manually export data from the BI system to create and deliver periodic reports to support monitoring tasks.

3. **Informed Decisions:** Once information had been made accessible and delivered to the managers, informed decisions could be made. When BI representations were faithful, the BI users indicated that managers could rely on the reports and make informed decisions. They also provided examples of some decisions made in the past without relevant information being available or using unfaithful reports, in which negative outcomes occurred. In addition, top divisional executives indicated that many opportunities for improving their division’s business were missed before the implementation of the BI system. Thus, the BI system had not only helped to prevent decision-making mistakes, it also had supported the identification of new business opportunities.

In addition to the hierarchical outcomes, the interviewees also mentioned two secondary outcomes. First, several users indicated that the quality of the available information in LGA had improved over time. They considered the improvement of information management as an
important outcome of using the BI system. In this regard, use of the BI system helped to make explicit the information management issues that LGA had experienced. For instance, middle managers became more conscious of the way in which their departments were entering data into transactional systems, which enabled them to make changes that improved the quality and timeliness of the input. Moreover, according to the users, the BI team was flexible and agile in solving data inconsistencies and upgrading data mart structures.

The process of improving the data quality through the BI system. So, basically they’re saying, because the data has to be put on BI and people are going to look at it, it has to be good. And because of that, the data’s being fixed. (TopExe-18)

Second, individuals who were recent hires, or who had moved to other departments or divisions of LGA, indicated that using the BI system to support a specific task allowed them also to learn about the organization in an efficient manner. Understanding the organization and the business environment helped business analysts to understand the decision-maker’s requirements.

I was new to the job as well so … I didn’t know what they were doing, and there was no other system that could tell me. Or, like I said I would have had to go to Finance to get all this information, whereas in two seconds … I could get a snapshot of how they were set-up and how they were running… . So that’s very good when you start a new job. (MidMan-17)

4.5.3 BI System

Finally, this section explores the characteristics of the BI system that would permit achieving the outcomes described in the previous section. Following the conceptual framework proposed in Chapter 3, the interviews included questions about the faithfulness of the BI system and the potential obstacles that would impede obtaining faithful representations. Representation theory assumes that individuals use information systems to obtain representations. If the representations
were faithful, they would provide a more informed basis for making decisions and taking actions. The representation concept was present in the interviewees’ responses about what they expected from the BI system. The interviewees repeatedly used the terms “picture” and “snapshot” as the outputs obtained by using the BI system.

\[
I \text{ expect it to give me a picture of my [division's] operation… So, it can give me a picture of what's gone on. (MidMan-16)}
\]

\[
I \text{ expect it to be an accurate representation … and snapshot of the business. (MidMan-08)}
\]

\[
Yeah, we can get a snapshot … like a snapshot of how the [Division] is going as of May, 2012 type of thing. (Bus.Ana-12)
\]

Faithfulness of the representation was specified as the necessary condition for obtaining positive outcomes from using the BI system. When the representations obtained using the BI system were perceived as faithful, BI users could rely them and then base their decisions on them. Reliability of the system, which means that BI system representations were consistent over time, was considered a key factor for using BI representations to support decisions.

\[
So it needs to be quick and reliable. So when you get the information you know you can trust it. You don’t need to find where there is an error. So the reliability is absolutely important. (TopExe-22)
\]

According to LGA’s BI users, the faithfulness of the BI system’s representations had been improved to a point at which discussions about the lack of faithfulness of the reports were replaced by discussions about the decisions that managers would make using the representations.
4.5.3.1 BI Deep Structure Characteristics

Before the implementation of the BI system at LGA, obtaining representations was a laborious task. Staff had to obtain representations by compiling data from multiple data sources. The process of collecting and integrating data was performed manually, and it could take days to be completed. To complete the task, the person performing it had to obtain access to each source system via the system owner. The implementation of the BI system offered a one-stop alternative for accessing more complete and up-to-date representations. By consolidating the data for decision support, the deep structures of each transactional system were merged to form the BI system’s deep structure. Thus, the main differentiating characteristic of the BI system’s deep structure was that it was composed of fragments of other system’s deep structures, which made it highly reliant on the quality of the source systems.

The design of the BI system’s deep structure was not focused on a particular manager’s decision task. Nonetheless, the decision tasks could be supported by the BI system’s deep structure. The scope of each portfolio offered enough information to cover most operational decision tasks and some strategic decision tasks. For some middle managers in charge of the operations of their divisions, the deep structure was far too complex for the simple queries they needed to perform. For instance, when middle managers had to act as intermediaries for other managers in the division, the complexity of the deep structure was an obstacle to designing the required report. The perceived complexity and magnitude of the BI system’s deep structure was also one of the triggers mentioned by the interviewees for delegating the direct use of the BI system.

Strategic decision tasks were more demanding in terms of the amount of data and queries needed to produce faithful representations. An important requirement for the case of strategic decision tasks was the incorporation of external information about the industry and LGA’s competition. Although the BI team had plans for including external data sources in the BI system’s deep structures, their efforts had focused on the consolidation of the internal sources of
information. Users had to find alternative methods to improve the faithfulness of representations of the decision task outside the BI system.

Users of the LGA BI system indicated that the faithfulness of the BI system depended on and could be improved by managing two characteristics:

1. **Accuracy**: Measuring the accuracy of the representation used to support a decision task can be difficult if there is no an easy way to observe the phenomena directly. BI users would need to have a preconceived perception about how the representation should look. The alternative method is to observe the things in the world directly in order to compare and audit the representation. The problem of observing things directly is its high cost and impracticality. Moreover, the reason for using a BI system in the first place is to avoid the need for direct observation. Nonetheless, in the case of the BI system users in LGA, the previous traditional form-based reporting systems were kept available for their use. It was also the case for middle managers to frequently use the transactional systems from which the BI system data was generated. In this light, BI users complained that the BI system deep structure was different from the representations of alternative reporting systems and transactional systems.

   *So you will often have the situation where you have the BI data, you have the [alternative reporting system X] data, you have the [alternative reporting system Y], and there’s some sort of mismatch. And I said, usually they are relatively small. And you go ‘Okay, so which do we take?’.* (TopExe-23)

Another factor mentioned by the interviewees under the term “accuracy” was that the BI system data must remain consistent over time. In particular, for longitudinal representation that shows trends, users who had obtained a representation with certain numbers about a specific year expected those numbers to remain constant. It was
especially problematic when an inconsistent representation had already been used for supporting a decision in a previous year.

There is no worse thing that going to [a meeting] and present let’s say a five-year trend data… So, you present what happened between 2005 and 2009 and then the following year you add one more year and the data don’t match for the overlapping bit… there is nothing worse than that… when you kind of showing that you don’t have a reliable set of that. (TopExe-22)

The BI system data was updated every day with the available information in the source systems. Nonetheless, users indicated that the BI system offered little support for decisions during the year – LGA’s normal business cycle – that could lead to remedial actions. Although the BI system was updated every day, the data was not coming in because it was not entered until the week before the official submission of reports to the government. In a similar manner, BI users mentioned that some processes performed by the clerks who were responsible for inputting the data on the systems were not done quickly enough. Consequently, lack of timeliness caused a sense of inaccuracy because the representation did not present information they knew should be included. Overall, LGA managers suggested that they were missing opportunities for early actions to be taken that could lead to improved business activities and performance.

2. Completeness: The BI system data was considered incomplete for a decision task if there was missing information that was relevant for the decision task. The users of the BI system indicated they could not rely on the validity of the report when the representation was incomplete. As a result, decision makers could not base their decisions on the representation. With the subsequent releases in both the core services
and research and development portfolios, incompleteness problems decreased in the BI system’s deep structure, and users’ trust in the representations increased.

The incompleteness problems arose from two sources. The first occurred when users were not able to obtain a representation that contained all the expected elements under a certain criterion.

_I can only know if there is a problem with BI or the systems that feed into BI if I selected a particular department and… it would be an unsuccessful report if the department that I selected didn’t contain all the [employees] within that department._ (BusAna-03)

The second source of incompleteness occurred when specific decision-task questions were not answered because needed data structures had not been captured and were not available in the representation. The LGA transactional systems that were used in the BI system data did not always store all the business transactions and processes associated with the business activity of interest. If they were captured, the information often was stored in spreadsheets that were difficult to integrate into the BI system data structures. Sometimes, relevant information such as information about competitors also came from an outside source. According to the users, such information would have an important impact on outcomes if it were integrated into the BI system data.

_It is complete at capturing quantitative and broad sociodemographic information… [BI] doesn’t capture attitudinal issues. Because we don’t collect that data._ (TopExe-25)

_That information is not captured in one system at the moment. It is captured within an office, but it is not captured in a centralized [LGA-wide] system. And because of that, BI is flawed because it doesn’t capture that. But it is not just BI that is flawed._ (BusAna-03)
4.5.3.2 BI Surface Structure Characteristics

As mentioned in the background, LGA had decided to pilot the delivery of the system using a license from Oracle Business Intelligence Discovered that was available at no extra cost. While the interface made access to the BI system data possible, managers, business analysts, and even the BI team project manager found the interface “clunky” and “unresponsive.”

...to format in Oracle Discoverer is very clunky to get columns where you want... and columns and rows in the right position... and not show redundant information. Unless you export it out and then delete the columns. I don't want! You can't just do that in that report. (Bus.Ana-21)

LGA’s BI users gave greater importance to the BI system data than the BI system interface. Several users suggested they would prefer to improve the data available for creating representations than replacing the interface. There were differences, however, between different groups of users about the relative importance of the BI system interface capabilities.

On the one hand, business analysts tended to access the BI system more frequently than managers. Because the main role of business analysts was to support decision makers, they spent a significant portion of their day querying, extracting, and analyzing data using the BI system. As a result of the business analysts’ familiarity with the BI system, they knew how to obtain the representations more efficiently than managers. Therefore, they were less concerned about the BI system interface.

On the other hand, managers complained that the current BI system interface did not allow efficient access to representations. In particular, top divisional executives only accessed the system directly when they perceived that obtaining a representation would take little time. If this were not the case, they would delegate the production of the representation to a subordinate. Middle managers were the group of users who complained most about the BI system interface. Because
they did not access the BI system as frequently as business analysts, they were less familiar with the
BI system’s interface functions. Therefore, they were more critical of the BI system interface.

While LGA’s BI users agreed that the main function of the BI system interface was to
provide access to the BI system data structures, they also suggested the BI system interface should
facilitate the manipulation of the representation format. This capability would make the
representation clearer for themselves and individuals with whom they shared the representation.

_A BI tool that helps to manipulate it and get it into a format that’s clear. Because I think_

_if you’re writing a report you can have too much information. You’ve got to think about_

_what your message is, what you’re wanting to show at the end._ (BusAna-21)

LGA had a common practice of forming committees to discuss the courses of action and
policies at the organizational and divisional level. Committees were led by a senior executive who
made use of the BI system either directly or indirectly to support their discussions. According to
the intermediaries who supported the executives, the representations obtained needed to be in the
right format to facilitate understanding and discussion among all members of the committee. In
the execution of the task of supporting the decision maker in the committee, intermediaries were
required to analyze and interpret the representation. In several cases, intermediaries had to produce
an official document with the findings. Intermediaries indicated that little time was given to them
for the analysis and interpretation of the report, because they spent most of their time accessing
the BI system to produce a faithful representation. They suggested that the BI system interface
could be improved to support not only the production of the representation but also the analysis
of the representation.
4.6 **DISCUSSION**

This section discusses the main findings of the exploratory case study. The aim of the discussion is to obtain a set of design requirements for the developing the models of BI system use and outcomes. Chapter 5 will present a detailed description of the proposed models.

4.6.1 **METHOD OF USE**

One assumption of the conceptual framework employed in the exploratory case study was that decision makers accessed the BI system directly to support their decisions tasks. However, the LGA case has been revelatory in the sense of providing evidence that a significant proportion of BI system users access the BI system to produce representations for other individuals in the organization. Of the 25 BI users interviewed, 20 indicated they had supported someone to use the BI system. The main implication of this finding is that both methods of use should be employed in the development of models of BI system use and outcomes.

The need for both methods of system use can be illustrated using the “BI utilization problem” as example. In Chapter 1, a review of the BI industry literature was presented. Surveys conducted in the industry reported BI usage as low as 8 percent. Industry consultants argued in trade seminars, conferences, and the media that low usage rates indicated BI systems were underused and not used to their full potential. Using the industry approach for measuring use, the usage rate of the BI system in LGA would have been deemed low if only users who directly accessed the system were counted. Indirect users would not have been counted in the ratio. As a result, the BI system might have been considered a failure.

The discussion about whether decision makers should use IT-based decision support systems directly dates to the late 1970s. DSS and EIS, both precursors of BI systems, are examples of systems that targeted decision makers in their inception. The common belief in academia and industry was that decision makers should be encouraged to use the systems directly (Alter, 1977).
Thus, each generation of IT-based decision support system has started by targeting decision makers at the strategic level. It has then moved toward lower levels of management. For instance, Watson et al. (1991, p. 14) argued that most EIS were “tailored to individual executives users” and were “used directly by executives without intermediaries.” Criticizing precursors of EIS, Watson et al. suggested that previous attempts to bring IT support to decision makers had failed because managers ended up not using them. By the early 2000s, EIS were also criticized because of the small proportion of decision makers who were using them (Poon & Wagner, 2001) and their having a focus on management control rather than strategic planning (Singh et al., 2002). Although decision makers can directly use BI systems to support their decision tasks, there are many scenarios where they delegate the use of the BI system to a subordinate. In consequence, it seems appropriate to include the direct and indirect methods of BI use as complementary models of BI systems use and outcomes.

Although advances in graphical and interactive interfaces and data processing speed and an increase in managers’ IT knowledge might facilitate decision makers’ direct access to BI systems, the evidence gathered in this case study tells a different story. While a small group of top executives in LGA accessed the BI system directly, a significant number of tasks were delegated. Although the lack of a user-friendly interface was highlighted as a reason for delegation, users suggested that the characteristics of the task also motivated delegation. In particular, users mentioned that employing an intermediary between the decision maker and the BI system was justified and a preferable approach when the task required (1) a significant amount of time and dedication, and/or (2) specific knowledge about BI system data and interface. Thus, depending on task characteristics, an indirect method of BI use would be more efficient and effective.

Literature on BI system success has not explicitly considered the indirect method in conceptualizations of BI system use. Although early calls were made during the late 1970s for considering a human intermediary in the use of a DSS (Alter, 1977; Keen, 1976; Swanson, 1978),
none of the subsequent generations of IT-based decision support systems have made explicit an indirect method of usage. Little is known about the necessary functions of BI systems and the necessary individual and collective conditions that would enable effective and efficient indirect use of BI systems.

4.6.2 User’s Decision-task Understanding

The analysis of the LGA case provided a classification of various roles performed by users. In both methods of BI system use, direct and indirect, the person who accessed the system must know how to access the representation. BI users sometimes spent significant time obtaining a representation.

So, it's a lot of playing around. Sometimes I've spent a day, or even you know, just trying

to get the right report and I would say timing is not the whole idea, but most of my day it

would feel like I just keep on running reports to see which is the correct one. (BusAna-11)

During the early days of the BI system implementation, users felt that the BI system was not easy to use. As they became more familiar with it and the decision tasks the system was able to support, their specific knowledge about acquiring representations increased. Choudhury and Sampler (1997), in their conceptual work about information specificity, note that knowledge specificity in acquisition

… is tied to the need for information filtering, that is, the need to discern relevant

information from the large amount of data to which an individual is exposed. To the extent

that this filtering process requires specific knowledge, information has high specificity in acquisition. (Choudhury & Sampler, 1997, p. 30)

Choudhury and Sampler (1997) linked the required specific knowledge in acquisition to information, leaving out of their theory the specific knowledge needed in relation to system functionalities. Although LGA’s BI system interface was not too difficult to use, the BI users
indicated it was easy to forget its functions if it was not used often. In this sense, they suggested that one of the main reasons that the access to the BI system was delegated was that decision makers in LGA did not need or did not have the time to access the system. In short, decision makers’ opportunity cost of acquiring the required specific knowledge for acquiring a representation was too high. Therefore, delegation was a more efficient approach in using the BI system.

Because many decision makers used the BI system indirectly, another important finding of this case study is that a high level of shared understanding between the decision maker and the intermediary is required to obtain and then effectively use the representation. Business analysts interviewed in the case argued that an important part their role was to understand the representation requirements of their decision makers. Moreover, some of the more senior business analysts argued it was also important to understand the purpose of the representation. Interestingly, business analysts who gave greater importance to understanding the purpose of the representation were able to describe BI outcomes in a more concise manner. The assumption was that understanding the decision task and its purpose allowed them to advise the decision maker about obtaining a more faithful representation of the decision task. In consequence, a greater shared understanding ensures that faithful representations are obtained and therefore more informed decisions are made.

Finally, the case study has shown that the main concern of users is to obtain accurate and complete representations from the BI system. Nonetheless, there was also the need for reformatting the representation so that it was easy to interpret and communicate. Vessey’s (1991) study about cognitive fit supports this requirement. Vessey argues that tables and graphs are employed for well-differentiated tasks. While tables should be employed when the task requires precise data values (symbolic tasks), graphs should be employed when the task requires comparisons of multiple data values or assessments of relationships (spatial tasks). Consequently,
the BI system interface might facilitate the reformatting of the representations. Presenting the representation in the right format for the decision makers facilitates their understanding of the representation, thereby facilitating its use for decision-making.

### 4.7 Conclusion

The case study has provided empirical evidence of the way in which BI systems are used in practice. The BI system has been beneficial for LGA through enabling more efficient and effective access to and analysis of relevant information for decision-making. The case study findings have provided insights about the different roles in the use of a BI system in a large organization. In particular, they have shown that a substantial amount of BI use is indirect.

Another important finding of the case was that BI systems are mainly used for operational decision tasks. Even when decision makers directly used the BI systems, they use them for monitoring purposes. For strategic decisions tasks, LGA top executives relied on senior business analysts with the specific knowledge required for the tasks. The BI system in these situations could not provide faithful representations. Therefore, senior analysts had to source the representations for the decision tasks from elsewhere.

Finally, the LGA case study has confirmed that representation theory is a useful theoretical foundation in which models of BI systems use and outcomes can be developed. The next chapter describes two proposed models that account for the direct and indirect method of BI system use.
CHAPTER 5: MODELS DEVELOPMENT

Chapter Overview

This chapter describes the initial models that account for BI system use and outcomes. Following Weber’s (2012) framework of theory components, the chapter describes the proposed models. The models were developed based on the outcomes findings of the exploratory case study and the related existing IS literature.

Background Study
Critical Analysis of the “BI utilization problem”: BI industry consultant and vendor’s views on the extent in which BI systems are used by organisations

Literature Review & Conceptual Framework
Analysis of the existing BI (including its predecessors) use and outcomes literature. Review of the existing IS use and outcomes theories. Development of conceptual framework

Exploratory Case Study
Analysis of how individuals use BI systems in a large government organization (LGA), and the outcomes obtained by their use

Initial Models Development
Design of direct and indirect BI system use and outcomes models

Follow-up Case Study
Evaluation of the proposed BI system use and outcomes modes in a big insurance company (BIC). Refinement of constructs and associations

Final Models of Direct and Indirect Use of BI Systems
Reflection on research findings and definition of final models
Chapter 5 – Models Development

5.1 Overview

The previous three steps followed in this research helped to better understand BI system use and outcomes phenomena. Chapter 1 presented the first step of this research, which comprised a review of existing industry literature concerning the use of BI systems. This initial step allowed an outline of a plan for this research to be developed, which was presented in Chapter 2. Chapter 3 included reviews of existing academic literature related to IS and BI systems use and outcomes conceptualizations and IS use and outcomes theories. The conceptual framework proposed as a result of the two initial steps guided the design, data collection, and analysis of the exploratory case study that was presented in Chapter 4. This initial exploratory phase was undertaken to better understand the phenomenon of BI system use and outcomes. Thus, the existing BI and IS literature and the findings of the exploratory case study are the foundations that permit the development of the models described in this chapter.

This chapter is divided into four sections. The first section describes the components of Weber’s (2012) framework for the development of models and theories. The second section presents a set of requirements that the models need to fulfil based on the findings of the exploratory case study. The third section presents the two models with a complete description of constructs and associations. The final section presents the design of a follow-up case study as the subsequent empirical step of this research.

5.2 Components of a Model

A model is an “abstract, simplified, concise representation of something else (phenomena) in the world” (Weber, 2012, p. 5). In this sense, a model facilitates understanding of the phenomenon that it is intended to represent. A model comprises concepts and relationships among those concepts.
Markus and Robey’s (1988) seminal article distinguished between two different approaches used by researchers to articulate a model that accounts for some phenomenon: variance models and process models. These approaches differ in terms of the type of concepts and type of relationships they use. While concepts in variance models are properties of things, concepts in process models are the things that form part of a particular event. Thus, process models describe relationships among concepts by proposing a sequence of events that account for an outcome. Variance models describe the relationship among concepts by describing a causal relation based on variations of the values of the properties of things. These statements about the relationships among the concepts of a model are also known as the model’s propositions. Researchers can specify the propositions of their proposed models using existing theories. Alternatively, they can articulate propositions through exploratory studies in which constructs and associations are identified via observation of the phenomena of interest. Clear and precise specifications of a model’s propositions are essential for facilitating the design of the empirical studies aimed to evaluate the validity of a model.

While the terms “models” and “theory” are sometimes used interchangeably, Weber (2012, p. 5) argues that “all theories are models, but not all models are theories.” For a model to be considered a theory, Weber contends that a rigorous specification of its parts and particular qualities of its whole must be satisfied. According to this view, only Gregor’s (2006) Type IV theories (theories for explaining and predicting) include the necessary qualities for being considered theories. The delimitation of Weber’s framework to exclusively Gregor’s Type IV theories does not mean that research conducted for other types of Gregor’s theories (Types I, II, III, and V) do not provide important contributions to knowledge. Rather, by providing a definition of theory, Weber aims to set the boundaries of his framework and consequently what type of models the framework will allow researchers to evaluate.
Weber's (2012) framework defines and explains the parts of a theory based on a generalized ontology proposed by Bunge (1977, 1979). The ontological view of Weber's framework enforces precise definitions of the parts and whole of theory. According to Weber, there are three parts that need to be precisely defined in a model for being considered a theory. These are constructs, associations, and states. A fourth part, events, is considered when the model accounts for a dynamic phenomenon, which is the case for process models. The first two parts of the models, constructs and associations, have been described earlier in this section using the terms concepts and relationships among concepts. Constructs are concepts that represent an attribute of a particular class of things. Therefore, a specification of a model must contain precise definitions of the classes of things before defining its constructs. Once the classes of things covered in a model are defined, a clear description of each construct must be specified (see also MacKenzie, Podsakoff, & Podsakoff, 2011, pp. 294-295). If the constructs are not well defined, then the associations among them will also be unclear.

The second part of Weber's (2012) framework is associations. Associations describe the relationships among constructs. There are different levels of precision for associations. At the lowest level of definitional precision, an association indicates an existing relationship without showing its sign. When signs are employed in associations, the specification of the associations incorporates a positive or negative relationship between the values for instances of one construct and the values for instances of the other construct. Associations can also be established as relational functions between constructs, where the value of a construct is the result of a predetermined function applied to the value of another construct, which is the case for process models. This could also be the case in variance models when the model specifies not only the signs of the relationships between its constructs but also the direction of those relationships. In this scenario, associations indicate whether the values of one of the constructs are obtained before the values of the other construct.
The third part of Weber’s (2012) framework is states. A collection of each of the possible values must be allocated to each construct of a model. The combination of each of the potential values of each construct in a model results in a matrix that determines the boundaries of the model. The specification of the constructs, associations, and possible states in a model determine its domain. The domain of a model is the set of instances to which the model can be applied. In consequence, a precise description of the parts of a model is needed to determine its boundaries and thus its domain.

The last part of Weber’s (2012) framework is events. Events are part of a theory when its aimed to account for dynamic phenomena. This is the case for process models (Markus & Robey, 1988) where “the history of values for instances of one of the constructs is conditional on a history of values of instances of the construct” (Weber, 2012, p. 8).

In summary, Weber’s (2012) framework requires definitions for the (1) class of things covered by the model, (2) set of corresponding properties of the things that form the constructs of the models, (3) list of associations and their underlying functions if needed, and (4) states of possible values that create the domain and boundary of the model. Following Weber’s framework, the following sections present the models proposed as the main outcome of the exploratory phase of this research.

### 5.3 Requirements for the Proposed Models

The previous section described the components of Weber’s (2012) framework that guide the specification of the proposed models at this stage of the research. Although the main objective of Weber’s framework is to provide guidance for evaluating of the quality of an existing theory, it can also be useful to researchers who are seeking to build new theories and models. The models described in this chapter follow the notion of theory as described in Weber’s (2012) article. In
particular, the specification of the models includes definitions about the constructs, associations, states, and boundaries of the models.

This section discusses a set of requirements that the models of this research need to fulfil. This step is considered critical before defining the models’ constructs, associations, states, and boundaries. As the research process followed in this thesis permits the iteration between evidence and existing academic literature, the requirements of the models presented in this section draw on the findings of the exploratory phase and existing IS literature. This is a common practice employed in case study research for improving the models proposed. As explained by Eisenhardt (1989, p. 544) “tying the emergent theory to existing literature enhances the internal validity, generalizability, and theoretical level of theory building from case study research.”

The following subsections discuss three aspects of the use of BI systems: (1) a BI system’s direct and indirect methods of use, (2) a BI system’s representational faithfulness, and (3) obstacles that impede BI outcomes (understanding of the BI task and the BI system’s interface capabilities.)

5.3.1 BI SYSTEMS’ DIRECT AND INDIRECT METHODS OF USE

The conceptual framework described in Chapter 3 defined BI system users as individuals who employ a BI system to perform a decision task. The framework did not explicitly specify whether BI users require interacting with the BI system directly or through other individuals. The examination of the patterns of use in the exploratory case study showed that alternative patterns of use coexist in the use of BI systems. As a result, a more precise definition of the class of thing BI system’s users is needed before formulating the models.

Although the definition provided by the conceptual framework was based on prior IS use literature, it did not cover the various types of users that make use of the BI system available in an organization. First, some individuals that make use of BI systems can decide whether they access the BI system directly or delegate their access to someone else. “Access” means that the individual
logs in and “interacts” with the BI system interface. Where the individual accesses the BI system directly, the BI system will be used to support the individual’s decision task. Where access to the system is delegated, the individual who accesses the system will be supporting the delegator in obtaining a representation of the decision task. As a result, two main roles can be distinguished in the use of a BI system: (1) the producer–user role, which is performed when the individual logs in and interact with the BI system; and (2) the consumer–user role, which is performed when the individual makes use of the obtained representation to support her/his decision task.

While the same individual performs the two roles in the direct method of BI system use, different individuals perform the roles in the indirect method of BI system use. In the direct method of BI system use, a decision maker personally logs in and interacts with the BI system and then uses the obtained representations to support her/his decision tasks. In the indirect method, the decision maker delegates access to the system to an intermediary. The intermediary logs in and interacts with the BI system to obtain a representation that is delivered to the decision maker. Once the representation is delivered to the decision maker, she/he can make use of the representation to support her/his decision tasks. Table 5.1 presents a summary of the different BI system users roles and describes the activity performed in each method of use.

<table>
<thead>
<tr>
<th>Table 5.1 Classification of Different BI System Users Roles</th>
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<tbody>
<tr>
<td><strong>Method of Use</strong></td>
</tr>
<tr>
<td>Direct Method</td>
</tr>
<tr>
<td>The BI system is used by an individual who accesses the system to support her/his decision tasks.</td>
</tr>
<tr>
<td>Decision Maker accesses the BI system to obtain a representation of the decision task</td>
</tr>
<tr>
<td>Decision Maker uses the BI system representation to support a decision</td>
</tr>
</tbody>
</table>

Indirect Method
The BI system is used by an individual via another individual to support the decision tasks of the first individual.

Intermediary accesses the BI system to obtain a representation of the decision maker’s decision task

Decision Maker uses the BI system representation that the intermediary delivers

(2a) BI System End-User
(2b) BI System Intermediary

Table 5.1 note: *Adapted from Eckerson (2006)
As a result of the different roles performed by BI system users during the direct and indirect methods of BI use, three classes of BI system users can be distinguished from the analysis of the exploratory case study.

For the direct method of use:

(1) The direct BI system user.

For the indirect method of use:

(2a) The BI system end-user.

(2b) The BI system intermediary.

The direct BI system user and the BI system end users are the individuals who perform decision tasks. The IS literature has targeted managers as the users of systems that are aimed to support decision-making (Keen & Scott Morton, 1978; Power & Sharda, 2007; Swanson, 1978; Watson & Haley, 1998). The management literature has consistently and frequently identified managers as the individuals within an organization who have the role of decision-making (Kotter, 1982a; Mintzberg, 1973). For this group of BI users, the BI system is a source of representations that can be used to support their decisions. Direct BI system users may access the BI system directly through its interface to access standard representations or to build new representations based on the existing BI system data structures. Whether the use of the BI system under this scenario can produce positive outcomes will be determined by the characteristics of the BI system, the decision task, and the direct BI system user. These factors are examined later in this chapter.

Although managers can access their BI systems directly, there are situations in which access to the system is delegated to an intermediary. This class of BI user is the third class of users found during the exploratory case study. The DSS literature refers to this role in the use of systems as “chauffeurs” (Keen, 1976) or “intermediaries” (Mann & Watson, 1984). The term “chauffeur” is
helpful to illustrate the role of an individual that has the task of “driving” another individual in her/his use of a system. Nevertheless, the term “chauffeur” can be misinterpreted by underestimating the capabilities required to perform the role. Prior research has identified the strategic role that intermediaries have in the use of DSS. Mann and Watson (1984, p. 28) observed that many organizations employ personnel with data processing, management science, and functional area skills to serve as information analysts. Often such personnel are MBA graduates with a Management Information System (MIS) specialization. They frequently serve as a liaison between the data processing group and a functional area or as an in-house consultant to a functional area.

BI systems intermediaries can receive descriptions of the decision-task requirements in various forms. For example, a brief conversation with a decision maker can lead to the creation of several reports that are obtained by using the BI system. The process of gathering the decision-task specifications does not guarantee that the intermediary is aware of the objective pursued by the BI system end user. Nevertheless, the intermediary role requires interacting with both the decision maker and the BI system in a way that the representations obtained in the BI system support the end user’s decision task.

During the late 1970s, IS researchers noticed that managers were reluctant to access DSS directly and started to consider alternative usage patterns. For instance, Alter (1977) suggested that the improvement of DSS interfaces would not be sufficient to change the behavior of busy managers who preferred to delegate their access to the DSS. He reflected: “If managers have neither the time nor the inclination to learn the assumptions and practical details underlying a decision support system, then they should be encouraged to use it only through intermediaries who do understand the details” (Alter, 1977, p. 112). Similarly, Keen (1976, p. 14) proposed to change the focus of development away from “bringing the manager to the computer.” Instead, he proposed an alternative usage pattern for DSS that he named “chauffeur-driven system” where the
manager relied on an experienced intermediary in the use of the DSS. For Keen (1976), under the viewpoint of the manager the chauffeur is the “system.”

Swanson (1978) described three different patterns of use of a DSS: (1) personal use, (2) chauffeur-driven use, and (3) interpersonal use (see Figure 5.1). He considered personal use and chauffeur-driven use alone to be inadequate as a basis for design because they did not account for how DSS were really used in his case study organizations. From his analysis of case study data on the use of an MIS, he concluded that end-users who tended to use the system directly were also candidates for being intermediaries. Thus, as Figure 5.1 shows, a system can be used by the end-user, by an intermediary, or by an end-user who also acts as intermediary for other end-users. He called for the design of DSS that considered the adaptive and interpersonal nature of its use and for the inclusion of the interpersonal method of use in theories about DSS use.

Although earlier research in IS indicated systems that support decision-making are not always accessed directly by end-users, later research about BI system use and outcomes has not included the indirect method of use. The findings of the initial exploratory case study suggest that the indirect method of use does not only cover a major part of the utilization of BI system use in organizations but also can be preferable and a more efficient and effective pattern of BI system use under particular circumstances. Better outcomes might arise, for example, when repetitive interactions occur between a decision maker and an intermediary to elicit decision-task requirements. The elicitation of requirements might improve the generation of more faithful representations of phenomena relevant to a decision task. More faithful representations enable more informed actions. Intermediaries who are more familiar with the BI system’s deep structure may not only be more efficient and effective in gathering relevant information to represent phenomena relevant to a decision task, they also may be able to provide insight about useful aspects of the BI system’s deep structure about which the decision maker is unaware.
The personal use model. Each manager (M) interacts directly with the computer-based system.

The chauffeur-driven use model. Each manager (M) interacts indirectly with the computer-based system, by means of an intermediary (I).

The adaptive interpersonal use model. Each manager (M) adapts uniquely to the computer-based system, interacting directly with the system and/or indirectly, by means of an intermediary (I) and/or other manager.
The focus of this discussion toward the inclusion of the indirect method of BI system use on the models proposed in this chapter does not aim to undermine the potential effectiveness of the direct method of BI system use. Rather, it proposes that both methods of BI system use should be considered in the models. The direct method of BI system use was an important part of how BI systems were used and how BI outcomes were realized in the exploratory case study. In particular, it was observed that several senior managers preferred to use the BI system directly to be informed about the current state of the performance of the business or validate certain assumptions about the nature of the business. Furthermore, despite the crucial role of middle managers as intermediaries of more senior managers in the use of BI systems, senior managers often decided to access the BI system directly to support their decisions. In this sense, the direct method of BI system use appears as a valid pattern of BI system use.

In summary, it seems appropriate to include both methods of BI systems use in the models. Although prior literature has shown that an important proportion of the use of BI systems (and its predecessors in the field of DSS) is indirect, there is little indication about the necessary features of BI systems and the necessary individual and collective conditions that would enable effective and efficient indirect use of BI systems. While the IS and DSS literatures have treated the delegation of the use of a particular system as a criterion for system failure, exploring the phenomenon of system use including both methods of use for BI will provide an alternative view on how BI systems can be used more efficiently and effectively. Thus, the models to be developed must address the following requirements:

**Requirement 1:** The models should include direct and indirect methods of use of BI systems to reflect the understanding that different methods of use can coexist and can independently be effective and efficient in the support of a decision–task.
Requirement 2: The definition of BI system user must include three classes of BI users:
(1) direct BI system user, (2) BI system end user, and (3) BI system intermediary user.
Relevant constructs must be included as properties of the different BI system users.

5.3.2 BI System Representations Faithfulness

A central component of the conceptual framework described in Chapter 3 was representation theory. Representation theory states that the purpose of an IS is to faithfully represent a domain (Weber, 1997, p. 73). Consequently, the conceptual framework incorporated the idea that BI systems’ main purpose is to provide faithful representations of the decision tasks supported by the system. The main proposition of the conceptual framework states that the level of faithfulness of a representation of phenomena relevant to the decision task would have a positive effect on the outcomes obtained through using the BI system. Accordingly, an unfaithful representation would negatively impact the BI outcomes.

At this stage of this research, whether BI users can discern between faithful and unfaithful representations had not been explored. The subsequent empirical phase explored the mechanisms that BI users might employ to evaluate the faithfulness of a given representation or whether they indiscriminately make use of BI systems representations. Nevertheless, when BI users perceived a low level of faithfulness, it can be argued that no actions are carried out based solely on the BI system representation. Therefore, the value of the outcomes of using the BI system to support that decision task will be low or non-existent. BI users can also decide not to use the BI system if they perceive the representation obtained is not faithful enough. The idea that the BI system will not be used if the level of faithfulness of the representation is below a certain threshold is consistent with the user’s perceived usefulness construct used in TAM (Davis, 1989). TAM argues that the level of
acceptance of a system is a function of the level of usefulness that is perceived by the user. In this sense, when the level of faithfulness of the representation is low, BI users will perceive that the BI system representation is not useful for supporting the decision task and therefore they will not use it. There is abundant evidence in the IS literature of the relationship between perceived usefulness and user acceptance (e.g., Venkatesh, Morris, Gordon, & Davis, 2003). Accordingly, this research can go a step further and explore this relationship employing the concepts of representation faithfulness and BI system outcomes.

Although TAM’s constructs help to understand why a BI system might be used, it does not consider the outcomes of using a BI system. The initial conceptual framework draws on Goodhue and Thompson’s (1995) task–technology (TTF) model, which is consistent with the notion that use itself is insufficient to understand how BI systems can be used effectively. For the BI system to be used effectively, the level of faithfulness of the representation of the phenomena must fit the decision task that the representation is aimed to support. Although a BI system might be used, a “poor fit” is likely to lead to problematic outcomes because of unfaithful representations.

During the exploratory case study, BI users strongly endorsed the concept of the level of faithfulness of the representation of the phenomena relevant to the decision task as the main factor that impacted the outcomes of using their BI system. The BI users interviewed in the exploratory case study were able to assess the level of faithfulness of the representation in relation to the task for which they had used the BI system. They made comments such as “it’s good enough,” “if it wasn’t high, I would not rely on it, so I will not use it,” and “it’s accurate but incomplete, so it’s useful but it can be better.” When BI users in the interviews were asked about a decision task during which they looked for representations in their BI system, they tended to answer with successful cases. To mitigate internal validity problems with the case, BI users were also asked about any specific decision task where use of the BI system did not provide a positive outcome. Responses indicated that the representation obtained in the BI system were considered not faithful. As a result, no decision had
been made, or a decision had been made using other or anecdotal sources of information. The BI users also mentioned that they were still uncertain about whether the most appropriate decision had been made. Moreover, they argued that these decisions were more difficult to implement than decisions that were supported by faithful representations. Therefore, the models to be developed must address the following requirement:

**Requirement 3:** Regardless of the method of use, the models should include a positive relationship between the level of faithfulness of the BI system representation of the phenomena relevant the decision task and the value of the outcomes obtained through using the BI system.

Although BI users in the exploratory case study were able to evaluate whether the level of faithfulness of the representations were highly faithful, moderately faithful, or unfaithful, they also referred to the BI system data structure where they obtained the representation under two dimensions: accuracy and completeness. These two dimensions are described in the following subsections.

**5.3.2.1 Accuracy**

During the exploratory case study, BI users argued that the BI system must be accurate to obtain a faithful representation of the phenomena relevant to the decision task. They explained that incorrect data stored in the BI system results in unfaithful BI system representations that are useless for the decision tasks at hand. Moreover, BI users also mentioned that the first outcome of using the BI system was the identification of inaccuracies in the source systems. They argued that the level of accuracy of the source systems limited the level of faithfulness of the representations that could be obtained in the BI system. As a result of their use of the BI system, BI users introduced remedial actions to fix incorrect records and improve the way the data was recorded in source
systems. According to the BI users, identifying inaccuracies in source systems would not be possible without having used the BI system. Thus, the models to be developed must address the following requirement:

**Requirement 4:** The models must include the accuracy of the BI system as a construct that positively impacts the level of faithfulness of the representation of the phenomena relevant to the decision task.

5.3.2.2 Completeness

The second dimension mentioned during the interviews was the level of completeness of the BI system. BI users argued that an incomplete system affects the level of faithfulness of the representation of the phenomena relevant to the decision task. They mentioned that sometimes information that was needed did not reside in the BI system because the data was not being collected or its source was external to the organization. BI users’ general assessment was that the initial delivery of the BI system had inaccuracies that were quickly solved through the interaction between BI users and BI developers. As the accuracy of the BI system improved, the focus moved to include other sources of data that enhanced the BI system completeness. BI users argued they needed more internal and external sources of data to address their requirements.

The completeness of a BI system can also be affected by the lack of data structures developed to group existing data. For example, a decision task might require a representation that has data presented by “age group.” While source systems might record an individual’s birthdate, they might not use an age-group categorization. BI developers can incorporate this “new data” in a BI system thereby making its deep structure more complete. Improving of the level of
completeness of a BI system is therefore a dynamic task. Thus, the models to be developed must address the following requirement:

**Requirement 5:** The models must include the completeness of the BI system as a construct that positively impacts the level of faithfulness of the representation of the phenomena that is relevant to the decision task.

### 5.3.3 Obstacles

The interviews employed in the exploratory case study included a set of questions about potential barriers that could impede achieving positive BI outcomes. The aim was to explore in some detail the nature of the relationship between faithfulness of the representation of phenomena relevant to a decision task in a BI system and the outcomes obtained by using the BI system.

The conceptual framework described in Chapter 3 is based on Burton-Jones and Straub’s (2006) argument that system usage is composed of three elements: (1) a user, (2) a system, and (3) a task. It was expected that conceptualizing BI system use and outcomes using these three elements would permit an in-depth exploration of how BI systems are used and what facilitates and undermines obtaining positive outcomes. The resultant conceptualizations based on the finding of the exploratory phase employ these elements. For example, “faithfulness of the representation of phenomena relevant to a decision task” incorporates a class of system (BI system) and a class of task (decision task). The same approach is followed to describe constructs that represent obstacles for realizing the potential BI system outcomes. The following subsections describe two concepts—“User’s understanding of the decision task” and “BI system interface capabilities”—which were
found to influence the level of BI systems outcomes that could be obtained given a certain level of faithfulness of the representation of the phenomena relevant to the decision task.

5.3.3.1 User’s Understanding of the Decision Task

During the exploratory case study, BI users who were interviewed indicated that a minimum level of understanding of the performed task requirements is needed to obtain positive outcomes from using a BI system. Regardless of the potential level of faithfulness of the representations that the BI system could provide, the outcomes could be diminished if the BI user does not understand the requirements or does not possess the knowledge required to interact with the BI system. For instance, BI system users might lack knowledge of business processes and key stakeholders because they are new in a company or have been assigned to a new role. As a result, BI system users might struggle to achieve positive outcomes even though the system is capable of providing a faithful representation of the phenomena relevant to the decision task.

The concept of understanding the decision task has been used in prior DSS research as one of the outcomes of DSS use. In his research about DSS development, Arnott (2006) argues that DSS are learning systems:

By using the system, the decision-maker will change his or her understanding of the decision task and the biases associated with that task. In reaction to this understanding, “the system analyst should redesign the DSS and construct a new versions or applications” (Arnott, 2006, p. 66).

Applying this iterative view about the use of a DSS to BI systems can explain why understanding the decision task through use of the BI system is a positive outcome for that particular instance of BI use. Moreover, the understanding gained of the decision task might facilitate the subsequent use of the BI system because the BI user might be able to articulate the decision-task requirements more effectively and would be more familiar with the BI system’s deep
structure. Therefore, each time the BI system is used for a particular decision task, understanding of that decision task will be improved. Consequently, each time more valuable outcomes might be obtained.

Adaptive design models for the development of DSS (Keen, 1980a) separate the roles of the analyst, who designs the DSS, and the decision maker, who is the end user of the DSS. The DSS analyst designs the DSS to support the decision-maker’s task. This conceptualization of the different roles in the use of a DSS is similar to the findings of the exploratory case study (discussed previously in this chapter in relation to different classes of BI system users). In particular, Keen’s analyst role is similar to an intermediary BI user. Under the scenario in which use of the BI system is indirect, responsibility for understanding of the decision task is shared between the decision maker and the intermediary. At the moment of delegation, the decision maker might communicate certain characteristics of the decision task to an intermediary. The intermediary might then analyze the requirements and use of the BI system to obtain a representation of the phenomena relevant to that decision task. The interaction between the decision maker and the intermediary may lead to the creation of new explicit and tacit knowledge that are the basis of the shared understanding of the team (Leonard & Sensiper, 1998).

Shared understanding of the decision task may be specially relevant when the BI system is used indirectly because the team formed by the decision maker and intermediary require a high level of team interdependence. Janz, Colquitt, and Noe (1997) describe interdependence as the degree to which members of a team depend on each other to perform a common task. As more team interdependence is needed for a given task, a greater degree of shared understanding may be found in the team. While shared understanding was not explicitly mentioned in Keen’s early DSS work, the development cycles of the Keen’s adaptive design model incorporate the notion that the analyst must understand the decision maker task (Keen, 1980a). In this light, the decision maker
should be encouraged to actively participate in the development process. Thus, the models to be developed must address the following requirements:

**Requirement 6:** The direct BI system use model must include BI user understanding of the decision task, a factor that affects BI systems outcomes.

**Requirement 7:** The indirect BI system use model must include the decision-maker’s and intermediary’s shared understanding of the decision task as a factor that affects BI system outcomes.

### 5.3.3.2 BI System Interface Capabilities

Although 1980’s DSS were technologically different from today’s BI systems, some of the concepts discussed in the DSS literature are still valid in relation to BI system use. The main critique of the direct method of use in the 1980’s was that efforts to improve DSS interfaces would have little effect on adoption of DSS by managers. While today’s graphical interfaces are more user-friendly than those provided with early DSS software, use of an intermediary is still more efficient and effective in some situations. Moreover, the capabilities of a BI system’s interface (or BI system’s surface structure) can facilitate or undermine BI system outcomes.

A frequent comment made by the BI system users interviewed in the exploratory case study was that existing BI system interfaces were a significant obstacle to creating high-quality representations of phenomena relevant to a decision task. They complained that BI systems often lacked features that facilitated access to required representations of phenomena relevant to a particular decision task. The problems included (a) the number of steps needed to obtain a
representation, and (b) the lack of functional features such as the option of saving a representation or transferring a representation to more suitable media.

In the exploratory study, BI system users also complained about the lack of features that would allow them to manipulate representations or to display representations in a different format. In this regard, previous research in the data-visualization field has explored the appropriateness of graphical versus tabular visualizations of representations. In particular, Vessey (1991) proposed a theory of cognitive fit. The theory accounts for the selection of the appropriate visualization for a given cognitive task. In this sense, cognitive fit aims to maximize the performance of the task by facilitating the processing of information through having an appropriate visualization to support the decision task. Based on cognitive fit theory, the BI system’s interface capabilities must facilitate the design of a visualization that supports the decision task. Thus, the models to be developed must address the following requirement:

**Requirement 8:** The models must include the BI system’s interface capabilities as a factor that can affect BI system outcomes.

### 5.4 Models of BI Systems Use and Outcomes

This section describes the initial models of the research using Weber’s (2012) framework (i.e., domain, constructs, associations, and states). The objective was to fulfil the eight requirements described in the previous section. The resultant models are the outcome of the analysis of the exploratory case study findings and the existing use and outcomes IS literature.

#### 5.4.1 Models Overview

To fulfil requirement 1, which states that the models must incorporate the direct and indirect methods of use, two separate models are proposed:
(1) The direct BI system use model.

(2) The indirect BI system use model.

Each model comprises seven constructs and five associations. The main difference between the models is the addition of an intermediary in the indirect BI system use model. The indirect BI system use model also has interactions between the BI system and the intermediary, and the intermediary and the decision maker.

Both models have the same focal construct (value of BI system outcomes). Furthermore, they incorporate a positive association between the faithfulness of the representation of the phenomena relevant to the decision task and the value of BI system outcomes. Figure 5.2 and Figure 5.3 show each model.
Figure 5.2 Direct Use of a Business Intelligence System

\[ \text{Value of BI System Outcomes} \]

**Propositions**

- **P1**: The Faithfulness of the Representation of the Phenomena Relevant to the Decision Task **positively affects** the value of BI System’s Outcomes
- **P2**: BI System’s Accuracy **positively affects** the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task
- **P3**: BI System’s Completeness **positively affects** the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task
- **P4d**: Decision Maker’s Understanding of the Decision Task **moderates** P3
- **P5**: BI System Interface Capabilities **moderates** P3
Chapter 5 – Models Development

Figure 5.3 Indirect Use of a Business Intelligence System

Propositions

\[ P_1 \]: The Faithfulness of the Representation of the Phenomena Relevant to the Decision Task \textit{positively affects} the value of BI System's Outcomes

\[ P_2 \]: BI System Accuracy \textit{positively affects} the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task

\[ P_3 \]: BI System Completeness \textit{positively affects} the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task

\[ P_{4i} \]: Decision Maker's & Intermediary's Shared Understanding of the Decision Task \textit{moderates} \[ P_3 \]

\[ P_5 \]: BI System Interface Capabilities \textit{moderates} \[ P_3 \]
The models have two distinguishable parts. The first part comprises the achievement of a certain level of faithfulness of the representation of the phenomena relevant to the decision task (P₁ and P₂) and the potential value of the BI system outcomes obtained through using the representation (P₃). The second part comprises the factors that might undermine or enhance achievement of BI system outcomes.

The models can also be understood using the lens of TTF (Goodhue, 1995). The technology (the BI system) has a fit with the task (decision task) when the BI system enables a faithful representation of the phenomena relevant to the decision task to be obtained. Nonetheless, the BI interface capabilities must enable the decision maker and intermediary to make use of the representation to obtain positive outcomes. According to TTF (Goodhue, 1995), a user’s characteristics are also relevant to obtaining positive outcomes. In this light, the proposed models take into account the level of understanding and shared understanding of the decision task needed to obtain positive outcomes when using the BI system.

### 5.4.2 CLASSES OF THINGS

The main class of things covered by the models is BI systems. Nevertheless, system use is complex because it requires consideration of other classes of things such as users and tasks. In this sense, the constructs described in this section are properties of three classes of things: BI system, BI users, and the supported decision task.

In the direct BI system use model, a decision maker accesses the BI system to support a particular decision task. As a result of that first interaction, the BI system provides to the decision maker a representation of the phenomena relevant to the decision task. Thus, three classes of things can be distinguished in the direct model: (1) a decision maker who uses a BI system to support a decision task, (2) the BI system used by the decision maker to provide representations of the
phenomena relevant to the decision task, and (3) a decision task that is supported by the BI system. Figure 5.4 shows the direct interaction pathway.

In the indirect BI system use model, a decision maker asks an intermediary to build a representation to support his/her decision task. The intermediary accesses the BI system to build and obtain a representation. The BI system provides a representation of the phenomena relevant to the decision task to the intermediary. Finally, the intermediary delivers the representation to the decision maker who can make a decision or who might then ask for a new representation. As a result, four classes of things exist in the indirect model: (1) a decision maker who asks an intermediary for a representation, (2) an intermediary who accesses a BI system to obtain a representation, (3) a BI system that is accessed by the intermediary to provide representations, and (4) a decision-maker’s decision task supported by the intermediary via his/her use of the BI system. Figure 5.5 shows the indirect interaction pathway.

The models comprise the three classes of BI system users described in requirement 2. While the direct model incorporates a construct about the level of understanding that the decision maker has about the decision task that the system representation is intended to support (“direct BI system user” in requirement 2), the indirect model incorporates a construct that involves the decision maker (“BI system end user” in requirement 2) and the intermediary (“BI system intermediary” in...
requirement 2). In this latter case, the model incorporates the level of shared understanding between the decision maker and the intermediary about the decision task as one of the constructs that affects the outcomes of using the BI system to support the decision task.

5.4.3 CONSTRUCTS

This section describes the constructs of the direct and indirect models of BI system use and outcomes. According to Weber’s (2012) framework, constructs are properties in general of classes of things. Seven constructs are detailed in the following sections.

5.4.3.1 Value of BI System Outcomes

As described in the exploratory case study, BI system outcomes can be represented by different levels on a hierarchy of outcomes (see Figure 5.6). At the lower level, BI system outcomes are obtained when the BI user is able to find information that was not available before using the BI system. In this scenario, the value of the BI system outcomes is positive; however, access to information *per se* may or may not have an impact on the decision maker and the organization. At the second and third level, the BI system representations impact how well the decision maker is informed about the phenomena of interest. If the representations are faithful for a particular decision task, decisions could possibly be made with the support of the BI system representations. As a result, the value of the BI system outcomes is higher when (1) the BI system offers a faithful representation of the decision task, and (2) the decision maker is using the faithful representation to support a decision task. In the case where decision makers support their decision tasks using unfaithful representations, the value of the outcome may be negative. Nevertheless, decision makers can decide not to support their decision using the BI system representation if they mistrust the faithfulness of the representation. Thus, the value of the outcomes of using the BI system might be zero or slightly negative because of the time and effort spent in obtaining the representation.
5.4.3.2 Faithfulness of the Representation of the Phenomena Relevant to the Decision Task

The faithfulness of the representation of the phenomena relevant to the decision task is an ancillary construct in the proposed models. It represents the degree of similarity to the real world provided by the representation of the phenomena relevant to the decision task that was obtained using the BI system. BI users need to rely on the BI system to make use of its representations. If BI users mistrust the system, they will not make use of the representations and no outcomes would be achieved.

5.4.3.3 BI System Completeness

The BI system operates as a repository where representations are generated to support a given decision task. The level of completeness that the BI system provides has a direct impact on the potential faithfulness of representation of phenomena relevant to the decision task. A BI system
can be deemed incomplete if it lacks a relevant part of the business subject area it is intended to represent. A complete BI system permits the creation of representations where all real-world phenomena that are relevant to a decision-making task are available to a decision maker.

Wand and Wang (1996) studied the dimensions of data quality based on the assumption that the main purpose of an IS is to provide a representation of an application domain. They argued that completeness must be understood as “the ability of an IS to represent every meaningful state of the represented real world” (Wand & Wang, 1996, p. 93). Their view provides a richer conceptualization of the construct than the common view in the literature that completeness is when all necessary values are included in the IS representation (Ballou & Pazer, 1985). The state-based definition provided by Wand and Wang (1996) fits the specification of the proposed models of BI system use and outcomes because completeness applies not only to the existence of particular data but also to the necessary data combinations. In particular, the BI system is incomplete when certain real-world states cannot be represented.

The completeness construct is complex because the information needed to support a decision task changes as the decision-making process unfolds. What the decision maker learns initially usually triggers new information requirements. Moreover, the data needed by decision makers are often recorded in various internal and external systems. Thus, including relevant data to support all future changes in the decision-task requirements is a hurdle for BI developers. There will be a constant need to improve the completeness of the BI system.

5.4.3.4 Business Intelligence System Accuracy

The second construct proposed as a property of the BI system is accuracy. Requirement 4 indicated that the level of accuracy available in the BI system has a positive relationship with the level of faithfulness of the decision task. Wand and Wang (1996) found that there was no commonly accepted definition of the term accuracy in the literature. They explain that the accuracy is
frequently defined by other terms such as “correctness”. According to Wand and Wang (1996, p. 87), “using one term to define the other does not serve the purpose of clearly defining either.” Anchoring the definition of accuracy to an ontological foundation such as representation theory, they explain that inaccuracies occur when the IS deep structure represents real world states incorrectly. Examples of this issue are the lack of precision or when the IS states are mapped to incorrect real-world states.

The transactional systems that the BI system incorporates often contain inaccurate data. BI system developers spend significant time and efforts to improve the level of accuracy in the BI system. When BI users access the BI system they assess the level of accuracy of the BI system. Generally, they compare the representations with representations that are obtained directly from source systems. The level of accuracy perceived is a determinant factor in the use of BI systems representations to effectively support decision tasks.

5.4.3.5 Business Intelligence System Interface Capabilities

As discussed earlier in this chapter, the level of flexibility and responsiveness of the BI system interface can interfere with obtaining BI system outcomes (requirement 8). In this regard, Burton-Jones and Grange (2013) introduce the concept of “transparent interaction” as one of the dimensions of effective system use. Transparent interaction is “the extent to which a user is accessing the system’s representations unimpeded by its surface and physical structures” (Burton-Jones & Grange, 2013, p. 11). In their effective-use model, transparent interaction enables easy access to the representations. In this sense, the BI system interface must facilitate easy acquisition of the representation of phenomena relevant to the decision task.

5.4.3.6 Decision-Maker’s Understanding of the Decision Task

The final construct in the direct model is the decision maker’s level of understanding of the decision task. This level of understanding is determined by the knowledge that the decision maker has about
the nature of the decision (stakeholders, business areas, and processes) and about the decision information requirements. User domain knowledge can enhance task performance when the decision support system is a good fit to the task (Davern & Kamis, 2010).

Decision makers also need to know which representations are relevant to the decision task and where and how to obtain them within the BI system. If decision makers do not use a BI system frequently, they might delegate their use of the system to an intermediary who is more familiar with the system.

5.4.3.7 Intermediary’s and Decision-Maker’s Shared Understanding of the Decision Task

The final construct of the indirect model is the intermediary’s and decision-maker’s shared understanding of the decision task. In a similar way that the decision maker’s level of understanding of the decision task could impede or enable the decision maker to access and use BI system representations and obtain positive BI system outcomes, the incorporation of an intermediary makes the understanding a shared construct between the decision maker and the intermediary.

The level of shared understanding is determined by the way the intermediary gathers and analyzes the requirements made by the decision maker about the representation of the decision-task characteristics. The greater the intermediary’s understanding of the decision he/she is trying to support, the more effective their use of the system is likely to be.

The team must share the knowledge about the decision-task domain. Thus, it might be preferable to employ intermediaries with a significant level of understanding about the decision task domain because they would be able to obtain more faithful representations of the phenomena relevant to the decision task.

Shared understanding, as a construct, has not being used in the BI literature. Nevertheless, it has been used in research that examines use of collaborative systems. Collaborative systems or
groupware are systems that support either distributed or collocated teamwork. For instance, Griffith, Sawyer, and Neale (2003) argue that greater levels of shared understanding are more likely when team tasks require a high level of interdependence among team members. Interdependence necessitates a high level of communication among team members, which should result in a high level of shared understanding. Delegating access to the BI system to an intermediary to obtain a representation for the decision tasks is highly interdependent task. If the intermediary does not effectively communicate with the decision maker, their shared understanding will be low and therefore positives outcomes from using the BI system are unlikely to be obtained.

Table 5.2 presents a summary of the models’ constructs and definitions.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Class of Thing</th>
<th>Attribute</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI System Accuracy</td>
<td>A given BI system</td>
<td>The extent of which the deep structure of the BI system provides accurate representations</td>
<td>✓  ✓</td>
</tr>
<tr>
<td>BI System Completeness</td>
<td>A given BI system</td>
<td>The extent of which the deep structure of the BI system provides complete representations</td>
<td>✓  ✓</td>
</tr>
<tr>
<td>Faithfulness of the Representation of the Phenomena Relevant to the Decision Task</td>
<td>A given decision task</td>
<td>The extent of which the representation of the phenomena relevant to the decision task is faithful</td>
<td>✓  ✓</td>
</tr>
<tr>
<td>Decision Maker’s Decision Task Understanding</td>
<td>A given decision maker</td>
<td>The extent of which the decision maker understands the decision task</td>
<td>✓  -</td>
</tr>
<tr>
<td>Intermediary and Decision Maker’s Shared Decision Task Understanding</td>
<td>A given decision maker and intermediary</td>
<td>The extent of which the decision maker and intermediary shared their understanding of the decision task</td>
<td>-  ✓</td>
</tr>
<tr>
<td>BI System Interface Capabilities</td>
<td>A given BI system</td>
<td>The extent of which the BI system interface capabilities are not an obstacle</td>
<td>✓  ✓</td>
</tr>
<tr>
<td>Value of BI System Outcomes</td>
<td>A given BI system</td>
<td>The value obtained from the use of the BI system</td>
<td>✓  ✓</td>
</tr>
</tbody>
</table>

5.4.4 Associations

The models contain two types of associations between constructs: direct and moderating. They also specify the positive or negative relationships between constructs. The associations between
the BI system constructs and the faithfulness of the representation of the phenomena relevant to the decision task are direct and positive. The association between faithfulness of the representation of the phenomena relevant to the decision task and the value of BI system outcomes is also direct and positive.

There are two moderating positive associations in each model. In the direct model, the decision maker’s understanding of the decision task and the BI system interface capabilities moderate the relationship between faithfulness of the decision task and the value of BI system outcomes. In the indirect model, the decision-maker’s and intermediary’s shared understanding of the decision task and the BI system interface capabilities also act as positive moderators between faithfulness of the representation of the decision task and the value of BI system outcomes. The following list presents the models’ associations in the form of research propositions:

P1. The faithfulness of the representation of the phenomena relevant to the decision task **positively affects** the value of BI system’s outcomes.

P2. BI system accuracy **positively affects** the faithfulness of the representation of the phenomena relevant to the decision task.

P3. BI system completeness **positively affects** faithfulness of the representation of the phenomena relevant to the decision task.

P4i. Decision-maker’s and intermediary’s shared understanding of the decision task **moderates** P1.

P4d. Decision-maker’s understanding of the decision task **moderates** P1.

P5. BI system interface capabilities **moderate** P1.
5.5 CONCLUSION

This chapter aimed to present the resultant models from the first empirical phase of this research which comprised an exploratory case study in a large government authority. The first step was to provide a set of requirements that the models needed to fulfil. Drawing and reflecting on the findings of the exploratory case study six propositions have been proposed about efficient and effective use of a BI system. The propositions are part of two models of BI system use and outcomes. The first model represents the use and outcomes of BI systems that are used by decision makers who access the BI system directly to support their decision tasks. The second model represents the use and outcomes of BI systems that are accessed by intermediaries of decision makers to support their decision tasks.

The next phase of this research is the evaluation of both models of BI system use and outcomes using a follow-up case study conducted in a different organization from the exploratory case study. The following chapter describes the follow-up case study in detail.
CHAPTER 6: FOLLOW-UP CASE STUDY

Chapter Overview

This chapter presents the second empirical phase of this research: a follow-up case study that evaluates the proposed BI system and outcomes in a large insurance company. The chapter details the findings from the analysis of the data collected during in-depth interviews with 22 BI users, seven direct BI users and 14 paired-individuals. The analysis of the case study data provided support for the models. The insights gained during this research phase helped to clarify and develop a better understanding of each construct and association in the models, which in turn permitted the refinement of the BI system use and outcomes models presented in Chapter 7.
6.1 INTRODUCTION

This chapter presents the second empirical phase of this thesis, which was undertaken using a follow-up confirmatory case study (Miles & Huberman, 1994, p. 17; Yin, 2018, p. 53). The aim of the follow-up case study was to evaluate and refine the models proposed in Chapter 5. Conducting a follow-up case study at a different site permitted the assessment of the validity of the propositions and the refinement of the constructs’ definitions and associations of the direct and indirect BI system use and outcomes models. The expected outcome of this research phase is more robust models that explain the nature of the use of BI systems and their outcomes.

6.2 RESEARCH DESIGN

To build the models of BI system use and outcomes two previous stages has been completed before conducting this follow-up case study. The first step was to propose a conceptual framework based on existing literature about IS and BI use and outcomes. This was followed by an exploratory case study where two initial models of BI system use and outcomes were proposed.

To validate the BI system use and outcomes models in the follow-up case study, an interview protocol was prepared based on each model’s propositions. (Appendices 8 and 9 present the interview protocols.) A semi-structured interview protocol was employed to allow the interviewees to cover issues about the effective use of BI system that were potentially not covered in the exploratory case study. Each construct and association were evaluated by assessing whether the associations between the constructs existed or if another construct also explained the phenomenon of BI system use and outcomes. The approach employed during the interviews was to ask interviewees to indicate a current decision task in which they had used representations that were obtained by using the organization’s BI system. In this manner, the interview questions related to interviewees’ decision tasks as the context for the model evaluation. Current decision tasks were preferred because the interviewees would be more likely to remember their use of the BI system.
and its outcomes. In addition, the approach was complemented by explicitly asking for any other case where the BI system was not effective or negative outcomes were obtained. Including a contrasting or negative example permitted the evaluation of the BI system use and outcomes models for both positive and negative outcomes. This approach was implemented because it was noticed during the pre-test interviews that interviewees tended to provide only successful cases. Therefore, an explicit question was required to obtain cases where the use of the BI system provided negative outcomes or no outcomes. Finally, the interview protocol also included questions that asked whether any constructs were missing in the proposed models.

As one outcome of the previous empirical phase was development of an indirect model of BI system use and outcomes to complement the direct-use model, the recruitment of participants needed to follow a different data-collection approach from the first study in order to capture instances of indirect BI system use. While for the evaluation of the direct only direct BI users need to be interviewed, a paired recruitment method was needed for the indirect model. Figure 6.1 shows that for each instance of the indirect model a given task Y, supported by a BI system X, accessed by an intermediary, and used by a decision-maker were required. As a result, the recruitment for the indirect BI system use and outcomes model was matched pairs of decision makers and their intermediaries. The interviews were conducted individually, first interviewing the decision maker and focusing on the decision task and the interaction with the intermediary, and second interviewing the intermediary focusing on the BI system representation and interface and the intermediary’s relationship with the decision maker.
The conditions described above determined the characteristics of the site for conducting the follow-up case study. The follow-up case study required a large organization in which a BI system solution was in place with instances of different levels of outcomes and different methods of use (indirect and direct.) The organization also needed to have a sufficient number of direct users (decision makers who used the BI system directly) and a sufficient number of matched pairs of decision makers and intermediaries both willing to participate in the research project. The following section describes the site selected for the follow-up case study.

### 6.3 BIC Case Background

Big Insurance Company (BIC) was the organization selected for this follow-up case study. The real name of the organization has been disguised as it was required by company senior executives. BIC is an Australian insurance provider headquartered in Melbourne with branches in all Australian states and territories. BIC works as an intermediary between providers, agencies, and brokers. It has over 4,000 employees, and its operational revenue is around A$11 billion. The business areas of BIC comprise four different segments and products. BIC is also part of an insurance
conglomerate that had driven a new strategy based on cost savings via the coordination of its
component companies. This included IT coordination.

BIC’s organizational structure is determined by the structures of its parent and subsidiary
companies. Senior management positions are sometimes shared with the parent company, and
senior managers from subsidiary companies report to BIC’s senior managers. Nevertheless, the
senior management structure of BIC is independent and similar to other large private sector
organizations in Australia. Its organizational structure is mainly functional, with areas such as
operations and finance being managed centrally. However, for sales and business development BIC
is organized divisionally. In this sense, the central functional level controls and supports the
divisional structure. Finance and operations are the most influential central functions.

The market in which BIC operates had exhibited high levels of competition during the
period of 2010 to 2013 (Wu, 2015). In particular, a key factor that affects the sales of insurance
products is their price. The competition in sales has driven the insurance companies in the
Australian market to cut their premium prices, but several natural disasters have also increased the
risk of certain policies. Consequently, a major challenge in the industry is to price insurance and
customize products to cover the unique circumstances of the client. To achieve a higher level of
efficiency, insurance companies have to price their products according to the risk of the individual
policy holders. Thus, companies search for and implement mechanisms to obtain more
information about the particular risks of their policies. Actuaries, a class of accredited business
professionals in the insurance industry, perform the analysis of the risk of each policy portfolio.
They must determine the value of a particular set of policies and consequently estimate the overall
business position of the company. In this environment, insurance companies need to obtain the
appropriate information at the right time to run their businesses efficiently and effectively.
Incorrect pricing decisions could lead to significant costs and loss of company value. Actuaries’
pricing decisions and the subsequent profitability of their portfolios determines the company’s stock price and value in the market.

BIC’s managers viewed the implementation and use of BI systems as critical to the conduct of their business. The implementation of a more robust BI system was seen as an important step toward the improvement of BIC’s business performance. As a result, the ongoing BI project captured the attention of BIC’s senior and middle managers. In particular, several decision makers commented during the interviews that they had postponed decisions about pricing of insurance products and risk analysis because they lacked relevant information and had concerns about data inaccuracies. They commented that the new BI system had allowed them to obtain relevant information to support their decisions and that the discussion was now focused on the actions to be taken rather than data inaccuracies. In this way, the work of the BI team on building the new enterprise BI system had high visibility in the different functions and divisions of BIC.

BIC’s Senior Manager of BI was the main contact and liaison person for this case study. The selection of the case was opportunistic: access to the case came through personal contacts of one of this student’s thesis supervisors. There was continuous contact with the Senior Manager of BI via email and face-to-face meetings. BIC’s Chief Finance Officer (CFO), who had overall responsibility for the BI project, gave formal approval to conduct the study.

BIC was selected for the case study because it (a) seemed to provide a typical scenario (Benbasat et al., 1987) of BI system use in large organizations, and (b) provided empirical data for the direct and indirect models of BI system use and outcomes proposed in the previous empirical phase. BIC’s matrix organization structure and competitive market presented a suitable context for replicating the findings of the exploratory case study and extending relationships and logic among constructs (Eisenhardt, 1989). BIC’s participants were more involved in decision-making than LGA’s participants and held more senior positions. The business cycles were also shorter for BIC. Thus, business decisions in BIC had more time pressure than those in LGA. Selecting BIC as the
organization for conducting this follow-up case study allowed this research to literally and theoretically replicate case situations (Yin, 2018, p. 55). Table 6.1 shows a comparison between the exploratory and follow-up case studies.

<table>
<thead>
<tr>
<th>Table 6.1 Exploratory and Follow-up Case Studies Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>LGA Exploratory Case Study</td>
</tr>
<tr>
<td>Approach: Exploratory</td>
</tr>
<tr>
<td>Ownership: Government (Public)</td>
</tr>
<tr>
<td>Activity: Government Authority</td>
</tr>
<tr>
<td>Number of Employees: 11,500</td>
</tr>
<tr>
<td>Data Collection Period: Apr-Jun 2012 3 months</td>
</tr>
<tr>
<td>Interviewees (participants): - 25 BI Users</td>
</tr>
<tr>
<td>Coverage: - 10 Divisions</td>
</tr>
<tr>
<td>- LGA’s Corporate Level</td>
</tr>
<tr>
<td>BIC Follow-Up Case Study</td>
</tr>
<tr>
<td>Approach: Follow-up Evaluation &amp; Refinement</td>
</tr>
<tr>
<td>Ownership: Corporation (Private)</td>
</tr>
<tr>
<td>Activity: Insurance Provider</td>
</tr>
<tr>
<td>Number of Employees: 4,000</td>
</tr>
<tr>
<td>Data Collection Period: Jul-Nov 2013 5 months</td>
</tr>
<tr>
<td>Interviewees (participants): - 3 Members of BI team</td>
</tr>
<tr>
<td>- 22 BI Users</td>
</tr>
<tr>
<td>- 7 BI Direct Users</td>
</tr>
<tr>
<td>- 14 Paired-Individuals</td>
</tr>
<tr>
<td>(8 Intermediaries &amp; 7 Decision Makers; one decision maker had two different intermediaries)</td>
</tr>
<tr>
<td>Interviewees Main Profile: Middle Management</td>
</tr>
<tr>
<td>Coverage: - 4 Business Areas</td>
</tr>
<tr>
<td>- 5 Functional Areas</td>
</tr>
<tr>
<td>- Finance</td>
</tr>
<tr>
<td>- Legal</td>
</tr>
<tr>
<td>- Operations</td>
</tr>
<tr>
<td>- Marketing/Sales</td>
</tr>
<tr>
<td>- Human Resources</td>
</tr>
</tbody>
</table>

The following section explains the data collection approach employed and describe the participants background and how they were recruited.

### 6.4 Case Study Data Collection Approach

BIC’s Senior Manager of BI provided a detailed description of the different phases that the BI project had undergone since his first contractual relationship with BIC (first as an external senior BI consultant and later as BIC’s Senior Manager of BI). He also personally contacted each potential participant in the research project and organized a group of direct user participants and a group of matched pairs of decision makers and their intermediaries.
The case study received ethics approval at the end of June 2013 (see Appendix 5). Consequently, data were collected during the second half of 2013. By this time, the main BI system had been used for more than 18 months. Three senior members of the BI team were interviewed before the main interviews for collecting data for evaluating the direct and indirect BI system use and outcomes models: the senior manager of BI, the information governance manager, and the project manager for the new data warehouse. These initial interviews provided the context and background story of the BI project. For example, the timeline presented in Figure 6.4 was developed from the information provided during the initial interviews.

The main interviewees were first asked about their decision tasks. It could have been the case that they attempted to use the BI system to support a given task but failed in obtaining any outcomes from their use. In asking participants about the level of outcomes achieved by their use of BI system, interviewees were asked for various scenarios of BI use. These scenarios included positive and negative BI system outcomes.

The main source of data came from semi-structured interviews with BIC’s BI direct and indirect users. The selection criteria for participants were (1) decision makers who used the BI system directly to obtain instances of use for the direct model of BI system use and outcomes, and (2) decision makers who used the BI system through an intermediary. In the indirect model, both the decision maker and the intermediary who supported that decision maker had to be identified to organize the interview sessions in the correct sequence; first the decision maker followed by the intermediary. The senior manager of BI progressively informed the researcher of potential participants and scheduled interviews personally. Once the interviews were confirmed, an email containing the formal explanatory statement about the research (Appendix 6) and the interview protocols were sent to participants in advance of the interviews.

The semi-structured interview protocols (see Appendices 8 and 9) were designed to cover all propositions for both direct (Figure 6.2) and indirect (Figure 6.3) BI system use and outcomes.
The protocol contained eight sections: (1) screening for direct or indirect use, (2) task description, (3) evaluating faithfulness of representation and the factors that affect the construct, (4) evaluating outcomes, (5) evaluating faithfulness of the representation and its influence on the outcomes, (6) evaluating the effect of the understanding and shared understanding of the decision task, (7) evaluating the effect of the BI system interface capabilities, and (8) reflection and new factors influencing the models, and alternative scenarios. The protocols were pretested outside the case study site by interviewing a BI consultant with more than 15 years of experience of using and developing BI systems. After conducting the first two interviews in BIC, minor changes were made to the initial questions about the faithfulness of the representation and its factors.
Figure 6.2 Direct Model of BI System Use and Outcomes - Propositions

Propositions

- **P₁**: The Faithfulness of the Representation of the Phenomena Relevant to the Decision Task positively affects the value of BI System’s Outcomes
- **P₂**: BI System’s Accuracy positively affects the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task
- **P₃**: BI System’s Completeness positively affects the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task
- **P₄d**: Decision Maker’s Understanding of the Decision Task moderates P₃
- **P₅**: BI System Interface Capabilities moderates P₃
Figure 6.3 Indirect Model of BI System Use and Outcomes - Propositions

Propositions

- **P₁**: The Faithfulness of the Representation of the Phenomena Relevant to the Decision Task positively affects the value of BI System’s Outcomes.
- **P₂**: BI System Accuracy positively affects the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task.
- **P₃**: BI System Completeness positively affects the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task.
- **P₄**: Decision Maker’s & Intermediary’s Shared Understanding of the Decision Task moderates P₃.
- **P₅**: BI System Interface Capabilities moderates P₃.
Twenty-two participants were interviewed during the study: 7 BI direct users, 7 BI indirect users, and 8 BI intermediaries (one indirect user was supported by two intermediaries). The interviews were conducted in BIC’s headquarters in Melbourne, Australia, between July and November 2013. The interviews were guided by the interview protocols. However, new questions were introduced to clarify responses and propose alternative scenarios. Alternative scenarios included asking the interviewees how different their responses would have been if the levels of the construct asked in the previous question were different from the level they observed. All participants agreed to being audio-recorded during the interviews, and the transcripts were sent to the interviewees for approval. The audio-recordings were not disruptive, and all participants freely answered the questions. Table 6.2 presents a complete list of BIC participants. Participants who provided the background of the case belong to the BI management group are coded using a letter M as a prefix followed by a correlative number. Decision makers who were direct BI users are coded using a letter D as a prefix followed by a correlative number. Decision makers who used the BI system indirectly through an intermediary are coded using a letter I as a prefix followed by the matched-pair number plus the letters DM to identify them as the decision makers. Intermediaries who supported the decision makers who use the BI system indirectly are coded with a letter I as a prefix and the number of the matched-pair plus the letters IM. These codes are used to differentiate the different roles the interviewees and how they were allocated to the indirect or direct model. The codes are also useful to identify the matched pairs between decision makers and their intermediaries.
<table>
<thead>
<tr>
<th>Study Group</th>
<th>Code</th>
<th>Position / Role</th>
<th>Area</th>
<th>Tenure</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI Management</td>
<td>M001</td>
<td>Senior Manager of BI</td>
<td>BI Team</td>
<td>4 years</td>
</tr>
<tr>
<td></td>
<td>M002</td>
<td>Information Governance Manager</td>
<td>BI Team</td>
<td>1.5 years</td>
</tr>
<tr>
<td></td>
<td>M003</td>
<td>Program Manager - Transformation and Change</td>
<td>BI Team</td>
<td>4.5 years (10 months in current role)</td>
</tr>
<tr>
<td>Decision Makers / Direct BI Users</td>
<td>D001</td>
<td>National Underwriting Manager, SME</td>
<td>Finance</td>
<td>24 years</td>
</tr>
<tr>
<td></td>
<td>D002</td>
<td>Senior Manager of Financial Accounting &amp; Regulatory Reporting</td>
<td>Finance</td>
<td>4 years</td>
</tr>
<tr>
<td></td>
<td>D003</td>
<td>Senior Manager Finance</td>
<td>Finance</td>
<td>5.5 years (10 months in current role)</td>
</tr>
<tr>
<td></td>
<td>D004</td>
<td>State Operations Manager</td>
<td>Operations</td>
<td>1.5 years</td>
</tr>
<tr>
<td></td>
<td>D005</td>
<td>Head of Financial Performance</td>
<td>Finance</td>
<td>6 years</td>
</tr>
<tr>
<td></td>
<td>D006</td>
<td>National Manager for Claims Operations</td>
<td>Operations</td>
<td>1.5 years</td>
</tr>
<tr>
<td></td>
<td>D007</td>
<td>National Manager for Channel Development</td>
<td>Marketing</td>
<td>5.5 years</td>
</tr>
<tr>
<td>Indirect Users &amp; Intermediaries</td>
<td>I001-DM</td>
<td>National Personal Insurance Manager</td>
<td>Operations</td>
<td>31 years</td>
</tr>
<tr>
<td></td>
<td>I001-IM</td>
<td>Senior Portfolio Analyst</td>
<td>Operations</td>
<td>6 years (3 months in current role)</td>
</tr>
<tr>
<td></td>
<td>I002-DM</td>
<td>Chief Financial Officer</td>
<td>Finance</td>
<td>20 years</td>
</tr>
<tr>
<td></td>
<td>I002-IM1</td>
<td>Finance Manager - Support Services &amp; Expense Systems</td>
<td>Finance</td>
<td>6 years</td>
</tr>
<tr>
<td></td>
<td>I002-IM2</td>
<td>Management Accountant</td>
<td>Finance</td>
<td>8 years (3 years in current role)</td>
</tr>
<tr>
<td></td>
<td>I003-DM</td>
<td>Head of Actuarial Reserving</td>
<td>Finance</td>
<td>11 years</td>
</tr>
<tr>
<td></td>
<td>I003-IM</td>
<td>Data and Integration Analyst</td>
<td>BI Team</td>
<td>15 years (12 years in current role)</td>
</tr>
<tr>
<td></td>
<td>I004-DM</td>
<td>Senior Manager of People Services</td>
<td>Human Resources</td>
<td>6.5 years (1 years in current role)</td>
</tr>
<tr>
<td></td>
<td>I004-IM</td>
<td>People Reporting Analyst Manager</td>
<td>BI Team</td>
<td>2.5 years (10 months in current role)</td>
</tr>
<tr>
<td></td>
<td>I005-DM</td>
<td>National Manager of Client Relationships</td>
<td>Business Development</td>
<td>10 years (5 years in current role)</td>
</tr>
<tr>
<td></td>
<td>I005-IM</td>
<td>Senior Business Analyst</td>
<td>BI Team</td>
<td>14 years (8 years in current role)</td>
</tr>
<tr>
<td></td>
<td>I006-DM</td>
<td>State Manager</td>
<td>Business Development</td>
<td>1 year</td>
</tr>
<tr>
<td></td>
<td>I006-IM</td>
<td>Manager of Sales Analytics</td>
<td>Business Development</td>
<td>7.5 years</td>
</tr>
<tr>
<td></td>
<td>I007-DM</td>
<td>Senior Manager for People and Culture</td>
<td>Human Resources</td>
<td>2 years (1 year in current role)</td>
</tr>
<tr>
<td></td>
<td>I007-IM</td>
<td>People Reporting Analyst</td>
<td>BI Team</td>
<td>1 year</td>
</tr>
</tbody>
</table>

*Tenure: the length of time the participant had been in the follow-up case study’s organization
At the beginning of each interview, the participants were asked to verbally agree with the consent form (see Appendix 6). Interviewees were also told that (a) the organization’s name would be disguised using the acronym BIC, and (b) no information that could lead to the identification of any individual would be disclosed in any reports on the project or to any other party. Interviews lasted between 60 and 70 minutes, and no interview was finished without completing the full interview protocol. Among those interviewed were BIC’s senior managers and analysts, middle managers, and BI developers. They represented BIC’s four business areas and five functional areas: finance, legal, operations, marketing/sales, and human resources (see Table 6.2).

The data collected was stored using transcription software that allowed synchronizing transcripts with their corresponding audios. The researcher reviewed the transcripts several times, not only to validate the transcripts but also to reflect on the data. The transcripts were emailed to all participants for their approval. All transcripts were approved by participants and imported to software for qualitative analysis (QSR International NVivo).

The analysis of the data was conducted in two phases. The first phase consisted of evaluating the propositions related to both models of BI system use and outcomes. The selected approach was the development of a case-level display matrix (Miles et al., 2014). This method permitted the evaluation of each proposition against various instances of use of BIC’s BI system. The second phase involved the analysis of the (a) contexts in which certain constructs were not considered as relevant to determine BI systems outcomes, and (b) nature of the associations between the constructs. Chunks of text were coded using descriptive codes (Saldaña, 2012, p. 70). The coded data was reorganized in tables and diagrams for condensation and analysis. The following section describes the BIC’s BI project and provides the context of the case.
6.5 BIC’s Business Intelligence Project

At the time of this study, BIC had fundamentally changed the way that its BI systems were delivered. Just three years before this study, BIC’s normal practice was to allow its different divisions to implement their own BI solutions with only partial support from the IT department. In contrast, for the two years prior to this study, BIC had made an effort to integrate and standardize the BI function. The quick wins that this new approach provided facilitated the implementation of another, more ambitious, phase. Three BI eras were distinguishable from the interviews with members of BIC’s BI team: (1) a Decentralized Era, (2) a Consolidation Era, and (3) a Customization and Specialization Era. Figure 6.4 presents a timeline of the delivery of BIC’s BI systems.

Decentralized Era: During this era the different functions and divisions of BIC implemented their BI solutions independently. This led to the proliferation of unrelated BI systems. As each system relied on different data sources and definitions, the reports about a particular subject area in one system were not equivalent to the reports obtained about the same subject area in other systems. Several interviewees commented that during the decentralized era it was usual to discuss the validity of the data rather than the interpretation of the data and the actions to be taken.

The discussion about data quality and the lack of an integrated BI solution led BIC to attempt two central data warehouse implementations before the current data warehouse (DW) solution. Each of these attempts failed. As a result, BIC engaged BI consultants to provide advice and to design a new strategy to improve the way their BI systems were delivered. The CFO decided to lead the project with a business-oriented approach rather than the previous IT-orientation. Thus, BIC commenced a transition from a Decentralized Era to a Consolidation Era in which a new BI governance structure was put in place.
Figure 6.4 BIC’s Business Intelligence Evolution Timeline

2009
- Many different BI systems employed by different BIC’s divisions and functions
- Several attempts of implementing a business-oriented DW

2010
- New Senior Manager of BI Appointed
- BI Team starts to report to the CFO

2011
- Commencement of migration of users to the actuaries’ DW

2012
- New Claims System data incorporated to the actuaries’ DW

2013
- New Claims System
- Commencement of migration of users to the actuaries’ DW

2014
- Delivery of the new business-oriented DW
- BIC Case Study
- Data Collection

Decentralised Era
Consolidation Era
Customization and Specialization Era
Consolidation Era: This era commenced with the recruitment of BIC’s Senior Manager of BI. The Senior Manager of BI had previously worked in BIC for more than two years as one of the external BI consultants of the Decentralized Era. Due to his advice and inputs to the design of the new BI governance and strategy, he was considered as the most appropriate person to lead the new BI and information management unit. The plan was to consolidate a new BI team outside the IT department in order to apply a more business-oriented approach. BIC’s senior management decided to relocate all the IT department BI personnel to the CFO’s office. In addition to the BI developers that were part of the IT department, several BI analysts and developers were dispersed across the organization reporting to managers from BIC’s divisions and functions. A group of these BI analysts was appointed to the new BI team, and a closer relationship was established with the BI analysts that remained reporting to BIC’s division managers. The BI team had an establishment staff of 47, including system architects, business analysts, and project managers. As a result of these changes, a new business monarchy BI governance was implemented in BIC. Business monarchy occurs when the decisions about IT, in this case BIC’s BI system, are made by senior business executives, or a group of senior executives Weill (2004). Others forms of governance are IT monarchy, in which the decisions are made by an individual or a group of IT executives, and a federal system, in which representative of all operating groups collaborate with the IT department.

Early in the Consolidation Era, the BI team identified that the BI system employed by actuaries already contained most of the information relevant not only for actuarial tasks but also general business decisions. The actuarial function is about managing the risk of what is underwritten, estimating the appropriate price of the insurance products, and calculating how much exposure the company has to disasters and accidents. According to BIC’s BI manager, the data that actuaries required represented about 80 percent of the data that BIC’s managers needed to run the business. The actuaries’ DW was implemented using the SAS data warehousing package. Actuaries
performed queries using the native SAS language or Futrix (a user-friendly interface written in SAS that allowed them to use drag-and-drop features to create reports). It was then decided to use Futrix as the official BI system for BIC’s business users.

During 2012, the BI team started to migrate users from their independent BI applications to the actuaries’ BI system. BIC employees referred to the actuaries’ BI system by the name of the BI application they accessed: Futrix. Alongside the migration of business users to the actuaries’ BI system, BIC decided to change its claims system. As a result, the BI team had to design a new ETL (extract, transform, and load) process to incorporate the new claims data into the actuaries’ DW. The BI team decided not to update any BI system other than the actuaries’ DW. As the actuaries’ DW became the most accurate and complete data source, business users who needed insurance claims data to support their decision tasks had no option but to migrate to the actuaries’ BI system.

Concurrently with the designation of the actuaries’ DW as the official company DW, the BI team reinitiated the enterprise DW project. The aim of the enterprise DW project was to incorporate more data relevant to business users. The company also evaluated different BI products to use as the BI presentation layer for the enterprise DW. Thus, BIC commenced to transition from a Consolidation Era to a Customization and Specialization Era in which more business-oriented solutions were planned.

*Customization and Specialization Era:* The consolidation of the BI team and new BI governance permitted BIC to deliver a more tailored solution for BIC’s functions and divisions. It was believed that due to the new BI governance, an enterprise DW was feasible. As mentioned above, BIC had attempted without success to implement two DWs during the Decentralized Era. The new BI team had worked for more than two years on the enterprise DW, and it had selected SAP Lumira as its BI presentation layer. SAP Lumira was selected because it was considered to offer an interface that would be easier to use by business users. BIC’s Senior Manager of BI explains
how the new configuration of the BI function contributed to the delivery of the new enterprise DW:

…we’ve been working on building this warehouse for years and years and never got anywhere, so we spent a lot of money not getting a lot of value, and one of the issues that was wrong with that we thought was the way we were approaching it… and so now what we’ve done is we’ve filled key roles with people we’ve hired… you know we’ve specifically picked [our team members]… so the data architect is our guy, the technical architect is our guy, the key analyst roles are all our people and so that we can’t abdicate that responsibility.

(M001)

The delivery of the new enterprise DW was considered the starting point for changing how BI systems were used in BIC. In particular, BIC’s Senior Manager of BI explained that in the previous eras the BI systems were mainly accessed by intermediaries. His vision was to make the BI system accessible to business users and, in particular, to decision makers. To achieve this objective, both the information management policies embodied in the enterprise DW and the selection of an easy-to-use BI presentation layer were considered essential to a successful delivery of the project. The Senior Manager of BI explained the new vision as:

…so what I’d really like to do is to get that laid across our toolsets so that we, or across our data, so that instead of people saying I need to answer a question and we answer it for them, instead what happens is they say I need to answer a question and we go and say, well here’s how you do it… you know teach a man to fish instead of give a man a fish type of deal. So that’s very much our mindset, that’s the reason we want to move to the business objects world [SAP Lumira]… (M001)

At the time of this study, the actuaries’ DW and BI system had been used for more than 18 months. Only a small proportion of users had had access to preliminary data on the new enterprise DW and BI system. There were also several stand-alone BI systems employed to support
various decision tasks. As the actuaries’ DW and BI system focused mainly on the information relevant to actuaries’ requirements, some business decisions needed other data sources. For areas such as business development, marketing, and human resources, the actuaries’ BI system did not provide all the required information. In contrast, areas such as finance had a high reliance on the actuaries’ BI system and could support their tasks using the actuaries’ DW.

In summary, BIC’s BI system portfolio evolved over a number of years. After several attempts to consolidate their information into a DW, it was discovered that the actuaries’ BI system provided information that could be used by several areas in BIC. The actuaries’ BI system consolidated data from different transactional systems and therefore was already a consolidated repository. This consolidation was also present in the work of the BI team. During the Decentralized Era, it was difficult to coordinate the efforts of the various BI developers and analysts. In the Consolidation Era, it was believed that the organizational relocation of the BI team and independence from the IT department facilitated their relationship with BIC’s decision makers and their BI system intermediaries.

The following section presents the results of the BIC case study data analysis. Both models of BI system use and outcomes are evaluated using the responses provided by the analysis of the data collected in BIC.

6.6 CASE STUDY ANALYSIS

This section presents the results of the analysis of interviews conducted to evaluate the propositions of the BI system use and outcomes models. Each construct is assessed by contrasting propositions and the case study data. The analysis of the 22 interviews conducted in BIC provided support for five of the propositions of the direct and indirect models of BI system use and outcomes. The only proposition that had a mixed response was the moderation of the relationship between the faithfulness of the representation and the value of BI systems outcomes by the BI
system interface capabilities. In addition, there were instances where BI users did not require a high level of BI system completeness to support a decision task to obtain positive outcomes. This suggested that for these participants no substantial improvements on BI outcomes would be obtained by increasing the level of the BI system’s completeness. Table 6.3 shows the results of the evaluation of the propositions in the case study. The following subsections provide a detailed description of the propositions’ evaluation.

<table>
<thead>
<tr>
<th>Proposition</th>
<th>Direct Use</th>
<th>Indirect Use</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>P1</strong></td>
<td>The faithfulness of the representation of the phenomena relevant to the decision task <strong>positively affects</strong> the value of BI system’s outcomes.</td>
<td>✓</td>
</tr>
<tr>
<td><strong>P2</strong></td>
<td>BI system accuracy <strong>positively affects</strong> the faithfulness of the representation of the phenomena relevant to the decision task.</td>
<td>✓</td>
</tr>
<tr>
<td><strong>P3</strong></td>
<td>BI system completeness <strong>positively affects</strong> faithfulness of the representation of the phenomena relevant to the decision task.</td>
<td>✓*</td>
</tr>
<tr>
<td><strong>P4i</strong></td>
<td>Decision maker’s and intermediary’s shared understanding of the decision task <strong>moderates</strong> P1.</td>
<td>na</td>
</tr>
<tr>
<td><strong>P4d</strong></td>
<td>Decision maker’s understanding of the decision task <strong>moderates</strong> P1.</td>
<td>✓</td>
</tr>
<tr>
<td><strong>P5</strong></td>
<td>BI system interface capabilities <strong>moderate</strong> P1.</td>
<td>m*</td>
</tr>
</tbody>
</table>

✓ = supported; m = mixed responses; na = Not Applicable; * = task-dependent
6.6.1 FAITHFULNESS OF THE REPRESENTATION EFFECT ON THE VALUE OF BI SYSTEM OUTCOMES.

This section presents the results of the analysis for Proposition 1 (P1): The faithfulness of the representation of the phenomena relevant to the decision task positively affects the value of a BI system’s outcomes. Figure 6.5 shows a representation of this proposition.

As mentioned previously in this chapter, the approach employed during the interviews was to request the interviewee to indicate a current decision task in which they had used representations that were obtained by using the organization’s BI system. To evaluate Proposition 1, interviewees were asked about the level of faithfulness of the representation that was used to support their current task and the outcomes that were obtained. They were also asked directly about how the level of faithfulness of the representation influenced the outcomes. Because for some users the term “faithfulness” could be confusing, the term was briefly explained using synonyms of the term in phrases like “faithfulness is how close the representation is to the reality,” or “faithfulness is how close to truthful the representation was.” In general, interviewees seemed to understand the term and easily provided explanations about why they perceived the level of faithfulness to be high or low. While no scale was explicitly used, interviewees tended to categorize the level of faithfulness as low, sufficient, high, and very high. During these questions, interviewees were asked why the level was not higher or lower. In several instances, interviewees changed their evaluations about the level of faithfulness of the representation. This means the interviewees had enough time to reflect about this construct and provide insights about the level of faithfulness and how outcomes were obtained at different levels. Finally, at the end of the interview, interviewees were asked to
think about a decision that could not be supported by the BI system and how their answers would
differ from their previous example of BI use.

Decision makers and intermediaries reported various levels of faithfulness of the
representations obtained to support their decision tasks. For example, actuaries required a very
high level of faithfulness of the representation to support their tasks. The analysis performed by
actuaries had a direct influence on the profit reported in BIC’s balance sheets. In addition, they
were liable for the profitability they reported. The profit reported by the company had an influence
on BIC’s share price and impacted managers’ bonuses. Actuaries needed to reconcile figures to
bank accounts within standard margins. In this sense, a lower level of faithfulness impeded
actuaries’ abilities to complete their tasks.

Participants also provided examples of instances in which the faithfulness of the
representation was considered low. For example, decision tasks performed by human resources
(HR) managers were not supported by their use of the BI system. No outcomes were obtained
because of the low level of faithfulness of the representations. HR managers attempted to use the
BI system via intermediaries to obtain representations about gender remuneration gaps and the
evaluation of incentives after parental leave periods. However, after several iterations, the low level
of faithfulness of the representation impeded HR managers’ use of the BI system and no outcomes
were obtained. One HR manager explained:

*If you are making a decision, particularly a decision involving large sums of money or a
huge risk, you need to be able to explain in detail questions about your data if you’re asked
that, and that all for me is about faithfulness… So, I would have seen probably seven
versions of that report when it was being drafted before it got to a final stage and still was
never signed off because of the problems that we came to learn about it later… Each time
I got that report the data was in a different spot…* (I004-DM)
In a similar manner, the intermediary that supported one of the HR managers also indicated that the level of faithfulness of the representation was low for several of the HR managers’ decision tasks. Because of the low faithfulness, the HR manager’s intermediary indicated that HR managers decided not to use the representation and that decisions were made without the support of any representation. The HR manager’s intermediary also argued that using a representation with a low level of faithfulness would have led HR managers to make incorrect decisions. When representations were not perceived as sufficiently faithful, the intermediary explained that HR managers showed symptoms of decision paralysis (Samuelson & Zeckhauser, 1988):

*It has caused a discussion about the data as opposed to focusing the discussion on action and getting things happening.* (I004-IM)

The phenomenon of decision paralysis (the decision makers disposition not to change the current situation) has been studied in the fields of psychology and economics. Anderson (2003) distinguished between three approaches: status quo bias, omission bias, and choice deferral. To explain status quo bias, Samuelson and Zeckhauser (1988) employed an economics theory: Akerlof and Dickens’ (1982) cognitive dissonance theory, and two psychology theories: Tversky and Kahneman’s (1974) prospect theory and Bem’s (1972) self-perception theory. Likewise, Ritov and Baron (1995) conducted several experiments to determine levels of regret due to omission bias. They defined omission bias as the decision maker’s inability to choose an outcome. While both status quo bias and omission bias are highly correlated and will likely result in the same outcomes, Schweitzer (1994) distinguished between the two by illustrating situations in which a decision maker can avoid following the status quo by exhibiting omission bias. Choice deferral, in turn, describes a different context of decision paralysis to the two previous approaches. Choice deferral occurs when decision makers decide not to choose an outcome and postpone their choice-making process (Dhar, 1996). Each approach for decision paralysis involves several factors that influence the likelihood that a decision maker may exhibit decision paralysis. An integrated view is provided
by Huber, Köcher, Vogel, and Meyer (2012) who classify the factors in three types: (1) preference uncertainty, (2) anticipated regret, and (3) evaluation costs.

The decision paralysis literature does not mention how data, information, or representations influence the existence of a status quo bias, omission bias, or choice referral. Nonetheless, when decision makers attempt to use a BI system to obtain a representation, the level of faithfulness of the representation can indirectly impact the likelihood of decision paralysis by affecting two of the direct factors mentioned above: preference uncertainty and evaluation costs. Preference uncertainty occurs when decision makers cannot certainly determine which alternatives best meet their goals (Anderson, 2003). Decision makers have a need to justify their decisions to themselves and others. When decision makers face uncertainties from potential optimal decision alternatives, they will look for alternative approaches to decrease their personal responsibility. One response to the need for certainty is through omission, maintaining the status quo, and delay (Huber et al., 2012). An example of this is the review that the HR manager was conducting about a maternity leave incentive program. She attempted to obtain a representation to assess the performance of the program to decide about its continuity or to provide advice for changes to the program. After several iterations, the BI intermediaries were not able to provide her with a sufficiently faithful representation (omission). According to the HR manager, BIC decided to continue with the program without any evidence of its success or failure (status quo). She also commented that the decisions about the extension of the program and the use of alternative programs were postponed several times (delay). In this example, it can be concluded that the lower the level of faithfulness of the representation relevant to the decision task, the higher the preference uncertainty, and therefore the higher the occurrence of decision paralysis.

The third type of decision paralysis, evaluation costs, offers a different cost perspective on the problem. Evaluation costs include the decision maker’s cognitive effort and time invested on search and analysis of information. According to Huber et al. (2012), these efforts are expenses
that can be considered as opportunity costs. If decision makers consider these efforts to be too costly, they will simplify their choice by selecting the avoidance option. While there was no evidence from the data collected in BIC that this effect occurs, it can be argued that the lower the faithfulness of the representation relevant to the decision task, the higher the perceived evaluation cost, and therefore the higher the occurrence of decision paralysis.

A common practice in the way BI systems were used in BIC was that decision makers and their intermediaries needed to iterate the decision process and had to use the BI system more than once to obtain a representation that supported their decision tasks. As a consequence, the decision process that is involved in building a representation of the phenomena relevant to the decision task is best viewed as an iterative process in which the faithfulness of the representation is continually assessed until the decision maker is comfortable with the level of faithfulness. The number of iterations seemed to be greater when the decision task was supported by an intermediary rather than directly by the decision maker. In particular, the intermediary and decision maker would assess the level of faithfulness before making use of the representation. They would not use a representation with a level of faithfulness that was considered insufficient because of the potential adverse outcomes. Nevertheless, when a certain level of faithfulness was achieved, the representation could be used to support the decision task. Any increment on the level of faithfulness would allow them to make, in the words of one of the participants, more “drastic changes.”

If we’re not confident we don’t use it, that’s why we invest significantly in making sure we are confident. We put some robustness around the development of the reports and understanding the information. We see different things occur by nature, because we’re close to it, we understand and whether that could be wrong or right, so we’ll identify some issues.

(I001-DM)
DSS theories can be transferred to BI to explain how decision makers assess the level of faithfulness and use the BI system representation to support their decision tasks (Clark et al., 2007). In particular, the “3–Gap” framework of DSS proposed by Kayande, De Bruyn, Lilien, Rangaswamy, and van Bruggen (2009) can be applied to this setting. Kayande et al.’s framework aimed at evaluating DSS in organizations. Their rationale is that DSS will be perceived as more valuable if it enables users to internalize the rationale behind the DSS recommendations. Kayande et al. (2009) explain that decision makers must initially conceptualize a problem and create a mental model of the decision environment. The mental model is an individual’s cognitive representation of a domain that supports understanding, reasoning, and prediction. The mental model representation of the task is then based on the decision maker’s previous experiences and current observations, which provide the framework for how that decision maker performs the task (Lim, Ward, & Benbasat, 1997; Wilson & Rutherford, 2016). (Kayande et al., 2009, p. 528).

The 3–Gap framework for DSS comprises the decision maker’s mental model, the DSS model, and the true model of reality (see Figure 6.6). The DSS model is a stylized representation of the real world. Kayande et al. (2009) argue that the accuracy of the DSS model might be assessed by the predictive power of the decision outcomes. This means that the gap between the DSS model and the true model (gap 2 in Figure 6.6) needs to be small for the DSS to provide high-quality decision support. This idea aligns with representation theory (Weber, 1997), which is the theory that informs this thesis’s conceptual framework, interview protocols, and models development. Representation theory argues that the basic function of all information systems is to provide a representation of some real-world phenomena that the system is intended to represent. The higher the faithfulness of the representation of the real-world phenomena, the better the system will be performing what it is intended to do. The foundations of both representation theory and the 3–Gap framework for DSS are based on the concept that IS, and in this particular case DSS, are intended to provide faithful representations of the domain relevant to the DSS.
The main focus of Kayande et al.’s (2009) 3–Gap framework for DSS is on reducing gap 1 via feedback mechanisms that might change the decision maker’s mental model. In particular, the change in the decision maker’s mental model is performed via deep learning. The assumption is that if gap 2 is small, the DSS model is faithful to the true model. Although in this study it is not assumed that gap 2 is small, the 3–Gap framework for DSS allows the conceptualization of the findings described in this section. In particular, the mechanisms proposed by Kayande et al. (2009) are based on the use of the DSS model and the iterations in the use of the DSS to improve the mental model. Likewise, it was found in the BIC case that decision makers and their intermediaries not only learned about the DSS model but also improved their expertise and expert judgment about the decision-task domain (Kahneman & Frederick, 2002). This helped them to evaluate the validity of the DSS model (gap 2). The users interviewed in BIC had used the BI system for almost 18 months. This is sufficient time for participants to have learned about the DSS model and the true model. This case shows that all gaps of the 3–Gap framework for DSS had decreased for most of the BI users. At the beginning of the BI system implementation the uncertainty about the DSS
models (gap 2) and the misconceptions about the true model (gap 3) impacted the BI users and made them more cautious in their decisions. As one intermediary explained:

> With a low level of faithfulness… we’d be a lot more cautious; we’d be making fewer changes, be less likely to make changes – drastic changes. We’d make very small changes here and there. I think with having a high level of faithfulness in the BI system allows us to make more radical changes, but more… what’s the word? Just more courageous changes.

(I001-IM)

Another example of the reduction of the DSS gaps, reported by the decision makers, was where the level of faithfulness was improved over time and superior outcomes were achieved. This was illustrated by one of BIC’s product managers who explained that the support of his decision tasks had been improved by the introduction of the BI system and the chance to build a more faithful representation of the phenomena relevant to the decision task. In the past, it was only possible to obtain a representation that was based on a set of assumptions that the decision maker had to make. Therefore, the improved faithfulness of the representation allowed him to more effectively make pricing decisions that could improve the likelihood of improving BIC’s insurance portfolio profitability. In this instance, a pre-existing representation was used and provided positive outcomes but the improved representation positively impacted outcomes.

> How do you determine which is a [profitable customer] and which is [not]? We use rating factors... Three years ago, it was more difficult for us to determine which was a [profitable customer] and which was [not]… By introducing more rating factors and using BI to analyze the outcomes of those, we were able to improve our understanding of the customers that we insured, and therefore try attract more of the good customers and happy to lose some of the bad customers because we increased their price. (I001-DM)

In summary, the analysis of the data collected in BIC provided support for Proposition 1. It also suggested that a set of thresholds could be established in which changes of the level of
faithfulness have different degrees of impact on the value on the BI system outcomes. In addition, it was observed that an absolutely faithful representation was not required to obtain positive outcomes. In this sense, partially faithful representations provided important outcomes for the decision makers. They were also used by decision makers to learn about the phenomena of interest and improve their understanding of the decision task and as proof of concept to assess potential improvements to the BI system data. These improvements should allow decision makers to obtain more faithful representations of the phenomena relevant to their decision tasks and therefore improved outcomes in the future. These characteristics of the association between these constructs are revisited later in this chapter on the section about the discussion of the findings.

6.6.2 ACCURACY AND COMPLETENESS EFFECT ON FAITHFULNESS OF THE REPRESENTATION

This section presents the results of the analysis for Proposition 2 (P2): BI system accuracy positively affects the faithfulness of the representation of the phenomena relevant to the decision task, and Proposition 3 (P3): BI system completeness positively affects faithfulness of the representation of the phenomena relevant to the decision task. A representation of these propositions is presented in Figure 6.7.
The approach employed during the interviews to evaluate Propositions 2 and 3 was to ask the interviewees to evaluate the level of accuracy and completeness of the BI system. This evaluation was provided in the context of the instance of BI use that the interviewees provided at the beginning of the interview. As mentioned earlier in this chapter, the interview protocol was modified after the first two interviews. During the first two interviews a new factor that affected the level of faithfulness of the representation relevant to the decision task was mentioned—namely, timeliness. While this factor was also mentioned in the exploratory case study at LGA, it was not common among the interviewees. In addition, the literature review detailed in Chapter 3 about BI system use and outcomes research showed timeliness as one of factors that affected adoption and use and outcomes of EIS (Bergeron & Raymond, 1992; Khalil & Elkordy, 2005; Rainer & Watson, 1995a; Salmeron, 2002). EIS are considered the predecessors to BI systems, which were commercialized in the early 1980s. The most current research about BI system use also incorporates timeliness indirectly via the concept of data/information quality (Bischoff et al., 2015; Isik et al., 2013; Popović et al., 2012). As a result, interviewees were asked about the level of
timeliness of the BI system and the way that this factor affected the level of faithfulness of the representation relevant to the decision task (new proposition).

Accuracy, completeness, and timeliness are factors that have been previously used as dimensions of data and information quality. In particular, based on an empirical study about the dimension of data quality, Wang and Strong (1996, pp. 31-32) define the factors as:

**Accuracy:** The extent to which data are correct, reliable, and certified free of error.

**Completeness:** The extent to which data are of sufficient breadth, depth, and scope for the task at hand.

**Timeliness:** The extent to which the age of the data is appropriate for the task at hand.

Decision makers and intermediaries reported that the level of accuracy and completeness of the BI system were relevant to determine the level of the faithfulness of the representation relevant to the decision task. Decision makers mentioned that there were instances where the lack of accuracy of the BI system led to unfaithful representations that could not be used by BIC's decision makers. Decision makers and intermediaries who had worked in BIC during the Decentralized Era (described in Section 6.4) indicated that the BI systems available at that time contained inaccurate data and that the level of faithfulness of the representations obtained was not sufficient. As a result, representations were continuously challenged by BIC’s managers. This had a critical effect on subject areas of the business that had shared interest across BIC’s organizational functions (such as pricing strategies and claims management). Under these circumstances, the discussions about the accuracy of data often constrained decisions that needed to be made. BIC’s BI users mentioned that decision processes were hampered by continuous discussions about the lack of faithfulness of the representations. As a consequence, several decision tasks suffered decision paralysis (as described in the previous section).
According to the decision makers and intermediaries, the new BI system, which was 18 months old at the time of this study, had a high level of accuracy of in its representations. As a result, decision makers were able to obtain representations that were sufficiently faithful to support their decision tasks. Nevertheless, the introduction of the new claims systems made them question the level of accuracy of the BI system. Initially, the process that imported the new claims data into the actuaries’ DW produced inaccuracies. BI users were also not familiar with the claims data that was imported to the DW. As a result, BI users pressured the BI team to improve the accuracy of the BI system data. As the level of accuracy affected the faithfulness of the representations, they were not able to use the representations until the inaccuracies were solved. In addition to the issues with the inaccuracies caused by the new claims systems, there were new semantic changes to the claims data structures that were interpreted as inaccuracies. The BI team had to explain the differences between the old and new claims system data to BI users, so BI users were able to familiarize themselves with the new BI system data structure. The level of BI system data accuracy was adjusted continuously, and BI users were able to learn about the new claims-related measures available in the BI system. The improved data accuracy in the BI system allowed BI users to obtain more faithful representations.

The level of completeness also affected the level of faithfulness of the representations obtained by BIC’s BI users. The actuaries’ DW contained information that permitted users to obtain representations of phenomena relevant to the actuaries’ tasks. As the actuaries’ DW was tailored to be used by actuaries, decision tasks support performed for intermediaries and decision makers from other BIC’s functions were challenged by the lack of faithfulness of the representations obtained in the BI system for their particular tasks. Although the BI system data was considered incomplete, BI users indicated that the representations obtained were critical to the support of the decision tasks, which meant they were used to support their decisions despite the lack of completeness. While the BI system provided only part of the information required, BI users
explained that representations obtained in the BI systems were accessible. Thus, incomplete data was preferable to no data.

We got everything that we could get out of the business intelligence tool, but then we also realized that we needed to use a whole heap of external sources as well, because the business intelligence tool takes an internal focus from our internal system... And it's a big problem with lots of decisions whilst, you know, being more informed and being an informed sceptic in some of the things that you do compared to actually making decisions without data, without information. (D007)

The decision makers and intermediaries who obtained representations in the BI system when the BI system was incomplete could find other information sources and combine representations outside the BI system. In several cases, the representations built outside the BI system were considered to be faithful to the phenomena relevant to the decision task. When BI users were asked whether they would prefer that the completeness of the BI system was improved so they could obtain a more faithful representation directly from the BI system, their answers varied. In particular, for decision tasks in which the final representations were considered sufficiently faithful and the manipulation required was not complex and time-consuming, the decision makers indicated that the cost of improving the completeness of the BI system data would potentially be higher than the benefits of obtaining the same level of faithfulness of the representation directly in the BI system. Nevertheless, most decision makers and intermediaries agreed that improving the completeness of the BI system data was required to obtain more faithful representations and support their tasks more effectively. Their comments provided support for Proposition 3—in particular, for decision tasks in which the lack of completeness hindered the use of BI representations to support their decision tasks. As the initial implementation of BIC’s BI system was based on the existing data structures of the actuaries’ data warehouse, users from areas such as marketing and human resources were expecting that new data sources would be
incorporated in the new enterprise DW to improve the completeness of the BI system. One of the marketing managers explained:

[The] BI team are obviously building as much as they can over a long period of time, taking data from all of our various systems. So, we need to work with them, but there’s obviously some market-facing needs which require additional data from external sources and maybe from some systems that haven’t been delivered yet from the BI team. So, we work closely with the BI team, but we also have to have a bigger, broader lens to ensure we capture all…. (D007)

Other business areas such as claims management and business operations, areas that generally operate in a more rapidly changing environment, have information requirements about the representation needed to support their decision tasks that were a constant challenge for the completeness of the BI system. In this sense, a representation that was considered faithful at one point in time could have its faithfulness reduced by the changes in the way the business operated. As the business processes change over time, the level of faithfulness of the representation might decrease due to the now incomplete BI system. For example, as mentioned above, BIC had decided to make their claims processing more efficient and replaced their claims management system with one that could incorporate the features of the new processes. The changes in the business processes and the changes in the source systems made the BI system data structures incomplete. The BI team worked toward the implementation of new data structures to increase the completeness of the BI system to support all BIC’s business areas. As a consequence, the level of completeness of the BI system was continually being challenged by continuous changes in the operations of the business. BI developers needed to monitor and follow up constant changes to maintain a level of completeness that allowed BI users to obtain representations that are sufficiently faithful to support decision makers. The following is an example of how the level of completeness affected the level
of faithfulness of the representations relevant to the decision task in BIC and how misalignments still exist between decision tasks requirements, BI system data, and representations.

[Level of completeness] is probably now more like 75 or 80 percent. But this is a known, it is low, but we expected it to be because we were building this new system and it was going to generate new reports. We as a business didn’t know what we would want, so we wrote requirements based on what we thought we knew. This is three years ago. The world has changed since then. The way that we do things is different. The information we want is different. But the BI team had to build the reports. They had to put a line in the sand and say, Here are the requirements. We need to now build reports against these requirements. It then took them a year to build those reports and in that year, our requirements kept changing in our minds. So, that by the time they delivered those reports we’ve got 50 or 60 percent of what we need. (D006)

The process described above is consistent with the evolutionary development process that has been central to DSS theory since its inception. Keen’s (1980a) adaptive design framework identifies several loops for evolution that naturally occur in the development of DSS. Evolutionary development theory seems to be transferable to BI systems. For example, it could be possible to determine and study the need for speed or tempo (Arnott, 2004) that might be required for a DW project in BIC or a similar organization.

The level of timeliness of the BI system data seemed to be only relevant for decision tasks that were time–dependent. Only decision makers from operational areas such as claims management mentioned the level of timeliness of the BI system data as an important factor that affected the faithfulness of the representation that was relevant to their decision tasks. That was also the situation for intermediaries that needed an integrated representation with data imported from different sources. They complained that the timeliness of both datasets was not consistent and that the resultant representation was not completely faithful. They were unsure about the
outcomes of decisions made using those representations. Thus, timeliness is a secondary factor that affects the faithfulness of the representation relevant to the decision task. The context of BI use and the level of time specificity of the decision tasks are factors that influence the effect of timeliness in both models of BI system use and outcomes.

In summary, the analysis of the interviews provided support for Propositions 2 and 3 and varied support for timeliness. It was also found that the BIC’s decision makers did not require the BI system data to be totally complete and accurate. A relatively high level of accuracy in comparison with the required level of completeness was considered critical for trusting the representation, and consequently, making use of the BI system to support their decision tasks. Accuracy and completeness were found to have a positive relationship with the faithfulness of the representation. However, BI users and decision makers were more demanding with accuracy than with completeness and unforgiving of inaccuracy. Although this finding varied across the decisions supported, all BI users interviewed in the case agreed that improving the level of completeness would provide them with a more faithful representation of the phenomena relevant to the decision task. The BI system would then be able to support their decisions in a more effective manner.

6.6.3 Understanding of the Decision Task

This section presents the results of the analysis for Proposition 4d: Decision maker’s understanding of the decision task moderates $P_1$, and for Proposition 4i: Decision-maker’s and intermediary’s shared understanding of the decision task moderates $P_1$. Figure 6.8 shows a representation of these propositions.
The approach employed during the interviews to evaluate Propositions 4d and 4i was to ask the decision makers who used the BI system directly about the level of understanding of the decision task they had at the time of using the BI system and how that level impacted on the outcomes of using the BI system. For the matched pairs of intermediaries and decision makers, it was decided to first interview the decision maker and use the decision tasks described for the interviews with their corresponding intermediary. Similarly, the question about the level of shared understanding of the decision tasks was to first ask the decision maker and later question the intermediary.

As a result of the findings of the exploratory case study, it was proposed that Propositions 4d and 4i had moderating effects on the level of faithfulness of the representation relevant to the decision task and the value of the outcomes obtained using the representation. It was proposed that the decision-maker’s level of understanding of the decision task and the level of shared understanding of the decision task between the decision maker and the intermediary could potentially strengthen, reduce, or change the direction of the relationship between faithfulness and the value of the outcomes. The analysis of the follow-up case study interviews suggests that the level of understanding of the decision task does moderate the relationship between the faithfulness of the representation and the outcomes of using the BI system to support the decision task. During the interviews, direct users explained how their understanding of the task enabled them to use the BI system effectively and how a lack of understanding might lead to negative outcomes:
I think there’s an element of danger unless you are a person who knows what they’re doing in trying to build a report. It can give you information and outcomes that aren’t reflective of what you’re looking for. It can be misleading information because of the parameters you put in. (I001-DM)

In a similar manner, indirect users and their intermediaries recognized that an adequate level of shared understanding was required to obtain positive outcomes given that the BI system provided them with faithful representations relevant to their decision task. For example, one of the indirect users who was interviewed explained that they discussed the requirements of the tasks with the intermediary and other managers involved in the decision task in an iterative manner. In this case, the intermediary attended meetings and was informed not only about the structure of the representation required but also about the purpose of the decision task and the general business agenda and strategy. The intermediary, therefore, was involved from the early stages of the decision-making processes, thereby allowing him “to provide more relevant data” (I002-DM). The decision maker also required the intermediary to provide an interpretation of the representation. The interpretation not only focused on the validation of faithfulness of the representation but also the surrounding factors that might had influenced the values in the representation. The intermediary had to investigate and explain the representation to the decision maker and others in meetings. On other occasions, the decision maker provided the intermediary with insights about why the representation contained certain values and its meaning to the business. The decision maker would share insights about business strategy and plans that were relevant for a future iteration of the representations built by the intermediary.

Another important aspect of the understanding of the decision tasks is the level of familiarity that the decision maker had with the decision task at a point in time. One direct user explained that because he was new in his position as general manager of one of BIC’s branches he could not obtain significant outcomes from the use of the BI system. His use of the BI system
provided him with a new level of understanding of the decision task. However, no decision was supported by his use of the BI system. When confronting a similar decision task, the decision maker expected that his previous experience and improved understanding of the decision tasks could facilitate obtaining positive outcomes from the use of the BI system.

"Part of the challenge with [the use of the BI system] was that insurance rankings are something relatively new to me. I was learning as I went along. Working out, what do I actually need to help make these decisions? It becomes even more iterative in that you don’t really know what you need when you start the task." (D003)

The analysis of the interview data about the shared understanding of the decision task revealed that BIC had different types of intermediaries. One important factor that contributed to explaining the different levels of shared understanding was whether the intermediary reported directly to the decision maker or supported the decision maker from the centralized BIC BI team. Intermediaries that reported directly to a decision maker could more precisely determine the requirements of the representation. In this scenario, a more personal-DSS like-approach was employed (Keen, 1980a) in which an individual developer (intermediary) builds a model (representation) to support a decision maker. The intermediaries that reported directly to decision makers did not have access to change the BI system data structures and struggled with the rigid BIC’s information governance. However, they seemed to better understand the purpose of the required representation and the managers’ mindset, objectives, and agendas.

An IS theory that helps to explain the different type of intermediaries and their interactions with the decision makers and the BI system is information specificity. Information specificity is a theory developed by Choudhury and Sampler (1997) that aims to explain how organizations can and should allocate their environmental scanning resources. It provides guidance about whether organizations should outsource their environmental scanning efforts and who can effectively acquire and use information in organization. The concept of information specificity describes the
conditions for determining whether the acquisition and use of information for a particular decision task can be delegated. The main argument of information specificity is that under different conditions and require minimum levels of information specificity, the delegation of the acquisition of the information can be more cost-effective and produce better outcomes than the non-delegated form and vice versa.

The concept of information specificity has two dimensions: knowledge specificity and time specificity. Individuals engaged in information acquisition and use must initially conceptualize a problem and create a mental model of the decision environment (Kayande et al., 2009). Based on this mental model, individuals must determine which information should be acquired for a particular decision. This process is influenced by an individual's familiarity with the problem and their knowledge base. The minimum level required to perform the information acquisition and use determines how specific is the knowledge that is required. For example, a manager may need a certain set of experience and knowledge to understand information from a report, dashboard, email, or conversation. They may also need specific knowledge to even perceive that a particular decision or set of information exists. This is knowledge specificity.

Information can also be specific with respect to time. Information that is high in time specificity must be acquired and used very shortly after it is available. This means that information can quickly lose its value if is not used immediately. Table 6.4 presents a 2 x 2 matrix proposed by Choudhury and Sampler (1997) that shows the various states of information specificity using the concepts of time and knowledge specificity in both information acquisition and use.
Choundury and Sampler (1997) do not explicitly indicate the type of systems for which information specificity might be relevant. Instead, they focus broadly in environmental scanning tasks. Nevertheless, information specificity has been found relevant to DSS. In particular, Iivari, Hirschheim, and Klein (2004) consider that knowledge specificity concerns the alignment of a particular DSS and its organizational context, and time specificity imposes requirements on the speed of the DSS. While information specificity has been mainly used in research aimed to determine the efficiency and effectiveness of outsourcing environmental scanning tasks (for example, Dibbern, Winkler, & Heinzl, 2008; Schemm & Legner, 2008), the concept of information specificity is relevant to DSS and BI. For example, decision tasks that are supported by the use of BI systems might require general knowledge in acquisition, and the decision maker can therefore delegate information sourcing to a subordinate or an enterprise BI system. In a similar manner, time specificity can explain why the acquisition of the information cannot be delegated and must be performed by a decision maker. Information specificity theory can be used to understand the broad variety of decision tasks that a BI system aims to support. They may have different time and knowledge specific requirements, and this may explain why it is difficult for a single BI system to support many managers. Iivari et al. (2004) found that knowledge specificity affects the alignment of a particular DSS and its organizational context and that time specificity imposes requirements on the speed of DSS development and operation.

Information specificity provides explanations of the types of intermediaries and the different patterns of BI indirect use. One decision maker and his intermediary reported having a
fluid relationship where conversations about how to use the representation and make decisions were frequent between the decision maker and intermediary. Both the decision maker and intermediary expected to share specific knowledge in use. Although the intermediary had a greater level of knowledge in acquisition than the decision maker, the decision maker was expected to understand what representations available in the BI system. The close relationship between the two individuals facilitated shared understanding, and therefore valuable outcomes were generally obtained.

The second type of intermediary were members of the BI team who had the role of modifying ETL processes and changing the BI data structures. These intermediaries had a more technical approach to BI than the intermediaries that reported directly to decision makers. Acting as direct intermediaries was not their main activity. They identified themselves more as system developers gathering requirements than decision-support providers. Their main focus was to identify issues with data marts. An example was the support of BIC’s valuation actuary. In this case, the intermediary could change the ETL process and recreate a set of data marts that were used by the actuaries to support their analytics tasks. The intermediary exhibited a sufficient level of understanding of the actuary’s decision. However, their responses about the value of the outcomes of BI system use differed. The intermediary described the outcomes in a functional manner as the provision of “an automated and centralized repository of information. one shop!” (I003-IM). In contrast, the actuary indicated that the outcomes of the use the BI system was the influence on the formulation of the strategy of the company and its overall value in the market. Although this use of the BI system presents a different pattern of use from the previous type of intermediary, the superior level of complexity on the acquisition of the representation and the frequency in which the information requirements evolved required an intermediary with technical knowledge to manipulate data with complex queries and not a more business-oriented analyst. In this instance, the intermediary did not exhibit a high level of knowledge in use, and the decision maker did not
exhibit a high level of knowledge in acquisition. A more service-oriented approach was employed. This means that all tasks performed by the intermediary were reported and scheduled (as is the case in more traditional IT development).

The third type of intermediary comprised members of the BI team whose main role was to support specific groups of decision makers. While these intermediaries reported to the BIC’s Senior Manager of BI, they worked directly with business users. They were allocated to support specific business areas that required the intermediary to have specific knowledge and understanding of the business area activities. For example, a group of three BI analysts supported human resources managers. The existing actuaries’ DW provided no relevant data for the human resources managers whose decision tasks concerned remuneration and career development. As the approach implemented by the Senior Manager of BI was to consolidate the BI resources into one centralized group of analysts and developers, the BI analysts appointed to support functional areas (such as human resources, marketing, and business development) were asked to gather requirements and create functional prototypes. This proved to be a challenging process in BIC. Decision makers recognized their lack of specific knowledge in acquisition. The lack of clarity about the requirements of the representations needed to support their decision tasks impacted the delivery of useful representations. The following are extracts of both the decision maker and intermediary in an instance of human resources tasks:

*I don’t think that anybody knew what was going on, so I don’t think, looking back, that I was particularly clear because it sounded like such an easy thing to do, I wasn’t aware of the complexities for the reporting teams…* (ID007-DM)

The intermediaries that supported these decision tasks indicated that the continuous changes in requirements impacted on the delivery of representations to support human resources managers.
Requirements weren’t clear from the beginning because it changed over time. We thought we had a clear understanding of what was required but then over time that changed. I think we asked the right questions, I think there was a level of disorganization from the decision maker’s end in not understanding what they required. (I007-IM)

As previously mentioned, the intermediaries and decision makers were required to iterate several times when engaging in the use of the BI system to support a decision task. For some decision tasks, BIC managers reported that after several iterations over a period of four months they were still unable to obtain a faithful representation relevant to their decision tasks. However, they also reported that the shared understanding of the task improved after each iteration, which helped with the delivery of other representations. One of the intermediaries suggested that the iteration between the intermediary and the decision maker was a “necessary approach” to be able to successfully deliver a faithful representation for the decision task to be supported, but it seemed to be only possible when time pressure was low. When the requested representation had to be delivered under time pressure, the requirements were difficult to interpret. Moreover, the decision maker had difficulty interpreting the representations obtained in the BI system.

In summary, the analysis of the data collected in the case provided support for Propositions 4d and 4i. Both understanding of the decision task in the case of the direct model and shared understanding of the decision task in the indirect model were considered critical to obtaining valuable outcomes. However, the indirect model identified and described patterns of use that were not covered by the direct model. In particular, a distinction needs to be included in the models for acquisition and interpretation of the representation. When the acquisition of the representation is delegated, the intermediary needs to understand the decision tasks via interactions with the decision maker. The intermediary also needs to have knowledge in acquisition of the BI data. While in the direct and indirect models the decision maker needs to interpret the representation in order to obtain outcomes of the use of the BI system, in the indirect model the intermediary can play the
role of advisor and explain the results and actively participate in the decision-making process. It was observed that different levels of delegation of acquisition and interpretation were in place and different types of intermediaries coexisted in BIC. This clarification of the constructs is revisited later in this chapter where the models are refined to include these findings.

### 6.6.4 Interface Capabilities

This section presents the results of the analysis for Proposition 5 ($P_5$): BI system interface capabilities moderate $P_1$. Figure 6.9 presents a representation of this proposition.

![Figure 6.9 Proposition 5](image)

All participants in the case study were asked about under what conditions the BI system interface capabilities influenced the value of BI system outcomes. In the case of the direct model, decision makers had to access the system and obtain representations. Their responses about interface capabilities concerned access to the representation, manipulating the format of the representation, and facilitating the interpretation of the representation. In questioning about the indirect model, intermediaries had similar responses to direct model of BI system use and outcomes and added interface capabilities that facilitated the communication of representations to the decision makers they supported. Decision makers under the indirect model related their answers to the different visualizations of the representations that they received via the intermediary’s use of the BI system. Analyzing the BIC interview data, it was clear that the BI system interface capabilities affected not only the association proposed in Proposition 1 but also the level of

Faithfulness of the Representation of the Phenomena Relevant to the Decision Task

$P_1$

+ $P_5$

Value of BI System Outcomes

BI System Interface Capabilities
faithfulness of the representation relevant to the decision task. The findings indicate that BI system interface capabilities affect two distinct steps, namely acquisition and use of the BI system representation, in the process of using the BI system. The following are two examples of direct users indicating that the interface will have an effect on the level of faithfulness of the representation:

If [the interface] is clunky and it's confusing, people may pull out the wrong information, which happens often. So, the quality of the interface, the quality of how the data's arranged, makes it easier for an end user to use and therefore makes the take up rate a lot higher.…

(D005)

The easier that is to access it and the more intuitive it is, so the more self-explanatory, you know, that interface is, the more like that people like me will use it to self-serve their reporting needs and, therefore, the more likely they are to understand what they're after.…

(D006)

Although several participants agreed with the proposition that the BI system interface moderated the relationship between the level of faithfulness of the representation and the value of BI system outcomes, they rated it as less critical than the understanding of the task and the level of faithfulness itself. In the interviews, the participants changed the topic several times to discuss issues with the representation faithfulness or a lack of understanding of the decision task. One of the factors mentioned by several interviewees that affected the level of agreement with Proposition 5 was the level of discretion with their use of the BI system. All users who accessed the BI system, both intermediaries and decision makers, felt a certain level of involuntariness in their use of the system. As a result, their level of discretion with system use was low. Intermediaries felt that their job depended on their adequate use of the BI system; therefore, they considered that their use of the BI system was compulsory. Although decision makers that used the BI system directly did not show the same level of obligation to use the system, they indicated that without it they could not
do their job properly. This is an important finding in the case because it has been largely sustained in the DSS literature that the potential users of a DSS can freely choose whether or not they actually use the system (Arnott, 2004; Keen, 1980a). In all cases, intermediaries that were using a BI system on behalf of a more senior manager had no discretion in their system use. Once information was provided by intermediaries, the decision makers did have some discretion in how they used the BI system output. This finding is opposed to the existing notion about the discretionary nature of DSS (Silver, 1990) and BI system (Popović et al., 2012) use.

The low level of discretionary use exhibited in BIC also influenced answers about the level of importance that an easy-to-use BI system interface could have for Proposition 5. As users felt their use of the system was not discretionary, they indicated that it was important for them to be familiar with the interface rather than relying on a sufficient level of BI interface capabilities. As several of these users spent a significant proportion of their day looking at data from the BI system, they felt that its lack of responsiveness with specific tasks impeded their ability to obtain outcomes. One direct user complained about the BI interface:

I think just speed of access. So Futrix is absolutely fantastic but depending on the report if it's a spark report, you can sit with the, we're all going and go and make a coffee, have a cigarette, come back and drink another coffee and it will still be going and then it's there. Because there's tons of stuff behind there, I don't understand what's in there. Lots of people don't understand what's in there but they expect you know, click, click, click, where's my report? (D004)

The responsiveness of the interface seemed to be an important factor for delegation of the use of the BI systems. Two direct users recognized they expected the BI system to be highly responsive. They suggested that they would call the BI team or they would send a request to one of the intermediaries that work for them or ask other decision makers if the BI system did not retrieve the representation instantly.
Finally, several users complained that the BI system interface did not allow them to manipulate the BI system representations. Therefore, they had to export data into MS Excel to adjust the data structure to build a faithful representation relevant to the decision task supported. As mentioned earlier in this chapter, BIC had pushed an information management and governance strategy that limited the creation of new metrics that were not validated by the information governance managers. To avoid having several “versions of the truth,” the BI system interface had its functions to create new categorizations and calculations disabled. This policy seemed to be ineffective because users found ways to export the data, change the structure, and build their own representations outside the BI system. While they continued using the BI system to support the task, they could not complete the needed decision support processes within the BI system.

In summary, in the BIC case study, BI system interface capabilities had a moderating effect on the relationship between the level of faithfulness relevant to the decision tasks and the value of BI system outcomes. Two different processes of influence on the faithfulness of the representation and the value of outcomes were described. The first process was the manipulation of the representation, which consisted of the BI system interface capabilities that allowed users to include or exclude categories and measures in the representation. The second process was the BI system interface capabilities that permitted users to have an effective and efficient interaction with the systems. This means that the interface needed to be responsive enough to maintain effective interaction with the BI system. Finally, different levels of familiarity and frequency of use can mitigate the negative issues with arising from unintuitive interfaces. BI users seem to find alternatives when the BI system interface capabilities are low. They will export representations to be manipulated in other PDSS such as MS Excel.
6.7 Prescriptive Insights Arising from the Case Study

This section presents two prescriptive insights arising from this follow-up case study: (1) decision-task characteristics and their impact on the BI system use and outcomes models, and (2) thresholds for level of faithfulness of the representation and value of BI systems outcomes.

6.7.1 Decision-Task Characteristics and Their Impact on the BI System Use and Outcomes Models

Another important insight that arose from the analysis of this follow-up case study data was the variety of relevant factors across the different decision tasks the participants provided. The characteristics of the decision tasks varied in terms of their urgency, frequency, and complexity. These characteristics impacted users’ perceptions of the factors that were relevant in both models of BI system use and outcomes.

The most noteworthy difference in the models was associated with how the timeliness of the BI system’s data influences the faithfulness of the representation relevant to the decision task. When participants perceived that their decision tasks had a significant level of urgency, the level of timeliness was deemed to be an important factor affecting the level of faithfulness of the representation relevant to the decision tasks. In a similar manner, frequent decision tasks, such as daily operational decisions, required timely BI system data. For example, BIC managers complained that at the beginning of the BI project, the data warehouse was updated only once a month. The improvements in the timeliness of the BI system data allowed them to obtain more faithful representations relevant to their decision tasks. Nevertheless, it was also found in the case study that timeless of the BI system data was not considered as relevant as the other two factors—namely, accuracy and completeness of the BI system data. In contrast to the previous example, participants described decision tasks that they performed once a month or year. While the BI system data needs to be timely to support decision tasks with different levels of frequency, the relevance of the
timeliness construct seems to be not as important for low-frequency decisions compared to
decision tasks related to day-to-day business operations.

Another insight that arose from the analysis was related to the level of completeness of the
BI system data. While all participants indicated that completeness impacted the level of faithfulness
of the representation relevant to the decision tasks, the importance of achieving high levels of
completeness differed across decision tasks. In particular, decision makers from the area of
Marketing mentioned that more complete BI system data would allow them to obtain more faithful
representations of the phenomena relevant to their decision tasks. Nonetheless, they understood
the challenges of completing and integrating the needed data because most of required data for the
representation relevant to the decision tasks was external to the organization. In contrast, finance
managers mentioned that for them the BI system data was sufficiently complete, because all the
data they needed was already contained in their internal financial systems. Hence, the characteristics
of the decision task supported by the BI system impact the perception and potential levels of
completeness in both models of BI system use and outcomes.

Finally, the analysis showed that some decision tasks were considered more complex than
others because they would pose challenges in acquiring a faithful representation and interpreting
the representation. Information specificity helps to explain why parts of the decision-task processes
were delegated to an intermediary. It was noticed during the case that the decision tasks mentioned
by the participants in BIC varied in their level of complexity. Several decision tasks were initiated
by questions and hypotheses about issues and opportunities in BIC’s businesses. Answering these
questions presented different challenges in the acquisition and use of the representations. This
resulted in a need for a clarification of the moderating constructs to distinguish between the
different effects on the acquisition and use of the information accessible via the representations on
the BI system. In particular, when the use of BI system is delegated by the decision maker to an
intermediary, the decision-maker’s level of understanding of the decision task needs to be explained
to the intermediary, but the decision maker does not need to have an understanding of the way the representation will be acquired. Moreover, the lack of understanding of the representation acquisition could be the principal reason for decision makers to delegate their access to intermediaries who understand the decision-tasks’ acquisition challenges. A similar example can be given for the BI interface capabilities. Certain BI interface capabilities facilitate the acquisition of the representation relevant to the decision task, and others facilitate the interpretation of the representation. Consequently, this case study provides a better understanding on how the moderating factors affect the different processes that involve supporting decision using a BI system. This is even more salient for the indirect model, in which different individuals are involved in different parts of the decision support process.

### 6.7.2 Thresholds for the Level of Faithfulness of the Representation and Value of BI Systems Outcomes

One of the assumptions of the models evaluated in this follow-up case study was that the association between the faithfulness of the representation of the phenomena relevant to the decision task and the value of BI system’s outcomes was linear. The data collected in this follow-up case study strongly suggest that the association does not follow a linear pattern but a logistic one, with an expected shape of a sigmoid curve (see Figure 6.10). This is an important finding because it suggests that improvements in faithfulness will have different impacts on the value of BI system outcomes (based on the initial level of faithfulness). Hence, when the level of faithfulness is considered sufficiently high, improvements in faithfulness will not offer significant improvements on the value of BI system outcomes. The opposite occurs when the level of faithfulness is initially low and is significantly improved. In this later case, the increase in value of BI system outcomes will also be significant.

One of the important consequences of this finding is that different thresholds could be potentially identified in the support of a decision task. There could be a situation where it is not
efficient and effective to improve the level of faithfulness because the return of the investment will be insignificant. The traditional economic principle that “more is better” will not apply to these situations. A substitution effect is more likely to occur if other decision tasks need support in which an improvement of the faithfulness has a more significant increase in the value of the BI outcomes.
Figure 6.10 Nature of the Relationship between Faithfulness of the Representation of the Phenomena Relevant to the Decision Task and Value of BI System Outcomes

Proposition 1
Faithfulness of the Representation of the Phenomena Relevant to the Decision Task positively impacts the value of BI System Outcomes.

- **Useless Representation Scenario**: Below the lower threshold, there are negative or no-outcomes.
- **Deficiently Useful Representation Scenario**: Improvements in faithfulness have significant impacts on outcomes.
- **Efficiently Useful Representation Scenario**: Beyond the upper threshold is not worthwhile to improve faithfulness.
- **Misrepresentation Scenario**: Negative outcomes.
The first refinement required for the models is to clarify the nature of the existing relationship between the level of faithfulness of the representation relevant to the decision task and the value of the outcomes. Proposition 1 is present in both the direct and indirect models of BI systems use and outcomes. It is the focal association in the models. It states that improvements in the level of faithfulness of the representation will improve the value of BI system outcomes. However, the follow-up case study results suggest that BI users were somewhat indifferent about improvements in the level of faithfulness of the representation relevant for their decision. This was when the BI user perceived that the level of faithfulness of the representation was sufficient to support the decision.

These differing impacts of the level of faithfulness were also found for the opposite scenario. In particular, BI users indicated that under a certain level of faithfulness of the representation they would not trust it. If they were to use it, negative BI system outcomes would be obtained. Until a sufficient level of faithfulness was achieved, they indicated that no BI systems outcomes could be obtained. As a result, a sigmoid function is proposed where the improvement of the value of the outcomes starts slowly, then increases rapidly, and finally levels off. A lower and an upper threshold were devised. Figure 6.10 shows the four possible scenarios.

Figure 6.10 has two identifiable thresholds that are represented by dashed lines. For representations in which the level of faithfulness is below the lower threshold, the value of BI system outcomes is negative (or no value is obtained). Above the lower threshold, the representation provides positive value of BI system outcomes. Each improvement in the faithfulness of the representation has a significant positive impact on the value of BI system outcomes. This trend starts to exhibit a decreasing return of scale as it approaches the upper threshold. Above the upper threshold, changes in the level of faithfulness of the representation have a minor impact on the value of BI system outcomes. BI users in this case might decide to
suspend any efforts to improve the level of faithfulness of the representation. Consequently, four different scenarios have been identified:

1. Efficient useful representation scenario – above upper threshold: This scenario occurs when the level of faithfulness of the representation is above the upper threshold. Improvements in the level of faithfulness do not offer significant positive improvements to the value of BI system outcomes.

2. Deficient useful representation scenario – between lower and upper threshold: This scenario occurs when the level of faithfulness of the representation is above the lower threshold and below the upper threshold. Improvements in the level of faithfulness in this scenario strongly impact the value of BI system outcomes.

3. Useless representation scenario – below the lower threshold: This scenario occurs when the level of faithfulness is positive and below the lower threshold. The value of BI system outcomes is negative or there are no outcomes. If the representation is used, negative value BI system outcomes will be obtained. If the representation is not used, no value of BI system outcome will be obtained.

4. Misrepresentation scenario: This scenario occurs when the level of faithfulness is negative. Only a negative value of BI system use can be obtained if the representation is used.

The clarification of the means by which the level of faithfulness of the representation affects the value of BI systems outcomes is a significant finding of this study. First, it means that there is no need to achieve a high level of faithfulness to start using the BI system effectively to support a task. The implication of the upper threshold for BI users and developers is that it will be sufficient and sometimes more efficient to improve the level of faithfulness of the representation until the upper threshold has been achieved. For decision tasks where the level of faithfulness of
the representation is slightly above the lower threshold, the value of BI system outcomes can be substantially improved by each unit of improvement in the level of faithfulness of the representation. Finally, representations that present a level of faithfulness below the lower threshold should be avoided because negative value of BI system outcomes will be obtained if there are used to support decisions. Improvements in the level of faithfulness of representations that are below the lower threshold will have no apparent effect on the value of BI system outcomes until the lower threshold has been surpassed.

The above reflection on the nature of the relationship between these two constructs assumes that use of BI systems is iterative. This means that BI users can access the BI system several times to improve the representation obtained and that BI developers who maintain the system’s data structures can also affect the potential level of faithfulness of several representations that support decision tasks. If these interventions are not possible due to constraints of the BI interface or lack of flexibility of BI developers, the clarification of the nature of the relationship between faithfulness of the representation of the phenomena relevant to the decision task and value of BI system outcomes can be used to assess the level of usefulness of the representations.

At a higher level, this clarification can also be used by enterprise BI teams to identify under-supported areas across the organization. Rather than focusing on subject areas in which representations obtained in the BI system are generally close to the upper threshold, enterprise BI teams can identify subject areas in which the returns on investment by achieving higher levels of faithfulness have a significant impact on the decision makers and the value of BI system outcomes. It was observed in both case studies that the enterprise BI teams tend to focus on areas in which the underlying data used for their enterprise data warehouses presented high levels of completeness and accuracy. This new conceptualization can help enterprise BI team managers to build a business case to improve the level of accuracy and completeness of the data that is needed to support under-supported subject areas.
6.8 CONCLUSION

This chapter has discussed the evaluation of the models of BI system use and outcomes proposed in Chapter 5. A follow-up case study conducted in a big insurance company (BIC) has shown that most of the propositions derived from these models are supported. New insights gained during the follow-up case study provide a basis for refining the models of BI system use and outcomes. This chapter has also provided insights about the nature of BI use and its outcomes. The sigmoid curve presented in Figure 6.10 is an important insight that provides clarification about the nature of the focal relationship of the models. The four scenarios described can also be used by organizations and their BI teams to evaluate their decision support practices and to focus on decision tasks that are under supported. Finally, several classifications were given that will facilitate refinement of the models. The final models are discussed in the next chapter.
Chapter 7 – Refinement of the Models

Chapter Overview

This chapter presents the final models of BI system use and outcomes of this research project. The initial models are refined and adapted to include the insights gained during the previous exploratory and confirmatory research phases. The refinement of the models also employs transferable IS, DSS and BI theories and models that help to explain the phenomena of BI system use and outcomes.

Background Study

Critical Analysis of the “BI utilization problem”: BI industry consultant and vendor’s views on the extent in which BI systems are used by organisations

Literature Review & Conceptual Framework

Analysis of the existing BI (including its predecessors) use and outcomes literature. Review of the existing IS use and outcomes theories. Development of conceptual framework

Exploratory Case Study

Analysis of how individuals use BI systems in a large government organization (LGA), and the outcomes obtained by their use

Initial Models Development

Design of direct and indirect BI system use and outcomes models

Follow-up Case Study

Evaluation of the proposed BI system use and outcomes modes in a big insurance company (BIC). Refinement of constructs and associations

Final Models of Direct and Indirect Use of BI Systems

Reflection on research findings and definition of final models
Chapter 7 – Refinement of the Models

7.1 Overview

This chapter presents the final models of this research project. The final models are the end product and the final step of the project. As Chapter 1 indicates, the aim of this research was “to develop models that explain BI systems use and outcomes.” The final models are the product of two consecutive empirical phases. Extant theories and models of IS, DSS, and BI use and outcomes were reviewed before and after each empirical phase to compare the insights gained with potential transferable theories. Enfolding the literature in this way allows a researcher to improve the validity of models (Eisenhardt, 1989) and therefore improves the models of this research. The following sections describe the final models of BI system use and outcomes.

7.2 Models Development Process

The development of the models of BI system use and outcomes described in this chapter was motivated by the results of a background study about the “BI utilization problem.” The background study identified a lack of models in the literature that explained the nature of BI system use and outcomes in organizations. The models’ development process was initiated by proposing a conceptual framework based on the existing IS literature, followed by an exploratory case study. The end product was the articulation of two initial models of BI system use and outcomes. Subsequently, a follow-up case study was conducted where the models were evaluated and refined. This section summarizes the development process of the previous stages.

Conceptual Framework Development: The aim of this stage was to develop a framework to be used as research lens and scope during the exploratory case study. To build the framework, definitions of BI systems and BI users were first collected and analyzed from the existing BI literature. The existing literature about BI system use and outcomes was gathered and analyzed in terms of the different constructs and associations employed not only for BI research but also its DSS predecessors. IS theories about use and outcomes were also collected and analyzed. In
Chapter 7 – Refinement of the Models

particular, the conceptual framework draws on the following three IS models and concepts: (1) Goodhue and Thompson’s (1995) task-to-performance chain and their concept of task-technology fit; (2) representation theory and the concept of faithfulness of the representation (Weber, 1997); and (3) Burton-Jones & Straub’s (2006) reconceptualization of system use. Figure 7.1 shows a diagram of the conceptual framework before the first empirical study.

Figure 7.1 Conceptual Framework - BI Systems Use and Outcomes

Exploratory Case Study: The first empirical study of this research aimed to explore the nature of BI system use and outcomes in practice. The conceptual framework guided the development of the semi-structured interview protocol used to interview twenty-five participants who were direct users of a BI system in a large government organization. The understanding of the phenomena of BI system use and outcomes was built via analysis of BI systems users’ views about the ways in which BI systems were used and the outcomes obtained from their use. The study also examined alternative patterns of BI system use and refined prior conceptualizations of BI systems outcomes through the identification of different outcomes measures. The insights gained during the exploratory case study were the foundations for the development of the initial models of BI system use and outcomes.
As a result of the understanding gained during the exploratory case study, two models of BI system use and outcomes were proposed. The analysis of the exploratory case study data indicated that two patterns of BI system use, a direct and an indirect method of use, coexisted in the studied organization. The patterns of use were able to coexist in an efficient and effective manner depending on the context of the supported decision task.

The approach employed to articulate the initial models of BI system use and outcomes was Weber’s (2012) framework about the components of theory. Weber’s framework defines constructs as attributes of classes of things and associations as relationships between constructs. As a result, seven constructs were proposed that described four classes of things: (1) a given BI system, (2) a given decision task, (3) a given decision maker, and (4) a given intermediary. More specifically, the constructs comprised: (1) BI system accuracy, (2) BI system completeness, (3) faithfulness of the representation of the phenomena relevant to the decision task, (4) decision maker’s decision-task understanding, (5) intermediary and decision-maker’s shared decision-task understanding, (6) BI System interface capabilities, and (7) value of BI system outcomes. The initial two models proposed a total of six associations in the form of research propositions. Four associations were common to both models, and one association and construct were adapted for each model because of the inclusion of the intermediary in the indirect model. The main association proposed was between faithfulness of the representation of the phenomena relevant to the decision task and the value of BI system outcomes. Two associations moderating the main association were proposed for decision-task understanding and BI system interface capabilities constructs. Finally, BI system accuracy and BI system completeness were associated directly with the faithfulness of the representation of the phenomena relevant to the decision task. Figures 7.2 and 7.3 show the initial models of BI system use and outcomes presented in Chapter 5. Chapter 5 detailed the development of the propositions of the two models of BI system use and outcomes.
Figure 7.2 Direct Use of a Business Intelligence System - Initial Model

Propositions

P1: The Faithfulness of the Representation of the Phenomena Relevant to the Decision Task positively affects the value of BI System’s Outcomes

P2: BI System’s Accuracy positively affects the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task

P3: BI System’s Completeness positively affects the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task

P4d: Decision Maker’s Understanding of the Decision Task moderates P3

P5: BI System Interface Capabilities moderates P3
**Figure 7.3 Indirect Use of a Business Intelligence System – Initial Model**

**Propositions**

- **P₁**: The Faithfulness of the Representation of the Phenomena Relevant to the Decision Task positively affects the value of BI System’s Outcomes
- **P₂**: BI System Accuracy positively affects the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task
- **P₃**: BI System Completeness positively affects the Faithfulness of the Representation of the Phenomena Relevant to the Decision Task
- **P₄ᵢ**: Decision Maker’s & Intermediary’s Shared Understanding of the Decision Task moderates P₃
- **P₅**: BI System Interface Capabilities moderates P₃
Follow-up Case Study: While the exploratory case study was the major breakthrough of this project, the follow-up case study was the largest empirical study in this project. To conduct this case study, a site was required where participants used their BI system not only directly but also via an intermediary. A novel approach was employed to evaluate the indirect model of BI system use and outcomes. Twenty-five participants were interviewed during the follow-up case study. For the indirect model, matched pairs of decision makers and their intermediaries were recruited. Participants included three BI managers, seven decision makers who used the BI system directly, and eight pairs of decision makers and their intermediaries (one decision maker was matched with two intermediaries). The following section describes the refinements to the models of BI system use and outcomes that arose from the insights gained during the follow-up case study presented in Chapter 6.

7.3 Refinements to the Models

This section presents the proposed changes to the models of BI system use and outcomes based on the understanding gained about the phenomena of BI system use and outcomes during the follow-up case study. The understanding of the phenomena of BI system use and outcomes gained during the follow-up case study generally confirmed the propositions of the proposed models as described in Table 7.1. Three insights from the follow-up case study are the foundation for the refinement of the two models of BI system use and outcomes.
Table 7.1 BI Systems Direct and Indirect Models’ Propositions – Follow-up Case Study

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<tr>
<td>P2</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>P3</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>NP</td>
<td>m*</td>
<td>m*</td>
</tr>
<tr>
<td>P4i</td>
<td>na</td>
<td>✓</td>
</tr>
<tr>
<td>P4d</td>
<td>✓</td>
<td>na</td>
</tr>
<tr>
<td>P5</td>
<td>m*</td>
<td>m*</td>
</tr>
</tbody>
</table>

= supported; m = mixed responses; na = Not Applicable; * = task-dependent

The first insight concerns the factors that influence the level of faithfulness of the representation relevant to the decision task. The first consideration for the models is that the BI system data completeness and its effect on the faithfulness of the representation of the phenomena relevant to the decision task (Proposition 3) did not have the same relevance for all decision tasks analyzed in the follow-up case study. The participants explained that even when the BI system data completeness was not high they were able to obtain sufficiently faithful representations relevant to the decision task supported. Additionally, a new proposition was included during the follow-up case study as another factor that affected the faithfulness of the representation of the phenomena relevant to the decision task—namely, BI system data timeliness. This proposition obtained mixed responses in regard to its relevance for both models because it was found to be only relevant for decision tasks that had a more operational or monitoring nature. It was clear in the follow-up case
study that operational decisions required a higher level of timeliness in the BI system than non-operational decisions. The third factor that affected the level of faithfulness of the representation was BI system data accuracy. This factor was found to be relevant for all participants in the follow-up case study (Proposition 2).

The second insight gained during the follow-up case study, and discussed in depth in the Chapter 6, was to define a more accurate result of the nature of the relationship between the faithfulness of the representation of the phenomena relevant to the decision task and the value of BI system outcomes. In addition to validating a positive relationship between faithfulness of the representation relevant to the decision task and the value of BI system outcomes, the analysis of the participants’ responses indicated the relationship was non-linear. The sigmoid function described in Chapter 6 and represented in Figure 7.4 shows that improvements in faithfulness of the representation will have a different level of impact on the value of BI system outcomes depending on the preliminary level of faithfulness of the representation relevant to the decision task. This is an important finding and must be considered when practitioners and academics make use of the resultant models of this research project. It provides guidance for evaluating how well a BI system supports decision tasks in an organization. Moreover, it can help to identify decision tasks in which the efforts to improve the potential faithfulness of the representations relevant to those decision tasks can produce significant improvements of BI system outcomes.
Figure 7.4 Nature of the Relationship between Faithfulness of the Representation of the Phenomena Relevant to the Decision Task and Value of BI System Outcomes

Proposition 1
Faithfulness of the Representation of the Phenomena Relevant to the Decision Task positively impacts the value of BI System Outcomes
Finally, the third insight gained during the follow-up case study was about the proposed moderating effects that the understanding of the decision task and BI system interface capabilities had on the relationship between the faithfulness of the representation relevant to the decision task and the value of BI systems outcomes (Propositions 4i and 4d and Proposition 5). While participants of the follow-up case study confirmed the moderating effects, it became clear that they referred to two different steps followed by decision makers and intermediaries in their use of the BI system to support a decision task. As mentioned in Chapter 5, Section 5.3.1, a distinction can be made between the roles performed by the decision maker and the intermediary. As reviewed in the development of the models of BI system use and outcomes, Eckerson (2006) differentiates between consumer–users and producer–users. As a result, this portrays two different processes in the use of a BI system: 1) acquisition of the representation, and 2) interpretation of the representation. While the differentiation of the roles was mentioned in the discussion of the development of the models, it was not included in the propositions presented in the initial models of BI system use and outcomes. Conducting the follow-up case study permitted revisiting the distinction between the two processes in more detail, and it is addressed in the refinement of the models. Table 7.1 shows the propositions of the initial models plus the new proposition “NP” that proposes that “BI system timeliness positively affects faithfulness of the representation of the phenomena relevant to the decision task.” The results of the follow-up case study examination of the proposition are also presented in the table. The following sections discuss in detail the refinements applied to the models of BI system use and outcomes and present the final models of BI system use and outcomes.

As Table 7.1 shows, most of the final models’ propositions are well-supported. Only two propositions had mixed support. The results are supported by the evidence collected in both case studies. They are founded on the conceptual foundations derived from previous IS and BI research. The results of this research support the findings of previous research in BI and its DSS
predecessors. This is the result of a rigorous research method that combined the results of the empirical case studies with previous research and relevant IS, DSS, and management theories. This novel approach permitted a reduction in the explanatory power of the final models of BI system use and outcomes to be avoided.

### 7.3.1 FACTORS INFLUENCING THE FAITHFULNESS OF THE REPRESENTATION

The final three factors included in the models of BI system use and outcomes that affect the level of faithfulness of the representation relevant to the decision task are presented below. For these constructs the term “user” is employed. The user is the decision maker in the direct model and the intermediary in the indirect model.

1. **BI system data accuracy**: This construct refers to a user’s perceptual assessment of the level of accuracy of the BI system data. In particular, accuracy is defined as the extent to which the BI system data is correct, reliable, and free of error (Wang & Strong, 1996).

2. **BI system data timeliness**: This construct refers to a user’s perceptual assessment of the level of timeliness of the BI system data. In particular, timeliness is defined as the extent to which the age of the BI system data is appropriate for the task at hand (Wang & Strong, 1996).

3. **BI system data completeness**: This construct refers a user’s perceptual assessment of the level of completeness of the BI system data. In particular, completeness is defined as the extent to which the BI system data are of sufficient breadth, depth, and scope for the task at hand (Wang & Strong, 1996).

The previous three constructs have been included in most of the studies about BI, EIS, and DW published in academic journals. Examples are the use of “quality of information” in
Bergeron and Raymond’s (1992) study about the factors that are relevant for the evaluation of EIS, “data quality” in Wixom and Watson’s (2001) study about the factors affecting data warehousing success, and “information content quality” in Isik et al.’s (2013) study about BI success. Consequently, the three constructs are relevant factors for the models of BI system use and outcomes proposed in this research project. The models are based not only on the findings of the two empirical phases of this research but also on the existing literature about BI system use and outcomes. Figure 7.5 shows a diagram with the three constructs and their associations with the level of faithfulness of the representation relevant to the decision task.
Figure 7.5 Accuracy, Timelines, and Completeness → Faithfulness

**Business Intelligence System**

- **BI System Data**
  - **Accuracy**
    - (High level of accuracy is required for being used)
  - **Timeliness**
    - Relevant for operational tasks
  - **Completeness**
    - If BI completeness is low then users will find other alternative or complementary sources

**Representation**

- New Proposition

**Faithfulness**

of the Representation of the Phenomena Relevant to the Decision Task

- Proposition is well-supported
- Proposition is moderately supported

[Constructs are measured via decision-maker's perceptions]
7.3.2 Refinement of the Moderating Effects

7.3.2.1 Decision-Task Understanding: The distinction between Acquisition and Interpretation

The first moderating constructs to be assessed in the refinement of the models of BI system use and outcomes relate to Proposition 1. They are (a) the decision-maker’s understanding of the decision task, and (b) the intermediary’s and decision-maker’s shared understanding. As discussed earlier in this chapter, two different types of understanding were identified as required for decision makers and intermediaries to obtain valuable BI system outcomes. The first type of understanding maintains its moderation on the relationship between faithfulness of the representation relevant to the decision task and the value of BI systems outcomes (Proposition 1). It refers only to the interpretation of the representation relevant to the decision task. The second type moderates the three constructs (BI system data accuracy, completeness, and timeliness) that affect the level of faithfulness of the representation relevant to the decision task. This type of understanding is what information specificity categorizes as knowledge specificity in acquisition. It is described by Choudhury and Sampler (1997, p. 29) as “information that can be acquired only by someone with the required specific knowledge.” The distinction between the acquisition and interpretation of representations has been discussed previously in the literature. For example, Daft and Weick (1984) define them as two sequential processes performed to support decision-making in organizations. Acquisition of the representation is defined as the scanning and data collection process an individual performs to obtain a representation relevant to the decision task. Interpretation of the representation is defined as the process of translating the meaning of the representation (adapted from Daft & Weick (1984)). This distinction is consistent with the concepts discussed during the follow-up case study. Figure 7.6 shows the final specification of the decision-task understanding constructs.
Figure 7.6 shows the distinction between knowledge in acquisition and knowledge in interpretation of the representation for both models of BI system use and outcomes. While the direct model of BI use specifies the decision maker as the individual who has the attributes *knowledge in acquisition* and *knowledge in interpretation*, the indirect model of BI use specifies the intermediary as the individual with the attribute *knowledge in acquisition* and both the intermediary and the decision maker with *knowledge in interpretation*. The follow-up case study showed that several intermediaries supported decision makers not only by accessing the BI system to obtain and subsequently deliver a representation relevant to the decision task but also by supporting the decision maker through
advice about the interpretation of the representation obtained. The follow-up case study revealed that several intermediaries have an important active role advising the decision maker. In those situations, the intermediary needs to exhibit a sufficient level of knowledge in interpretation of the representation in order to obtain valuable BI system outcomes.

### 7.3.2.2 BI Interface Capabilities: Distinction between Manipulation and Navigation

The second moderating construct to be addressed in the refinement of the models of BI system use and outcomes is the role of BI system interface capabilities as moderators of Proposition 1 (Faithfulness → Outcomes). In a similar manner to decision-task understanding (section 7.2.2.1), the follow-up case study permitted identification of two different capabilities of the BI system interface that facilitated or impeded obtaining valuable BI system outcomes: (1) BI system interface capabilities for accessing the BI system data to obtain and manipulate a representation, and (2) BI system interface capabilities for navigating and visualizing the BI system representation. Figure 7.7 shows the refinement of the BI system interface capabilities construct.

![Figure 7.7 BI System Interface Capabilities - Refined](image)

Figure 7.7 shows the two refined constructs were identified during the analysis of the follow-up case study data about the BI system interface capabilities construct initially proposed after the exploratory case study. The different levels of the BI system interface representation
manipulation capabilities can facilitate or impede obtaining sufficiently faithful representations relevant to the decision task. As mentioned in development of the initial models of BI system use and outcomes in Chapter 5, section 5.4.3.1, Burton-Jones and Grange (2013) proposed that efficient and effective use of systems depend on a significant level of transparent interaction present in systems' surface and physical structures. According to Burton-Jones and Grange (2013), transparent interaction enables easy access to the representations. In this sense, the BI system interface must facilitate easy acquisition of the representation of phenomena relevant to the decision task. Thus, the BI system interface representation manipulation capabilities map Burton-Jones and Grange’s (2013) transparent interaction construct as both influence facilitating or impeding to obtain a faithful representation relevant to the decision task.

Similar conceptualizations about the BI system interface capabilities have been proposed in recent studies of BI system use and outcomes. For example, Isik et al. (2013) proposed that an important factor affecting BI success was that the BI system’s technological capability be flexible and integrated with other systems at the data and application level. Popović et al. (2012, p. 731) included two constructs called “data integration” and “analytical capabilities” in their model about BI success and maturity. These two constructs are based on the idea that BI systems’ interfaces can help to manipulate the representation and present it the best way possible for decision makers. While Isik et al.’s (2013) and Popović et al.’s (2012) studies did not use the same conceptualizations proposed in this research for the refinement of the BI system interface construct, they show the need to understand how different capabilities of the BI system interfaces impact on different stages of BI system use.

7.3.2.3 New Moderating Propositions

The previous constructs about decision-task understanding were refined into two constructs for the direct model and two constructs for the indirect model of BI system use and outcomes. The main differentiator between each model’s constructs is the distinction between acquisition and
interpretation of the representation relevant to the decision task. One new proposition was then added to each model of BI system use and outcomes. Furthermore, the existing propositions related to the moderating effect of decision-task understanding on the relationship between faithfulness of the representation of the phenomena relevant to the decision task and the value of BI system outcomes were refined. In particular, the decision-maker’s knowledge in interpretation of the representation and the intermediary’s and decision-maker’s knowledge in interpretation of the representation replace the original moderating association. The new proposition encompasses a moderating association on the relationship between BI system data completeness, accuracy, and timeliness with the faithfulness of the representation relevant to the decision task.

The refinement of the associations for the constructs related to the BI system interface capabilities followed a similar pattern to the refinements described for understanding the decision-task constructs. For both models of BI system use and outcomes, a new proposition was added that comprises a moderating effect of BI system interface representation manipulation capabilities on the relationship between BI system data completeness, accuracy, and timeliness and the faithfulness of the representation. A refined moderating association for the BI system interface navigation and visualization capacities replaces the previously proposed moderating association of BI system interface capabilities on the faithfulness of the representation and the value of BI system outcomes association. Figure 7.8 and Figure 7.9 show the final models for BI system use and outcomes based on the understanding gained during the entire research project.
Figure 7.8 Final BI System Use and Outcomes Model – Direct Method

Decision Maker’s
Decision Task Understanding

- Decision Maker’s Knowledge in Acquisition of the Representation
- Decision Maker’s Knowledge in Interpretation of the Representation

Faithfulness of the Representation of the Phenomena Relevant to the Decision Task

P3 & P4

Decision Maker’s Knowledge in Acquisition of the Representation

- New Proposition

BI System Interface Capabilities

- BI System Interface Navigation and Visualisation Capabilities
- BI System Interface Representation Manipulation Capabilities

Value of BI System Outcomes

P1

✓ Proposition is well-supported
m Proposition is moderately supported
* Emerging new proposition
[Constructs are measured via decision-maker’s perception]
Figure 7.9 Final BI System Use and Outcomes Model – Indirect Method

- Intermediary's understanding of the decision maker's task acquisition and its sources
- Intermediary's understanding of the decision maker's task purpose and potential outcomes
- Intermediary's understanding of the representation acquisition and its sources
- Decision maker's understanding of the representation acquisition and its sources

Proposition is well-supported
Proposition is moderately supported
* New Proposition

BI System Interface Capabilities
- Navigation and Visualisation Capabilities
- Representation Manipulation Capabilities

Faithfulness of the Representation of the Phenomena Relevant to the Decision Task

Value of BI System Outcomes

+ P2 & P3

- Intermediary's understanding of the decision maker's task acquisition requirements
- Intermediary's understanding of the decision maker's task purpose and potential outcomes
- Intermediary's understanding of the business domain
- Decision Maker's understanding of the representation acquisition and its sources

Faithfulness of the Representation of the Phenomena Relevant to the Decision Task

Proposition is moderately supported
* New Proposition

Accuracy, Timeliness, Completeness

P1

- Intermediary's Knowledge in Acquisition
- Intermediary's Knowledge in Interpretation

P4i

+ P5

- Intermediary's Knowledge in Acquisition
- Decision Maker's Knowledge in Interpretation

P4i

+ P5

+ New Proposition
7.4 Theory Classification

The aim of this project was “the development of models that explain the nature of BI system use and outcomes.” The term “models” has been used during this research following Weber’s (2012) notion of theory. Thus, it is possible to evaluate the models of BI system use and outcomes as potential theories. This section classifies the models of BI system use and outcomes into the various types of theory described by Gregor (2006).

To provide guidance to the IS field, Gregor (2006) developed a classification of theories based on an examination of the structure of theory in IS. As a result of her analysis, five types of theories are distinguished: Type I–theories for analysis; Type II–theories for explanation; Type III–theories for prediction; Type IV–theories for explanation and prediction; and Type V–theories for design and action. As stated in Chapter 2, this research aimed to develop a Type-IV theory for explanation and prediction. During the analysis of the findings of the follow-up case study, a prescriptive approach was used that attempted to predict the values of BI system outcomes. However, the models have not been tested to assess their predictive power. Thus, the models of BI system use and outcomes are better defined as with Type-II theories for explanation because the models provide explanations but do not aim to predict values of the models’ constructs with precision.

The models of BI systems use and outcomes were developed to fill gaps in the academic literature and practice that concerns the nature of BI system use and outcomes. Each construct and association in the models emerged via the analysis of the existing literature and empirical studies in which each construct and association were evaluated and refined. The use of a BI system not only followed a direct pattern of use as traditionally presented in the academic and industry literatures. Instead, the models show that two patterns of use (direct and indirect) coexist in the organizations studied. The inclusion of an intermediary explains how some BI systems are used in practice. In particular, using the decision maker and the intermediary in the modes of BI system
use and outcomes helps to articulate better explanations of the efficient and effective delegation of the use of BI systems in organizations. This helps to improve an understanding of the phenomena of BI system use and outcomes.

7.5 CONCLUSION

This chapter has presented the final models of BI system use and outcomes. The models are the results of three research stages: (1) building a conceptual framework, (2) an exploratory case study, and (3) a follow-up case study.

The models refinements involved (a) including a new construct, \textit{BI system data timeliness}, as one of the factors that influence the faithfulness of the representation relevant to the decision task, (b) for understanding the task construct, distinguishing between knowledge in acquisition and knowledge in interpretation of the representation relevant to the decision task, (c) for the BI system interface capabilities construct, distinguishing between BI system interface representation manipulation capabilities and BI system interface visualization and navigation capabilities, and (d) new propositions about moderating associations on the relationship between BI system data completeness, accuracy, and timeliness and the faithfulness of the representation relevant to the decision task.

Finally, the chapter ends with a classification of the resultant type of theory about final models of BI system use and outcomes. The models of BI system use and outcomes are classified as Type-II theories for explanation.
CHAPTER 8: CONCLUSION

Chapter Overview

This chapter presents the conclusion of the thesis. It provides an overview of the research and summarizes the academic and industry contributions of the findings. Finally, the chapter presents the limitations of this research and outcomes of this research and identifies future research opportunities.

- **Background Study**
  Critical Analysis of the “BI utilization problem”: BI industry consultant and vendor’s views on the extent in which BI systems are used by organisations.

- **Literature Review & Conceptual Framework**
  Analysis of the existing BI (including its predecessors) use and outcomes literature. Review of the existing IS use and outcomes theories. Development of conceptual framework.

- **Exploratory Case Study**
  Analysis of how individuals use BI systems in a large government organization (LGA), and the outcomes obtained by their use.

- **Initial Models Development**
  Design of direct and indirect BI system use and outcomes models.

- **Follow-up Case Study**
  Evaluation of the proposed BI system use and outcomes modes in a big insurance company (BIC). Refinement of constructs and associations.

- **Final Models of Direct and Indirect Use of BI Systems**
  Reflection on research findings and definition of final models.
8.1 INTRODUCTION

The importance of BI is well documented. Industry surveys have consistently reported that BI is one of the highest priorities for CIOs (Gartner Inc, 2013). It is also reported as the largest organizational IT investment in 2017 and has been the largest since 2009 (Kappelman et al., 2018). The background study detailed in Chapter 1 showed that the BI industry tends to oversimplify the nature of BI usage. A lack of understanding of how BI systems are used and what drives more efficient and effective use makes it difficult to evaluate BI system project success or failure. Research on BI systems is one of the least-published types of DSS research in prestigious academic journals (Arnott & Pervan, 2008). For these reasons, this thesis sought to examine and understand the nature of BI systems use and outcomes.

8.2 THESIS AIM AND PROCESS

The primary aim of the research described in this thesis was to develop models that explain the nature of BI system use and outcomes. The research undertaken used a three-phase design. The first phase was to develop a conceptual framework based on existing information system (IS) theories (Creswell, 2003; Neuman, 2011). The conceptual framework was based upon Goodhue and Thompson’s task-to-performance chain and their concept of task-technology fit (1995), representation theory and the concept of faithfulness of the representation (Weber, 1997), and Burton-Jones & Straub’s (2006) reconceptualization of system use. The second phase was an exploratory case study conducted in a large government organization. Twenty-five in-depth interviews were conducted. The participants were BI users who knew about and used the organization’s BI system. The insights gained during the exploratory case study provided the foundation for two initial models of BI system use and outcomes. Subsequently, in the third phase, a follow-up case study was conducted to validate and refine these initial models. Twenty-five participants from a large insurance company were interviewed using a semi-structured protocol.
To evaluate the initial models’ propositions, seven decision makers who used their BI system directly were interviewed. In addition, a novel approach that matched pairs of decision makers and intermediaries was used to gather data about the patterns of indirect use of BI systems. The insights gained during the follow-up case study were used to modify and refine the initial models of BI system use and outcomes (see Chapter 2 for a full discussion of the research approach). Chapter 7 presented these final models. This chapter will summarize the key findings of the research and their implications for practice, discuss the limitations of the research, and identify opportunities for further research.

8.3 SUMMARY OF FINDINGS

The initial background study about what the BI industry calls “the BI utilization problem” that motivated this thesis suggested a lack of understanding of the nature of BI system use and outcomes in the BI literature. The BI industry employed poor measures of BI system use to promote the view that BI systems were not used to their full potential. Also, only few articles have been published in the academic literature about how BI systems are used in organizations. In this light, the main products of this thesis are the models of BI system use and outcomes specified in Chapter 7, Section 7.3. When building these models, the following findings were obtained:

*There are two fundamental patterns of BI system use:* At an early stage, the exploratory case study revealed that decision makers did not always use their BI system directly. During interviews with BI users, some responded that they did not make decisions. Instead, they indicated that they reported to a decision maker who was the main user of the BI system’s outputs. No previous study of enterprise-scale BI systems had uncovered these patterns of use. The research reported in this thesis is the first to examine both direct and indirect patterns of use empirically.

*The importance of the intermediary’s role:* The follow-up case study showed that different types of intermediaries exist. Differences arose because of the level of involvement intermediaries had
with a decision maker and their understanding of the decision task the BI was used to support. Some were expert only in acquiring the representation relevant to the decision task, while others also were expert in interpreting the representation relevant to the decision task. The latter group sometimes acted as advisors in the decision-making process. Further research is needed to examine various types of intermediaries, their relationships with decision makers, and their specific knowledge in the use of BI systems.

There is a low degree of discretion in BI system use: Both the exploratory and follow-up case studies revealed little discretionary use of BI systems. In both case studies, participants indicated they could not avoid using the BI system because it was the only source of obtaining the representations they needed to support decision-making. This sense of compulsory use of the BI system was stronger for intermediaries. In several situations, the main role of the intermediary was to use the BI system to support one or more decision makers. In that context, use of the BI system was compulsory with an intermediary spending most of their work day using the BI system. Decision makers also suggested that they were forced to use the BI system directly or indirectly because they were expected to justify their decisions with BI data. Thus, the level of discretionary use seems to be lower than the level previously reported in the BI literature.

The faithfulness of the representation relevant to the decision tasks positively affects the value of BI system outcomes: The inclusion of the construct faithfulness of the representation relevant to the decision task is the first use of this construct in DSS research. It provides a novel way of conceptualizing how BI systems produce value. For a particular decision task, participants agreed that an improvement in the faithfulness of the representation relevant to the decision task positively affects the value of BI system outcomes. This is the focal relationship in both models of BI system use and outcomes. Nonetheless, this research also found that the relationship between representational faithfulness and the value of BI system outcomes is not linear. Instead, it follows a sigmoid function. As a result, increasing the faithfulness of the representation relevant to the decision task
will have a different effect on the value of BI system outcomes depending on their initial values. For an initial starting point where the faithfulness is high, changes in faithfulness will have no significant impact on the value of BI system outcomes. In contrast, when the initial starting point of the faithfulness is moderate, changes in faithfulness will have a significant impact on the value of BI system outcomes (see all potential scenarios in Chapter 7, Figure 7.4). This finding is important because it provides information about the nature of BI system use and outcomes when a totally faithful representation is not the main objective for BI users and developers. Rather, BI users and developers need to achieve an acceptable level of faithfulness and focus their efforts on decision tasks for which improvements in representational faithfulness will have a major impact on the value of BI system outcomes (decisions where the representations are either slightly faithful or have very low faithfulness).

A lack of faithfulness produces uncertainty: A lack of faithfulness of the representation relevant to the decision tasks produces the following effects in organizations: (1) decision makers do not use the representation to support the decision tasks; (2) decision makers make incorrect decisions based on the unfaithful representations; and (3) decision makers show symptoms of decision paralysis (Samuelson & Zeckhauser, 1988)—status quo bias (Tversky & Kahneman, 1974), omission bias (Baron, 1995), or choice deferral (Dhar, 1996).

BI system use is iterative: Decision makers and intermediaries use BI systems in an iterative manner. The same decision tasks require support over time. Decision makers and intermediaries also learn over time about the BI system data and the phenomena relevant to the decision tasks. With BI system use, their questions also evolve, and their knowledge about how to access the representations and how to interpret them improves. This research did not follow the use of a BI system over time to evaluate the iterations. Rather, this finding is based on the responses given by participants in the follow-up case study. Participants continually reported how the value of BI system outcomes increased when they had used the system repeatedly for the same task.
BI system data completeness, accuracy, and timeliness affect faithfulness: Three constructs — completeness, accuracy, and timeliness — have a positive effect on the faithfulness of the representation relevant to the decision task. Nonetheless, participants in both case studies were particularly aware of the minimum level of BI system data accuracy they needed to obtain a faithful representation for a decision task. BI system data completeness was found to be an important factor in determining whether to use other sources of data to support decisions. Finally, BI system data timeliness was found to be relevant for decision tasks that were operational in nature. It was less relevant for long-term planning decision tasks.

A lack of understanding of the decision task can be an obstacle in obtaining valuable BI system outcomes: For the direct and indirect models of BI system use and outcomes, a low level of decision maker and intermediary understanding of the decision task impedes obtaining valuable BI system outcomes. A common issue related to the lack of understanding was intermediaries not knowing the details of the decision task they had to support. Further research is needed to develop a better understanding of how collaboration and building shared understanding can be increased between decision makers and intermediaries in their use of a BI system.

Relative lack of importance of the BI system interface: BI users tolerated what would normally be considered to be a lack of BI system interface capabilities. While participants in both case studies complained about a lack of capabilities of their BI systems, they tended to focus more on BI system data issues. While this finding is not conclusive (given that only two BI systems were studied), it suggests that the effects of BI system interface capabilities need to be examined in more detail.

8.4 Contribution to Practice

The understanding gained during this research that is embodied in the models of BI system use and outcomes contributes to the development, implementation, and use of BI systems in practice.
The following paragraphs highlight this research’s main contributions to the development, implementation, and use of BI systems in organizations.

The models can inform BI system implementations: Organizations can use the models of BI system use and outcomes to evaluate their BI system implementations. For example, BI practitioners could adopt the models and develop a questionnaire based on the final models. Conducting an evaluation using the models can be useful as a means to identify decision tasks that are not well supported and gaps in the current use of a BI system. The models can also be employed to identify different patterns of BI use in an organization.

A guide for BI practitioners: BI practitioners can use the models to assist their decisions about funding and development efforts in relation to their BI system. For example, BI practitioners can employ the description detailed in Chapter 7, Section 7.3, about the nature of the relationship between faithfulness of the representation relevant to the decision task and the value of BI system outcomes. The four scenarios described present different returns on investments in terms of improving representational faithfulness. BI practitioners can decide whether to invest in improvements in the faithfulness of the representation relevant to the decision task when the potential improvements to the value of BI system outcomes are marginal. Alternatively, they can identify decision tasks where investing in improvements in faithfulness can potentially offer significant increases in the value of BI system outcomes.

A demystification of BI adoption: This research examined the nature of BI system use and outcomes in organizations. The background study detailed in Chapter 1 analyzed what is known in the BI industry as “the BI utilization problem.” The evidence collected and the findings of this research confirm that the BI industry approach to “the BI utilization problem” is an oversimplification of BI system use in practice. In particular, this research shows that different patterns of BI use can efficiently and effectively coexist in organizations. Not considering all patterns of BI use will lead IT departments to underestimate BI adoption rates. Moreover, this
research also shows that each instance of BI use can lead to different values of BI system outcomes. Thus, measuring BI adoption simply by counting the number of individuals in an organization who use a BI system is not a good proxy for the value of BI system outcomes to an organization.

8.5 LIMITATIONS

The results of this research have provided a better understanding of the phenomena of BI system use and outcomes. Nonetheless, the resultant models and the findings of this research should be viewed in the light of the following limitations:

- Both case studies were conducted in large organizations in Australia. Therefore, generalization must be made with caution to other types of organizations with different cultural beliefs, sizes, industries, and markets.

- The results of this research might be limited by the influence that the researcher’s understanding and perspectives had on the analysis of the qualitative data. The researcher has more than 15 years of experience in building BI systems, which might affect his interpretation of the participants’ responses. However, this concern is mitigated to some extent because (1) the researcher did not have previous knowledge of the BI systems studied and did not know any of the participants, and (2) the findings were discussed and debated with the researcher’s doctoral supervisors, frequently with the support of participants’ quotes and full transcripts.

- Logistically it was not possible to interview participants on more than one occasion. The high level and status of the participants in this research made it difficult to schedule the interviews, sometimes almost impossible. Many appointments had to be rescheduled several times, and the researcher had to travel to different locations to get
a brief time with the participants. While follow-up interviews could have reduced biases and improved the development of the models, they could not be scheduled.

- The maturity level of the implementations of the BI systems in the case studies could limit the results of this study because BI systems continually evolve after their initial implementation. As the BI systems evolve, BI users gain experience in the use of their BI system. In particular, they become more familiar with the BI system interface, and the BI system data potentially becomes more accurate, complete, and timely. While it was not possible to re-visit the same sites, the cases were selected because their BI systems had been implemented for at least 18 months before data collection. This permitted participants’ narratives to be historical—they could compare their current use of their BI system with their initial use and the period before the implementation of the BI system. As a result, the data collected contained insights about the evolution of the BI system and how BI system outcomes were affected.

- The generalizability of the resultant models of BI system use and outcomes is limited by the small number of BI systems and organizations studied. Nonetheless, the objective was to explore in depth the nature of BI system use and outcomes rather than to explore widely but in little depth. In particular, the use of case studies is suitable when the aim is to obtain a deep understanding of the phenomena under investigation (Eisenhardt, 1989). Nonetheless, case studies also can be used for testing propositions (Dul & Hak, 2007). Lee and Baskerville (2003) explain that statistical generalizability used in quantitative research is only one form of generalizability. Typically single case studies have been published in the BI use and outcomes literature (e.g., Shollo and Galliers, 2016; Watson, Fulller and Ariyachandra, 2004). Moreover, this research project included 50 interviews, in two large organizations, across 10 divisions in the exploratory case study and five functional areas in the follow-up case study. The use of
a two-stage, sequential case-study research design, with a first case study to explore the nature of BI systems use and outcomes and then the follow-up case study to evaluate and refine the research models, is rarely used in the BI literature.

### 8.6 Suggestions for Further Research

The research findings have demonstrated that the topic of BI system use and outcomes needs further exploration—in particular, to obtain a better understanding of how intermediaries should interact with their decision makers. Some areas identified for future research are:

1. **Explore further the impact of behavioral economics on the ways decision makers and intermediaries interact and use a BI system:** Behavioral economics was used to explain the consequences of the lack of faithfulness on decision makers in Chapter 6. Constructs such as status quo bias, omission bias, and choice deferral helped to explain the decision-makers’ behaviors when the BI system could not support them. Further research could draw on behavioral economics and conduct empirical studies to build models that explain in more detail the interactions between decision makers and intermediaries.

2. **Investigate intermediaries’ roles in efficiently and effectively using the BI system to support decision makers:** This research has been the first empirical study that has incorporated the indirect pattern of BI use as an efficient and effective pattern of use. Further research is needed to explore the different roles of intermediaries and how they can provide an efficient and effective way of using BI.

3. **Testing the models using surveys as the research method:** To evaluate the level of generalizability of the models of BI system use and outcomes, a survey method could be used with a large sample to cover different decision tasks across many organizations. This will evaluate the models’ generalizability and test the model’s predictive power.
(4) Conduct a design science project to create a framework to evaluate the use of existing BI systems in organizations: As mentioned in Section 8.4, the models of BI system use and outcomes could form a foundation to assist BI practitioners in evaluating their BI implementations. A design-science project could adopt the models of BI system use and outcomes and create an artefact that could be used to evaluate BI systems.

8.7 CONCLUDING COMMENTS

This research was motivated by a relative lack of understating of the nature of BI system use and outcomes in both the BI industry and academic research. High-quality published research on the topic of BI system use and outcomes is limited. Nonetheless, BI systems are continually ranked as a top priority for organizations. BI practitioners rely on BI vendors’ and BI consultants’ opinions and publications about the issues relating to BI system implementation and adoption. This research provides important insights about the nature of BI system use and outcomes that are applicable to BI practice. In addition, this research has contributed to IS theory with the development of the direct and indirect models of BI system use and outcomes. It has proposed and provided evidence of an alternative pattern of indirect BI use that can be efficient and effective. As a result, the role of intermediaries in BI system use has been highlighted.

Further research could improve the explanatory and predictive power of the models of BI system use and outcomes. Nonetheless, the current models are a significant step towards a better understanding of BI system use and outcomes phenomena. The constructs and associations included in both models are the result of a rigorous research process based on two in-depth empirical studies. The results can be used with confidence by BI practitioners and academics who are interested in conducting research on the topic of BI system use and outcomes.
REFERENCE LIST


APPENDIX I: EXPLORATORY CASE STUDY

ETHICS APPROVAL

Monash University Human Research Ethics Committee (MUHREC)
Research Office

Human Ethics Certificate of Approval

Date: 22 March 2012
Project Number: CF12/0761 – 2012000332
Project Title: Understanding Business Intelligence Systems Outcomes
Chief Investigator: Prof David Arnott
Approved: From: 22 March 2012 To: 22 March 2017

Terms of approval

1. The Chief investigator is responsible for ensuring that permission letters are obtained, if relevant, and a copy forwarded to MUHREC before any data collection can occur at the specified organisation. Failure to provide permission letters to MUHREC before data collection commences is in breach of the National Statement on Ethical Conduct in Human Research and the Australian Code for the Responsible Conduct of Research.
2. Approval is only valid whilst you hold a position at Monash University.
3. It is the responsibility of the Chief Investigator to ensure that all investigators are aware of the terms of approval and to ensure the project is conducted as approved by MUHREC.
4. You should notify MUHREC immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.
5. The Explanatory Statement must be on Monash University letterhead and the Monash University complaints clause must contain your project number.
6. Amendments to the approved project (including changes in personnel): Requires the submission of a Request for Amendment form to MUHREC and must not begin without written approval from MUHREC. Substantial variations may require a new application.
7. Future correspondence: Please quote the project number and project title above in any further correspondence.
8. Annual reports: Continued approval of this project is dependent on the submission of an Annual Report. This is determined by the date of your letter of approval.
9. Final report: A Final Report should be provided at the conclusion of the project. MUHREC should be notified if the project is discontinued before the expected date of completion.
10. Monitoring: Projects may be subject to an audit or any other form of monitoring by MUHREC at any time.
11. Retention and storage of data: The Chief Investigator is responsible for the storage and retention of original data pertaining to a project for a minimum period of five years.

Professor Ben Canny
Chair, MUHREC

cc: Prof Ron Weber, Mr Felix Lizama
APPENDIX 2: EXPLORATORY CASE STUDY

EXPLANATORY STATEMENT

**Project:** Understanding Business Intelligence Systems Outcomes.

My name is Felix Lizama. I am a PhD student in the Caulfield School of Information Technology at Monash University. In conjunction with Professor David Arnott and Professor Ron Weber, I am conducting research into supporting managerial decision-making with IT-based information systems. This research is aimed at exploring the use and outcomes of business intelligence systems.

The aim of this study is the development of a framework that models various business intelligence systems outcomes. In the project, participants from each organization will be interviewed using a semi-structured approach. During the interviews, the researcher will take notes, and if the interviewee agrees, the session will be audio taped. The interviews will take between 30 to 40 minutes. The questions will be emailed to you before the interview date.

Participation in the research project is completely voluntary and you may choose to cease your involvement at any time. There will be no adverse effect on you if you choose not to be involved.

In this project, the chief investigator and myself will conduct the interviews. I will perform the data analysis and write the PhD thesis, and related scientific papers. The information you provide will remain confidential. The only people who will have access to the information will be myself, and Professors Arnott and Weber. The documents relating to the project will be stored according to University regulations in a locked cabinet in a locked office at Monash University and electronic information will be stored on a password-protected computer. The information will be retained for five years and will be disposed of in a confidential manner. No individual participant will be identifiable in the publications and presentations that arise from the project. All publications arising from the project will be posted on the Monash DSS Lab website.

If you are interested in the aggregate research findings, you can contact Felix Lizama on his mobile number: +61 412 765 272; or his email: felix.lizama@monash.edu

<table>
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<tr>
<th>If you would like to contact the researchers about any aspect of this study, please contact the Chief Investigator:</th>
<th>If you have a complaint concerning the manner in which this research (CF12/0761 – 2012000332) is being conducted, please contact:</th>
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<tr>
<td>Professor David Arnott Faculty of Information Technology Monash University Caulfield School of IT</td>
<td>The Secretary The Standing Committee on Ethics and Research Involving Humans (SCERH) Research Grants &amp; Ethics Branch, Building 3D Monash University, VIC 3800</td>
</tr>
</tbody>
</table>

Thank you.

Felix Lizama
APPENDIX 3: EXPLORATORY CASE STUDY
CONSENT FORM

Project Number: CF12/0761 – 2012000332

Project: Understanding Business Intelligence Systems Outcomes.

NOTE: This consent form will remain with the Monash University researcher for their records.

I agree to take part in the above Monash University research project. I have had the project explained to me, and I have read the Explanatory Statement, which I will keep for my records. I understand that agreeing to take part means that:

☐ I agree to be interviewed by the researcher ☐ Yes ☐ No
☐ I agree to allow the interview to be audio-taped ☐ Yes ☐ No
☐ I agree to make myself available for a further interview if required ☐ Yes ☐ No

☐ I understand that my participation is voluntary, that I can choose not to participate in part or all of the project, and that I can withdraw at any stage of the project without being penalized or disadvantaged in any way.

☐ I understand that any data that the researcher collects from the interview for use in reports or published findings will not, under any circumstances, contain individual or organization names.

☐ I understand that I will be given a transcript of data concerning me for my approval before it is included in the write up of the research.
☐ I understand that any information I provide is confidential, and that no information that could lead to the identification of any individual will be disclosed in any reports on the project, or to any other party.

☐ I understand that data from the interview/transcript/audio tape will be kept in a secure storage and accessible to the research team. I also understand that the data will be destroyed after a 5 years period unless I consent to it being used in future research.

Name: 
..............................................................................................................................

Signature: 

Date: ....... / ....... / ..........
APPENDIX 4: EXPLORATORY CASE STUDY
INTERVIEW PROTOCOL

Interview Protocol
“Understanding Business Intelligence Systems Outcomes”
Semi-Structured Interviews

Introduction

My name is Felix Lizama. I am a PhD student in the Caulfield School of Information Technology at Monash University. In conjunction with Professor David Arnott and Professor Ron Weber, I am conducting research into supporting managerial decision-making with IT-based information systems. This research is aimed at exploring the use and outcomes of business intelligence systems.

Interviewee: _________________________________________________________________

Date: _____/_____/_______ Time: _____:______ Location : _______________________

Position: __________________________________________________________________

Icebreaking…

Part I – Manager Role and Tasks

Could you please describe your role in the organization (not in terms of the "official job description," but in terms of what you actually do)? ...Who do you report to? How many people report to you?

Transitional question to introduce Business Intelligence (BI) as main topic.

Definition of BI:
I would like to talk about Business intelligence. Business Intelligence systems or BI systems will be defined as: “Business intelligence (BI) is a broad category of applications, technologies, and processes for gathering, storing, accessing, and analyzing data to help business users make better decisions”. (Watson, 2009)

Part II – The nature of BI system usage

Could you please mention the BI systems that you / or your division/organization use? How familiar are the/those BI system(s) to you? How often do you use them?

What do you use the BI system for? How would you classify the way you use the BI system?: (indirect use/ direct use) Who is the main ‘client’ of the analysis you perform with the BI system (you or someone else)?
How would you classify the level in which the BI systems are delivered?

- [ ] INDIVIDUAL (just one user or a small group of users is using the system)
- [ ] DIVISIONAL (a functional/divisional unit uses the system)
- [ ] ORGANIZATIONAL (a widespread use of the system)

How would you classify the type of decision tasks that BI is supporting, Strategic, Tactical or Operational? Could you please identify decisions in which you don’t use BI and those when BI is indispensable? If possible can you provide examples of the use of BI?

- [ ] STRATEGIC TASKS
- [ ] TACTICAL TASKS
- [ ] OPERATIONAL TASKS

**Part III – Measures of Effectiveness**

How faithful do you think the BI system represent what it is really happening in your organization / industry? How relevant is the BI system in getting understanding of what is happening in your organization / industry?

![Scale of Importance]

In your opinion, what are the obstacles that impede BI systems to be a faithful representation of what is happening in the organization and industry? In general, what do you expect from the different BI systems that you use?

What would you consider are the outcomes of using BI for you and your division/organization? If you see more than one, are there any differences in terms of the level of these outcomes (more relevant ones versus the non-so relevant ones?)

Can you explain, how do you and your organization measure that outcome? Why do you think the way you measure the outcomes of BI systems is appropriate? Is there any other way you would consider?

Overall... How would you classify the outcomes of the BI system use?
APPENDIX 5: FOLLOW-UP CASE STUDY ETHICS APPROVAL

Monash University Human Research Ethics Committee (MUHREC) Research Office

Human Ethics Certificate of Approval

Date: 25 June 2013
Project Number: CF13/1889 – 2013000993
Project Title: Understanding the Nature of Business Intelligence Systems Use and Outcomes
Chief Investigator: Emeritus Prof David Arnott
Approved: From: 25 June 2013 To: 25 June 2018

Terms of approval
1. The Chief investigator is responsible for ensuring that permission letters are obtained, if relevant, and a copy forwarded to MUHREC before any data collection can occur at the specified organisation. Failure to provide permission letters to MUHREC before data collection commences is in breach of the National Statement on Ethical Conduct in Human Research and the Australian Code for the Responsible Conduct of Research.
2. Approval is only valid whilst you hold a position at Monash University.
3. It is the responsibility of the Chief Investigator to ensure that all investigators are aware of the terms of approval and to ensure the project is conducted as approved by MUHREC.
4. You should notify MUHREC immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.
5. The Explanatory Statement must be on Monash University letterhead and the Monash University complaints clause must contain your project number.
6. Amendments to the approved project (including changes in personnel): Requires the submission of a Request for Amendment form to MUHREC and must not begin without written approval from MUHREC. Substantial variations may require a new application.
7. Future correspondence: Please quote the project number and project title above in any further correspondence.
8. Annual reports: Continued approval of this project is dependent on the submission of an Annual Report. This is determined by the date of your letter of approval.
9. Final report: A Final Report should be provided at the conclusion of the project. MUHREC should be notified if the project is discontinued before the expected date of completion.
10. Monitoring: Projects may be subject to an audit or any other form of monitoring by MUHREC at any time.
11. Retention and storage of data: The Chief Investigator is responsible for the storage and retention of original data pertaining to a project for a minimum period of five years.

Professor Ben Canny
Chair, MUHREC

cc: Prof Ron Weber, Mr Felix Lizama
APPENDIX 6: FOLLOW-UP CASE STUDY
EXPLANATORY STATEMENT

Project: Understanding the Nature of Business Intelligence Systems Use and Outcomes.

My name is Felix Lizama. I am a PhD student in the Caulfield School of Information Technology at Monash University. In conjunction with Professor David Arnott and Professor Ron Weber, I am conducting research into supporting managerial decision-making with IT-based information systems. This research is aimed at exploring the use and outcomes of business intelligence systems.

The aim of this study is the development of models that explain business intelligence systems use and outcomes. In the project, participants from each organization will be interviewed using a semi-structured approach. During the interviews, the researcher will take notes, and if the interviewee agrees, the session will be audio taped. The interviews will take between 30 to 40 minutes. The questions will be emailed to you before the interview date.

Participation in the research project is completely voluntary and you may choose to cease your involvement at any time. There will be no adverse effect on you if you choose not to be involved.

In this project, the chief investigator and myself will conduct the interviews. I will perform the data analysis and write the PhD thesis, and related scientific papers. The information you provide will remain confidential. The only people who will have access to the information will be myself, and Professors Arnott and Weber. The documents relating to the project will be stored according to University regulations in a locked cabinet in a locked office at Monash University and electronic information will be stored on a password-protected computer. The information will be retained for five years and will be disposed of in a confidential manner. No individual participant will be identifiable in the publications and presentations that arise from the project. All publications arising from the project will be posted on the Monash DSS Lab website.

If you are interested in the aggregate research findings, you can contact Felix Lizama on his mobile number: +61 412 765 272; or his email: felix.lizama@monash.edu

If you would like to contact the researchers about any aspect of this study, please contact the Chief Investigator:
Professor David Arnott
Faculty of Information Technology
Monash University
Caulfield School of IT

If you have a complaint concerning the manner in which this research CF13/1889 – 2013000993 is being conducted, please contact:
The Secretary
The Standing Committee on Ethics and Research Involving Humans (SCERH)
Research Grants & Ethics Branch, Building 3D
Monash University, VIC 3800

Felix Lizama
PhD candidate
Monash University
APPENDIX 7:  FOLLOW-UP CASE STUDY
CONSENT FORM

Project Number: CF13/1889 – 2013000993

Project: Understanding the Nature of Business Intelligence Systems Use and Outcomes

NOTE: This consent form will remain with the Monash University researcher for their records

Do you agree to take part in the Monash University research project titled ‘Understanding the Nature of Business Intelligence Systems Use and Outcomes.’ You have had the project explained to you, and you have read the Explanatory Statement, which you can keep for your records. You understand that agreeing to take part means that:

☐ You agree to be interviewed by the researcher ☐ Yes ☐ No

☐ You agree to allow the interview to be audio-taped ☐ Yes ☐ No

☐ You agree to make myself available for a further interview if required ☐ Yes ☐ No

☐ The participant understands that her/his participation is voluntary, that she/he can choose not to participate in part or all of the project, and that she/he can withdraw at any stage of the project without being penalized or disadvantaged in any way.

☐ The participant understands that I will be given a transcript of data concerning her/him for her/his approval before it is included in the write up of the research.

☐ The participant understands that any information she/he provides is confidential, and that no information that could lead to the identification of any individual will be disclosed in any reports on the project, or to any other party. The data that the researcher collects from the interview for use in reports or published findings will not, under any circumstances, contain individual or organization names.
The participant understands that data from the interview/transcript/audio tape will be kept in a secure storage and accessible to the research team. She/he also understands that the data will be destroyed after a 5 years period unless she/he consents to it being used in future research.

Name: 
.......................................................... ..........................................................

Signature: 

Date: ....... / ....... / ............
APPENDIX 8: FOLLOW-UP CASE STUDY INTERVIEW PROTOCOL (DIRECT USE)

Interviewee: _________________________________________________________________

Date: ____/ _____/ _______ Time: _____:_______ Location: _________________________

Position: ____________________________________________________________________

Years/Months in the organization: ______________________________________________

Could you briefly describe your role in the organization? Who do you report to? How many people report to you?

[Filter Question] ---- (Check for direct use)
Have you directly used the BI system to support any decision or task?

☐ Yes … How often? ____________ (go to question 2)

☐ No … Have you delegated the use of the BI system or have you asked other person to gather information to support a decision? ☐ Yes … Candidate to indirect use protocol ☐ No

[Task Description] ---- (Contextualize and limit the direct use of the BI system to a specific decision task)

Can you please describe an important current decision task in which you have used the BI system?

+ Rationale: A current and important decision will be more likely to be remembered in higher detail.

* [Faithfulness] ---- (P1 & P2)
How faithful (or the degree of fidelity) was the BI system representation?

How accurate was the BI system representation of the decision task?

How complete was the report’s representation of the decision task? Did you need other sources of information? Did you require new or modified reports?

How timely was the report? Was the information current?

* [Outcomes]

What were the outcomes of the use of the BI system for that decision?

How influential was the system in achieving those outcomes?

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* [Faithfulness \( \rightarrow \) Outcomes] ---- (P3)

How did the faithfulness (or fidelity) of the representation influence the outcomes? (for the task)

* [Understanding of the decision task] ---- (P4)

How would you classify the level of shared understanding of the task? And under what conditions did your understanding of the task affect the outcomes? (for the task)

* [BI interface capabilities] ---- (P5)

How appropriate was the BI system interface capabilities for the manipulation of the representation? Under what conditions did the BI system interface capabilities affect the outcomes? (for the task)
Has been any other case where the BI system did not provide a useful representation for a particular decision task? If Yes, why were the main issues?

Was there any other factor that was important in the use of the BI system that could improve or decrease the outcomes? (for the task)
APPENDIX 9: FOLLOW-UP CASE STUDY
INTERVIEW PROTOCOLS
(INDIRECT USE)

DECISION MAKER

Interviewee: _________________________________________________________________

Date: ____/ _____/ ________ Time: ______:________ Location: ______________________

Position: __________________________________________________________________

Years/Months in the organization: _____________________________________________

* [Tasks]

Could you briefly describe your role in the organization? Who do you report to? How many people report to you?

Can you please describe an important current decision task in which you have used reports that were obtained by ................... using the BI system?
+ Rationale: A current and important decision will be more likely to be remembered in higher detail.

How often do you require reports from ………………… ? Does this person report to you?

* [Faithfulness] ---- (P1 & P2)

How faithful (or the degree of fidelity) was the report’s representation?

How accurate was the report’s representation of the decision task?

How complete was the report’s representation of the decision task? Did you need other sources of information? Did you require new or modified reports?

How timely was the report? Was the information current?
* [Outcomes]

What were the outcomes of the utilization of those reports for that decision?

How influential were the reports in achieving those outcomes?

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* [Faithfulness → Outcomes] ---- (P3)

How did the faithfulness (or fidelity) of the representation influence the outcomes? (for the task)

* [Understanding of the decision task] ---- (P4)

How would you classify the level of shared understanding of the task with the person that built the reports?

Under what conditions did the shared understanding of the task with the person that built the reports affect the outcomes? (for the task)

* [BI interface capabilities] ---- (P5)

How appropriate was the report layout or format?

Under what conditions did the reports’ layout or format affect the outcomes? (for the task)

* [Extra]

Has been any other case where you could not obtain a useful report for a particular decision task? If Yes, why were the main issues?
Was there any other factor that was important in the use of these reports that could improve or decrease the outcomes? (for the task)
INTERMEDIARIES

Interviewee: _________________________________________________________________

Date: ____/ _____/ ________ Time: ______:________ Location: ______________________

Position: ____________________________________________________________________

Years/Months in the organization: ______________________________________________

* [Tasks]

Could you briefly describe your role in the organization? Who do you report to? How many people report to you?

Mr(s)………………… (DM) has indicated that you have support him/her providing reports for: …………………… (Task). Could you please describe that task and how you used the BI system to support it?

* [Faithfulness]

How faithful (or the degree of fidelity) was the BI system representation of the task supported?

How accurate was the BI system representation of the task supported?

How complete was the BI system representation of the task supported? Did you need other sources of information? Did you have to manipulate the BI system representation?

How timely was the report? Was the information current?
* [Outcomes]

What were the outcomes of the use of the BI system for that task?

How influential was the system in achieving those outcomes?

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* [Faithfulness → Outcomes] ---- (P3)

How did the faithfulness (or fidelity) of the representation influence the outcomes? (for the task)

* [Understanding of the decision task] ---- (P4)

How would you classify the level of shared understanding of the task between you and the person you supported?

Under what conditions did the shared understanding of the task (between you and the person you supported) affect the outcomes of using the BI system? (for the task)

* [BI interface capabilities] ---- (P5)

How appropriate was the BI interface capabilities in facilitating the creation of the reports?

Under what conditions did the BI system interface capabilities affect the outcomes? (for the task)

* [Extra]
Has been any other case where the BI system did not provide a useful representation for a particular decision task? If Yes, why were the main issues?

Was there any other factor that was important in the use of the BI system that could improve or decrease the outcomes? (for the task)