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HOW BUSINESS INTELLIGENCE CREATES VALUE

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Abstract
Assessing IT business value has long been recognized as a major challenge, stemming largely from the considerable variability in the role and contribution of IT. This study examines the business value associated with business intelligence (BI) systems, suggesting that business value assessment is largely contingent on system type and should consider its unique contribution. The study adopts a process-oriented approach to evaluating the value contribution of BI, arguing that it stems from the improvement of business processes. The study develops and tests a research model that explains the unique mechanisms through which BI creates business value. The model draws on the resource-based view to identify key resources and capabilities that determine the impact of BI on business processes and, consequently, on organizational performance. Furthermore, the research model seeks to analyse the manner in which the organizational approach to innovation moderates the business value of BI. Analysis of data collected from 159 managers and IT/BI experts, using Structural Equations Modelling (SEM) techniques, shows that BI largely contributes to business value by improving both operational and strategic business processes. Further, it highlights the effect of the organizational approach toward exploration on transforming BI resources into capabilities and further into business value.

Keywords: Business Intelligence (BI), Business Value, Resource-Based View (RBV), Exploration and Exploitation, Structural Equations Modelling (SEM)
1 Introduction

A plethora of studies have examined the business value of IT, increasingly showing evidence for contribution and positive organizational impact. However, this stream of research has predominantly focused on the business value of an overarching IT concept, and paid less attention to the value gained by specific classes of systems. This study suggests that IT business value largely depends on system type, and therefore its evaluation requires a careful analysis of the unique manner by which each category of systems creates business value. This study focuses on the business value of Business Intelligence (BI) systems, which are considered in today’s business environment as a promising source of IT business value. BI systems represent the natural evolution of Decision Support Systems (DSS) and put a strong emphasis on data-driven decision making, based on the integration of multiple data resources that reflect different aspects of organizational activity. Our underlying assumption is that BI is unique in its potential to generate both strategic and operational value through the seamless integration of organizational data to support decisions at different levels. Although BI is frequently considered by industry as a significant source of business value, not much research has been done to examine this value and the mechanisms through which it is created.

This study contributes to that end by addressing two key questions - (1) What is the business value gained by implementing BI systems? (2) What are the mediating mechanisms through which this value is created? This study argues that, in addition to BI resources and capabilities, there are other organizational characteristics that affect the creation of BI-driven business value. Research has attributed significant importance to the interaction between IT resources and organizational characteristics, identifying this interaction as the basis for the creation of competitive advantage (Melville et al., 2004). This study takes a process-oriented approach to evaluating the impact of BI on organizational performance (Elbashir et al., 2008; Popovic et al., 2010), arguing that the business value of BI stems from its contribution to the improvement of key business processes. Drawing on the Resource-Based View (RBV) of the firm, we develop a research model that identifies key BI resources and capabilities as possible explanatory factors of the impact of BI on business processes and performance. We also use the model to analyse the manner in which the organizational approach to innovation moderates the business value of BI. The analysis is based on data collected from 159 managers and industry experts in the BI domain. It shows that BI largely contributes to business value by improving both operational and strategic business process. Further, it highlights the effect of exploration on transforming BI resources into capabilities and business value. In the remainder of this work, we first provide some theoretical background and highlight its contribution to the development of our research model and the associated hypotheses. Following a description of our research methodology and data collection procedures, we analyse the data using Structural Equations Modelling (SEM) techniques, and discuss the results and their implications. To conclude, we highlight the key contribution of our study, discuss its limitations, and propose directions for future research.

2 Theoretical Development

DSS for aiding organizational and managerial decision-making processes started to emerge in the 1960s and 1970s. BI, as an overarching term for DSS that are based primarily on integrated organizational data resources, was first introduced by Howard Dressner (1989), then a research fellow at Gartner Group: “BI is concepts and methods to improve business decision making by using fact-based support systems”. BI tools aim at improving the quality and accuracy of the information used in the decision making process, as they simplify the storage, identification, and analysis of information (Negash, 2004). A BI system lets users, at all organizational levels, access data, interact with it, and analyse it toward improving business performance, discovering new opportunities, and increasing efficiency. A well-designed BI system offers a global view of the entire organization, permits analysis of business activities from multiple perspectives, and enables rapid reactions to business environment changes (Matei, 2010).
Some studies have emphasized the organizational impact of BI, suggesting that the introduction of BI systems implies not only technological enhancement, but also a revolution in the way that business activities and decision-making processes are performed and managed. Davenport (2006) highlights the transition toward a culture of fact-based decision-making, which is typically supported by the adoption of BI technology. Wixom et al. (2008) discuss factors that lead to BI maturity, such as senior management commitment, investment in human skills, and forming a culture of openness and information transparency. These benefits may explain the growing worldwide investment in BI systems in recent years, reaching a magnitude of more than 10 Billion USD in 2010, with an estimated annual growth of ~14% (http://www.gartner.com/it/page.jsp?id=1642714).

2.1 Theoretical constructs

The RBV has repeatedly been used in research on IT business value (Bharadwaj, 2000; Wade and Hulland, 2004; Melville et al., 2004). Central to this theory is the perception that firms possess resources that are valuable, rare, and non-substitutable in order to achieve competitive advantage and superior long-term performance. Adopting the RBV, research has identified several IT resources that can serve as a source of competitive advantage, such as IT infrastructure, IT human capital, and IT strategy (Bharadwaj, 2000). The RBV literature notes that investment in technology alone, without complementary capabilities, cannot guarantee competitive advantage, as technology resources may not be valuable, rare, or non-substitutable (Bharadwaj, 2000; Melville et al., 2004).

Wade and Hulland (2004) define resources as a set of assets and capabilities that are available and can be used to identify and respond to business opportunities and threats. Ross et al. (1996) identify three types of IT resources: human capabilities, technology assets, and human relations. In general, IT assets are easier to imitate or substitute and, therefore, they cannot serve as a potential source of competitive advantage. In contrast, IT capabilities, which represent the integration of IT assets and organizational capabilities, are harder to imitate or substitute and, therefore, represent a potential source of competitive advantage.

2.1.1 BI assets

Our study suggests that an organization must possess certain resources that would permit successful adoption and utilization of BI. The study defines two types of BI assets, suggesting that both have significant influence on the business value that stems from the adoption of BI:

**BI system:** The physical IT asset must be present, and it must be managed well in order to confer competitive advantage (Melville et al., 2004). Davenport (2006) argues that getting the "right" technology, i.e., BI software and computing hardware, is necessary for becoming an organization that uses analytics as a main element of its strategy. A typical BI system includes components such as a data warehouse (DW) – a large-scale repository of integrated organizational data – and the hardware for managing and storing it, automated Extract-Transform-Load (ETL) utilities for transferring and transforming data within the system, and software platforms for developing end-user tools such as reports, On-Line Analytical Processing (OLAP) utilities for on-line investigation of data, digital dashboards, data mining tools, and possibly others. The combination of these infrastructural technologies and tools creates a technological environment that enables organizations to acquire better BI capabilities, which can lead to better decision making and to improved organizational performance.

**BI team:** IT human resources have been recognized as a critical component for IT-based competitive advantage (Bharadwaj, 2000; Fink and Neumann, 2007; Melville et al., 2004). For example, Ross et al. (1996) define IT human resources as technical, business understanding, and problem-solving orientation skills of the IT team. More examples are technical expertise, including application development, integration of multiple systems, and maintenance of existing systems, and managerial skills, including the ability to identify appropriate projects and motivate development teams to complete those projects (Melville et al., 2004). As the main objective of BI is to help decision makers understand the business environment and achieve business goals, the importance of human assets...
within the BI environment is well understood (Popovic et al., 2010). BI experts need to have the ability to express complex ideas in simple terms and the relationship skills to interact with managers and decision makers (Davenport, 2006). BI human assets encompass both technical and managerial skills related to BI implementation and use. Technical skills are the abilities to develop new applications, integrate multiple systems, and maintain existing systems (Melville et al., 2004). Managerial skills are primarily related to the ability of the BI team to align BI with organizational strategy and processes.

2.1.2 BI capabilities

Ross et al. (1996) argue that while organizations gain business value from IT, the value stems from organizational capabilities and not directly from IT assets. On the basis of this reasoning, it can be argued that business value stems from BI capabilities, which mediate the impact of BI assets, and not directly from the assets. BI capabilities are critical functionalities of BI that help the organization to improve its performance and to adapt to change (Watson and Wixom, 2007). This study distinguishes between two types of BI capabilities: operational and strategic. The logic behind this distinction is the different resources and processes involved in using BI for operational and strategic purposes. However, regardless of these differences, both strategic and operational BI capabilities are largely contingent on the BI assets described above, and are considered hard to imitate by competitors, as they largely depend on unique organizational characteristics.

Strategic BI capabilities: BI systems were originally developed for strategic purposes, such as measuring organizational performance and supporting market segmentation (Matei, 2010). Negash (2004) notes that the strategic uses of BI include corporate performance management, customer relations optimization, business activity monitoring, and traditional decision support. According to Wixom et al. (2008), "open data philosophy" and "culture of data" are fundamental BI concepts. These two capabilities enable organizations to gain more value from their BI systems. Bogza and Zaharie (2008) identify a number of BI dimensions that can be used to define strategic BI capabilities: (1) breadth - the extent to which the BI system integrates functions and technologies across the organization, (2) depth - the extent to which the system reaches those who need it in a way that is relevant to them, (3) completeness - the extent to which the system represents a comprehensive, end-to-end platform, and (4) advanced analytics - the extent to which the system delivers predictive insights, not just hindsight. Strategic BI capabilities include executive decision-making capabilities, which are top management usage of BI to identify opportunities that can leverage the current business, and analytical capabilities, which refer to the abilities of the BI system to provide strategic intelligence to executives (Maghrabi et al., 2011).

Operational BI capabilities: Although BI systems initially aimed at supporting strategic-level processes and tasks, today BI is widely used at all hierarchical levels of the firm and often serves operational-level processes and tasks (Matei, 2010). Operational BI capabilities include the widespread use of modelling and optimization (Davenport, 2006), the ability to analyse information and create knowledge out of it, the amount of cooperation and knowledge sharing among departments, and the ability to acquire new knowledge using the system. Furthermore, they include performance management and reporting capabilities that provide operational intelligence to executives (Maghrabi et al., 2011).

2.1.3 Business value

This study takes a process-oriented approach to define the value that stems from the development of BI capabilities. IT business value is defined as the impact of IT on organizational performance, comprised of both the intermediate process level and the organizational-wide level (Melville et al., 2004). A few studies have examined the relationship between BI and business value on the basis of the notion that the impact of BI systems is primarily reflected in business process improvements (Elbashir et al., 2008; Popovic et al., 2010; Wixom et al., 2008). In this study, in accordance with our distinction
between strategic and operational BI capabilities, we define two conceptualizations of business value associated with BI:

**Strategic business value**: Value reflecting the creation of a competitive advantage by supporting strategic objectives – e.g., identifying business opportunities and threats, running successful R&D, and improving financial performance (Davenport, 2006).

**Operational business value**: Value reflecting improvements in internal processes – e.g., enhancing customer relations or saving cost and time (Watson and Wixom, 2007).

### 2.1.4 Exploration and exploitation

Beyond the constructs discussed so far, this study considers the effect of two organizational characteristics, exploration and exploitation, on the relationships between BI assets and capabilities. The distinction between exploration and exploitation, as two core types of organizational activities, has been discussed extensively in the literature. Exploration includes activities such as search, variation, risk taking, experimentation, play, flexibility, discovery, and innovation, while exploitation includes activities such as refinement, choice, production, efficiency, selection, implementation, and execution (March, 1991). Scholars have argued that organizations need to become "ambidextrous" in terms of their mechanisms of innovation, by developing exploratory and exploitative capabilities simultaneously in various organizational units (Gupta et al., 2006; Jansen et al., 2006). Units engaged in exploratory innovation pursue new knowledge and develop new products and services for emerging customers or markets, while units pursuing exploitative innovation rely on existing knowledge and extend existing products and services for existing customers. This study sees exploration and exploitation as two different types of innovation in organizational units (Jansen et al., 2006). Exploratory innovations are radical innovations, designed to meet the needs of emerging processes or markets. Exploitative innovations are incremental innovations, designed to meet the needs of existing processes or markets.

### 2.2 Model formulation and research hypotheses

Next, we describe our research model and hypotheses (Figure 1). Guided by the RBV, we distinguish between BI assets, which are conceptualized as the BI system that the firm implements and the team that it establishes to implement and maintain it, and BI capabilities, which reflect how the firm is making use of those BI assets. As discussed above, BI capabilities, strategic and operational alike, largely depend on the BI system.

**H1a**: BI system is positively associated with operational BI capabilities.

**H1b**: BI system is positively associated with strategic BI capabilities.

An important aspect of every BI system is the BI team. Organizations that establish a strong BI team are more likely to have an effective BI system. In addition, a high-quality BI team will likely contribute to the creation of high BI capabilities based on the ability to deploy the BI system and align it with organizational needs. Therefore, it is reasonable to hypothesize that, in addition to the positive impact of the BI team on the BI system, the team has a positive impact on BI capabilities, beyond the impact driven directly from the system. In other words, the BI system serves as a partial mediator of the relationship between the BI team and BI capabilities.

**H2a**: BI team is positively associated with BI system.

**H2b**: BI team is positively associated with operational BI capabilities.

**H2c**: BI team is positively associated with strategic BI capabilities.

The model describes a direct effect of BI capabilities on value gained at the organizational level. Earlier, we suggested that BI capabilities create business value at two levels: strategic and operational (Elbashir et al., 2008; Popovic et al., 2010). The next hypotheses suggest that the value is derived from
BI capabilities and not directly from the BI system, because the use of the system in organizational routines, and not the system itself, is the source of business value.

**H3a:** Operational BI capabilities are positively associated with operational business value.

**H3b:** Strategic BI capabilities are positively associated with strategic business value.

![Figure 1. The research model](image)

We next hypothesize that exploration and exploitation moderate the creation of strategic and operational BI capabilities, respectively. While exploitation moderates the relationships between BI assets and operational BI capabilities, exploration moderates the relationships between BI assets and strategic BI capabilities. Exploitation is focused on improving existing business processes and, therefore, is associated with the operational level. Exploitation requires decision-making capabilities from the BI users who deal with the daily operations of the organization (Maghrabi et al., 2011). Based on the ability of exploitative organizations to introduce incremental innovations to existing business, the following hypothesis is formulated:

**H4:** Exploitation moderates the relationships between BI assets and operational BI capabilities.

Similarly, exploration is focused on exploring new areas and expanding the organization by doing so. Executive decision-making is related to exploratory innovation (Jansen et al., 2006) and strategic BI capabilities are associated with BI for exploration (Maghrabi et al., 2011). Based on the ability of exploratory organizations to introduce radical innovations in the form of new business processes, the following hypothesis is formulated:

**H5:** Exploration moderates the relationships between BI assets and strategic BI capabilities.

## 3 Empirical Analysis

The primary challenge in our empirical analysis lies in the ability to capture the BI resources (assets and capabilities) that create business value and the organizational characteristics (i.e., exploration and exploitation) that affect the relationship between BI resources and business value. This challenge motivated us to employ a field study approach. Our methodology used a Web-based instrument – a common data collection method in studies on the business value of IT and BI (Elbashir et al., 2008; Tallon et al., 2000). To analyse the collected data, we used SEM techniques with the AMOS 18 software and maximum likelihood estimation (MLE). SEM techniques depict all of the relationships among constructs involved in the analysis (Hair et al., 2010).

### 3.1 Instrument development and data collection

Our questionnaire instrument adapted measures from previous studies, where possible. However, we had to develop new measures for some of the constructs in the research model. The strategic and operational business value constructs were operationalized by adapting 16 measures from Elbashir et
al. (2008). The strategic and operational BI capabilities and the BI system were not based on an existing instrument, given the limited empirical research in this area. These constructs were, therefore, operationalized based on the existing BI literature. In total, six items were used for the BI system, six for operational BI capabilities, and seven for strategic BI capabilities. The BI team construct was operationalized by six measures adapted from Ross et al. (1996). Finally, exploration (six measures) and exploitation (seven measures) were operationalized by measures adapted from Jansen et al. (2006). All questionnaire items used seven-point Likert scales anchored at the ends by "strongly disagree" and "strongly agree". The questionnaire also included background questions about the organization and respondent. The initial instrument was pre-tested in three semi-structured interviews with IT/BI managers as a way of improving its clarity, relevance, and completeness. Following these interviews, the instrument was updated and finalized.

This study focuses on the relationship between BI and business value from an RBV perspective. This focus requires the assessments of business managers, IT managers, and BI managers, who are highly familiar with both the technological aspects of the BI system and the organizational aspects of their company. Tallon et al. (2000) concluded that the use of executives' perceptions in investigating IT business value is effective in the sense that perceptions are a good proxy for objective measures of realized value. Because this study tested the impact of BI at both strategic and operational levels, the study identified BI managers, IT managers, and business managers as the appropriate population for achieving the research objectives. The final questionnaire instrument was administered to the target population through a large, cross-sectional, Web-based survey. The target population was reached through emails, with a cover letter and a link to the questionnaire Web page. The e-mails were distributed only once, with no reminders.

Overall, a total of 178 questionnaires were returned, but 19 were dropped – 5 for a significant number of missing values and 14 for not answering any question regarding a specific construct. For the remaining 159 questionnaires, we tested the possibility that IT/BI managers provided different ratings than other managers. T-tests comparing the responses of IT/BI managers with those of the rest of the sample found statistically significant mean differences only for two out of the 54 questionnaire items: one in operational business value and one in strategic business value. Therefore, the possibility that respondent position biased our collected data was rejected.

### 3.2 Measurement model

Prior to testing the model and hypothesized relationships, the six primary model constructs (excluding exploration and exploitation) were tested for construct reliability, unidimensionality, convergent validity, and discriminant validity. The procedure for the estimation and respecification of the measurement model followed the standard SEM methodology (Hair et al., 2010), where the measurement model was revised by dropping items (one at a time) that shared a high degree of residual variance with other items. Given the broad scope of the measurement model, a confirmatory factor analysis showed satisfactory model fit. The overall $\chi^2$ of the measurement model was 723.526 with 419 degrees of freedom (df). The adjusted $\chi^2$ (ratio of $\chi^2$ to df) was 1.73 ($\chi^2_{419} = 723.526$), below the recommended threshold of 3. Almost all fit indices - CFI at 0.936, IFI at 0.937, NFI at 0.861, and RMSEA at 0.068 - were within the accepted levels for confirmatory factor analysis.

All Construct Reliability (CR) values were above the commonly used threshold of 0.70, suggesting good reliability (Hair et al., 2010). Standardized item loadings for the revised measurement model were above 0.70 for all items (significant at the $p < 0.001$ level), representing satisfactory convergent validity (Gefen et al., 2000). In addition, all Average Variance Extracted (AVE) values were above the recommended threshold of 0.50. Discriminant validity was assessed by comparing two nested models for each pair of constructs in the measurement model: an unconstrained model that frees the correlation between the two constructs and a constrained model that connects all items to a single construct (equivalent to setting the correlation between the two constructs to 1). A significantly lower $\chi^2$ value for the unconstrained model indicated that the constructs were not perfectly correlated and
provided evidence of discriminant validity (Hair et al., 2010). The \( \chi^2 \) difference was significant \((p < 0.01)\) for all possible paired comparisons of the constructs. Table 1 presents the correlation matrix, including CR and AVE values for the constructs.

<table>
<thead>
<tr>
<th>Construct</th>
<th>CR</th>
<th>AVE</th>
<th>BIS</th>
<th>BIT</th>
<th>OBIC</th>
<th>SBIC</th>
<th>OBV</th>
<th>SBV</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI System (BIS)</td>
<td>0.924</td>
<td>0.671</td>
<td>0.819</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BI Team (BIT)</td>
<td>0.957</td>
<td>0.815</td>
<td>0.859</td>
<td>0.903</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operational BI Capabilities (OBIC)</td>
<td>0.924</td>
<td>0.709</td>
<td>0.800</td>
<td>0.756</td>
<td>0.842</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strategic BI Capabilities (SBIC)</td>
<td>0.923</td>
<td>0.753</td>
<td>0.744</td>
<td>0.690</td>
<td>0.779</td>
<td>0.868</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operational Business Value (OBV)</td>
<td>0.795</td>
<td>0.632</td>
<td>0.610</td>
<td>0.496</td>
<td>0.605</td>
<td>0.529</td>
<td>0.795</td>
<td></td>
</tr>
<tr>
<td>Strategic Business Value (SBV)</td>
<td>0.843</td>
<td>0.710</td>
<td>0.502</td>
<td>0.449</td>
<td>0.525</td>
<td>0.489</td>
<td>0.843</td>
<td>0.843</td>
</tr>
</tbody>
</table>

*Table 1.* Correlation matrix; diagonal elements are the square roots of AVE.

### 3.3 Structural model

As a first step, we estimated the hypothesized model without the moderating constructs of exploration and exploitation (Figure 2). Generally, our model fit indices indicated that the research model was supported by the sample data. The adjusted \( \chi^2 \) at 2.029 \((\chi^2_{247} = 866.56)\), CFI at 0.907, IFI at 0.908, and RMSEA at 0.081 were all within accepted levels, except for the NFI that was below the threshold of 0.90. Considering the relative complexity of the research model with its six constructs, these model-fit results were considered satisfactory.

![Figure 2. Results for the general structural model](image)

The hypotheses tested in this model, except for one, were supported by the data. The results showed that BI system was significantly associated with BI capabilities, both operational (standardized coefficient of 0.633) and strategic (standardized coefficient of 0.625), supporting H1a and H1b. H2a was supported as well, as BI team was strongly associated with BI system (standardized coefficient of 0.858). The path between BI team and operational BI capabilities was significant at the 0.1 level, and thus BI system served as a partial mediator for operational BI capabilities, supporting H2b. However, H2c was not supported, as the path between BI team and strategic BI capabilities was not statistically significant, indicating that BI system served as a full mediator between BI team and strategic BI capabilities. The path between operational BI capabilities and operational business value was highly significant (standardized coefficient of 0.613), and so was the path between strategic BI capabilities and strategic business value (standardized coefficient of 0.498). These significant paths supported H3a and H3b, respectively, showing that BI capabilities, operational and strategic, were strongly associated with business value.
We performed an additional rigorous test to reject the possibility that the significant paths in the structural model were a consequence of common method bias, resulting from the use of a single instrument to measure all constructs. A common methods variance factor was added to the structural model and all items of the endogenous constructs were loaded on this factor as well, in addition to their respective constructs (Fink and Neumann, 2009). In so doing, the variance of the responses to a specific item was partitioned into three components: trait, method, and random error. Comparing the structural parameters with and without the common methods factor represented a test of common method bias. A very similar pattern of significant paths was obtained - all hypotheses supported in the research model, except for H3b, were also supported in the model containing the common method factor - ruling out the possibility of common method bias.

### 3.4 Multi-group analysis

To test the moderating effects of exploitation (H4) and exploration (H5), we conducted a multi-group analysis, which compares the path coefficients across subgroups of each moderator. A Principal Component Analysis (PCA) using the Varimax rotation method was performed for the exploration and exploitation items, and a factor score was calculated using the regression method. The dataset was median-split according to each factor score, and the analysis was performed twice (high versus low exploration, high versus low exploitation).

Differences in path coefficients across subgroups were analysed by estimating a series of nested multi-group models (Fink and Neumann, 2009; Hair et al., 2010). First, the structural model was estimated by allowing all parameters to be free across subgroups. Second, all model parameters were constrained to be equal across subgroups. When the difference in $\chi^2$ values between the constrained and unconstrained models was statistically significant, it indicated that the models were different and a moderating effect might exist. Next, a particular path was constrained to be equal across subgroups. When the difference in $\chi^2$ values between the constrained and unconstrained multi-group models (with one degree of freedom) was statistically significant, it indicated a difference in path coefficients between subgroups and that the particular path was, therefore, affected by the moderator. This procedure was implemented systematically per moderator for the three paths originating from BI team (H2a, H2b, and H2c) and the two paths originating from BI system (H1a and H1b).

The results for the moderating effect of exploitation (Table 2) show the unconstrained standardized path coefficients in each subgroup (as if each subgroup was estimated independently), the constrained-unconstrained $\chi^2$ path differences, and their statistical significance. The $\chi^2$ difference between the unconstrained model and the fully constrained model was 23.977 (with 32 df, $p > 0.1$), indicating that no significant differences existed between the high and low exploitation subgroups. Despite this finding, a more rigorous test was performed, as explained in the previous paragraph. When particular paths were constrained across the two exploitation subgroups, no significant differences in $\chi^2$ were found. Therefore, H4 was not supported, implying that exploitation had no moderating effect on the creation of operational BI capabilities.

<table>
<thead>
<tr>
<th>Path</th>
<th>Difference in $\chi^2$ (1 df)</th>
<th>$p$</th>
<th>Low Exploitation (N=79)</th>
<th>High Exploitation (N=80)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI Team $\rightarrow$ BI System</td>
<td>0.140</td>
<td>0.708</td>
<td>0.889***</td>
<td>0.766***</td>
</tr>
<tr>
<td>BI Team $\rightarrow$ Operational BI Capabilities</td>
<td>0.236</td>
<td>0.627</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>BI Team $\rightarrow$ Strategic BI Capabilities</td>
<td>0.006</td>
<td>0.938</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>BI System $\rightarrow$ Operational BI Capabilities</td>
<td>0.173</td>
<td>0.677</td>
<td>0.554**</td>
<td>0.683***</td>
</tr>
<tr>
<td>BI System $\rightarrow$ Strategic BI Capabilities</td>
<td>0.565</td>
<td>0.452</td>
<td>0.505*</td>
<td>0.613***</td>
</tr>
</tbody>
</table>

+ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 2. Moderating effect of exploitation
Similar to the above, the results for the moderating effect of exploration (Table 3) show the unconstrained standardized path coefficients in each subgroup, the constrained-unconstrained $\chi^2$ path differences, and their statistical significance. The $\chi^2$ difference between the unconstrained model and the fully constrained model was 63.142 (with 32 df, $p < 0.01$), indicating a significant difference between high and low exploration subgroups. In order to pinpoint this moderating effect, a series of tests constraining particular paths across the two exploration subgroups was performed. As shown in Table 3, the difference in $\chi^2$ between the unconstrained model and the model with the constrained path between BI team and strategic BI capabilities was significant at the 0.1 level ($\chi^2 = 2.942$, $p = 0.086$). Similarly, the difference in $\chi^2$ for the path between BI system and strategic BI capabilities was significant ($\chi^2 = 10.16$, $p < 0.01$). Therefore, H5 and the moderating effect of exploration were supported.

<table>
<thead>
<tr>
<th>Path</th>
<th>Difference in $\chi^2$ (1 df)</th>
<th>$p$</th>
<th>Low Exploration (N=79)</th>
<th>High Exploration (N=80)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI Team → BI System</td>
<td>0.091</td>
<td>0.762</td>
<td>0.864***</td>
<td>0.840***</td>
</tr>
<tr>
<td>BI Team → Operational BI Capabilities</td>
<td>0.175</td>
<td>0.675</td>
<td>NS</td>
<td>0.328**</td>
</tr>
<tr>
<td>BI Team → Strategic BI Capabilities</td>
<td>2.942</td>
<td>0.086</td>
<td>0.388*</td>
<td>NS</td>
</tr>
<tr>
<td>BI System → Operational BI Capabilities</td>
<td>0.749</td>
<td>0.386</td>
<td>0.494*</td>
<td>0.626***</td>
</tr>
<tr>
<td>BI System → Strategic BI Capabilities</td>
<td>10.160</td>
<td>0.001</td>
<td>NS</td>
<td>0.977***</td>
</tr>
</tbody>
</table>

$+ p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001$

Table 3. Moderating effect of exploration

These results indicated that the impact of BI team on strategic BI capabilities at a high level of exploration was mediated by BI system, with no direct effect. In contrast, at a low level of exploration, BI system had no impact on strategic BI capabilities, which depended only on the BI team.

4 Discussion

In general, the results confirm the hypothesized effects of BI resources on organizational performance. The findings show that improving the BI team has a positive effect on the BI system which, in turn, positively affects both strategic and operational BI capabilities. As expected, operational and strategic BI capabilities positively affect performance at the operational and strategic levels, respectively. These findings confirm that organizations do gain value from investing in BI and that this value is generated by improving business processes. These findings are consistent with previous BI business value research, which highlights the impact of BI on business processes (Elbashir et al., 2008; Popovic et al., 2010; Wixom et al., 2008).

The results shed light on the role that the BI team plays in turning investments in BI into value-contributing assets and capabilities. The direct effect of the BI team on BI capabilities indicates that the BI system partially mediates the creation of operational BI capabilities. In other words, operational BI capabilities are generated from the BI system, but these capabilities also depend directly on the BI team. Conversely, at the strategic level, the direct path between BI team and strategic BI capabilities was non-significant. This indicates that the BI system fully mediates the creation of strategic BI capabilities. A possible explanation for this difference is that the BI team has closer and more intensive interaction with end-users at the operational level. Due to this interaction, the team has high impact on how well the BI system is integrated in these processes. It is reasonable to assume that at the strategic level of the firm (corporate executives) there is a weaker interaction between the BI team and the end-users, possibly due to the limited ability of senior decision makers to dedicate the time for that. Hence, the improvement of strategic BI capabilities is gained mainly by the BI system itself, and less by the ongoing interaction between the BI team and the end-users.
H4 suggests that exploitation moderates the creation of operational BI capabilities. However, the results show no significant differences between the two subgroups of high and low exploitation. All paths that were significant for the low exploitation subgroup were also significant for the high exploitation subgroup. Therefore, it can be concluded that the organizational level of exploitation has no moderating effect on the creation of operational BI capabilities.

In contrast, some variability could be detected for exploration. The results reveal significant differences in two paths across the two subgroups of high and low exploration. First, a significant difference was found in the path between BI system and strategic BI capabilities ($p < 0.01$). This path was significant in the high exploration subgroup and non-significant in the low exploration subgroup. The path between BI team and strategic BI capabilities also showed a significant difference ($p < 0.1$). This path was significant in the low exploration subgroup and non-significant in the high exploration subgroup. This finding suggests that two different mechanisms are at play in the two types of organizations. For the high exploration subgroup, the BI system serves as a full mediator, which means that the entire impact of the BI team on strategic BI capabilities is generated through the BI system. In contrast, for the low exploration subgroup, the BI system does not have a significant effect on strategic BI capabilities. This does not imply that the BI system contributes nothing at the strategic level. The implication of this finding is that investing only in the BI system, with no complementary investments in the BI team, will not lead to improvements in strategic BI capabilities in organizations characterized by low exploration.

### 5 Conclusions

This study aims at investigating the business value of BI and at understanding its underlying mechanisms. The study shows that BI has positive effects at both the operational level (e.g., improving routine production and service processes) and the strategic level (e.g., improving response to environmental changes). The findings emphasize the important role of BI in organizations today and its impact on their performance. In addition, the findings reveal the importance of investing in BI assets – system and team – in order to achieve this value. The study also tests the moderating effects of exploitation and exploration, and the results confirm that this effect exists for exploration.

This study offers a comprehensive view of BI business value and the conditions under which it evolves. Our findings may lead to improved prioritization of BI investments and to better understanding of their organizational contribution. BI capabilities, strategic and operational, are identified as potential sources of business value.

The proposed directions for future research are derived from the study's limitations, which include the need to revalidate the model with a larger and more homogenous sample. The cross-sectional design used in this study implied the collection of data from organizations that vary in their business environment, organizational culture, and technological requirements. Although this study takes into account two organizational characteristics as contingency factors (i.e., exploration and exploitation), there are other potential factors that can cause performance variance, such as organizational culture. In addition, the measures of operational and strategic business value are based on subjective assessments. Although the subjective measures, which are widely used in research on IT business value, were assessed for potential biases, it is desirable that future studies obtain objective performance measures of the business value of BI.
References


