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Business intelligence success: The roles of BI capabilities and decision environments

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ABSTRACT

This study examines the role of the decision environment in how well business intelligence (BI) capabilities are leveraged to achieve BI success. We examine the decision environment in terms of the types of decisions made and the information processing needs of the organization. Our findings suggest that technological capabilities such as data quality, user access and the integration of BI with other systems are necessary for BI success, regardless of the decision environment. However, the decision environment does influence the relationship between BI success and capabilities, such as the extent to which BI supports flexibility and risk in decision making.

1. Introduction

Business intelligence (BI) continues to be a top priority for many organizations, and the promises of BI are rapidly attracting many more proponents [29]. Organizations are grappling to make sense of the rapidly increasing volume, velocity, and variety of data generated by both internal and external resources. Consequently, BI has become a critical foundation of competition for many organizations and has consistently been ranked among the top two agenda items of senior executives over the last several years [57]. Business intelligence continuously ranks as one of the most widely searched terms on gartner.com [80] and remains a topic of interest in academic and practitioner research [74].

One overarching theme that has surfaced in the research is that the BI used within an organization must suit the problem space, or decision environment, within which it is used and that this match is key to BI success [20]. However, practitioner-oriented publications and academic research suggest that this success has not yet been realized in many organizations and that users do not necessarily make the connection between their BI capabilities and the decision environment [42].

BI capabilities are critical functions that help an organization improve both its adaptation to change and its performance [92]. Although BI capabilities have been studied from organizational [e.g., 27] and technological [e.g., 58] perspectives, some organizations fail to achieve BI success [50]. This may be because the relationship between the decision environment and BI capabilities has remained largely unexamined. Examining this relationship is important, however, because the primary purpose of BI is to support decision making in organizations [15]. The purpose of this paper is to provide a better understanding of BI success by examining the impact of BI capabilities on BI success in the presence of different decision environments. Specifically, the paper seeks to address the following research questions:

(1) What is the relationship between various BI capabilities and BI success? and
(2) What is the influence of the decision environment on the relationship between BI capabilities and BI success?

2. Background

Various definitions of BI have emerged in the academic and practitioner literature. While some broadly define BI as a holistic and sophisticated approach to cross-organizational decision support [1,64], others approach it from a more technical point of view [16,94]. In this study, we define BI as a system comprised of both technical and organizational elements that presents its users

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with historical information for analysis to enable effective decision making and management support, with the overall purpose of increasing organizational performance [90]. In the following sections, we discuss the relevant research on BI success, BI capabilities, and the decision environment.

2.1. BI success

BI success is related to the positive value an organization obtains from its BI investment [79]. Organizations have implemented BI to achieve a variety of organizational benefits; therefore, BI success is defined differently by different organizations, depending on the benefits expected from the BI initiative [62]. BI success may represent the attainment of benefits such as improved profitability, reduced costs, and improved efficiency. Many organizations struggle to measure BI success. Some seek to quantify tangible benefits and use explicit measures, such as return on investment (ROI) improvements in operational efficiency or the increased profitability of the organization. Others conclude that their BI is successful if the ''costs are reasonable in relation to the benefits accruing'' [68] (p. 83). Other companies are interested in measuring intangible benefits. These include whether users perceive the BI as mission critical, how much stakeholders support BI and the percentage of active users [44]. Specific BI success measures differ across organizations and even across instances of BI within an organization. For example, one firm may implement BI to achieve better management of its supply chain, while another may adopt it to achieve better customer service. In our study, BI success is defined as the positive benefits organizations achieve through their use of BI.

Research suggests that a lack of fit between an organization's BI and its goals and characteristics is one reason for a lack of BI success [25,91]. Organizations that have achieved success with their BI implementations have worked to ensure that their BI is consistent with their corporate business objectives, and much research on BI success focuses on the alignment between BI and business objectives [61]. However, little is known about the role BI capabilities play in achieving this goal. Although there is a body of research addressing BI capabilities, it has remained largely silent on the role of BI capabilities in achieving the necessary match between BI and the decision environment in which it is implemented. However, many BI success stories indicate the importance of using BI with the necessary capabilities and for the right purposes to achieve BI success [81].

2.2. BI capabilities

Adapting to today's rapidly changing business environment requires agility from organizations, and BI plays an important role in enhancing this agility with the capabilities it provides [17]. With the right capabilities, BI can help an organization predict changes in product demand or detect an increase in a competitor's new product market share and respond quickly by introducing a competing product [92]. BI capabilities have been examined by practitioner-oriented research, especially from the BI maturity model perspective [26]. However, BI capabilities have remained largely unexamined in academic literature.

BI capabilities can be examined from both organizational and technological perspectives. Technological BI capabilities are sharable technical platforms and databases that ideally include a well-defined technology architecture and data standards, while organizational BI capabilities are assets that support the effective application of BI in the organization, such as flexibility and shared risks and responsibilities [75].

The extent to which an organization can leverage business intelligence is related to the capabilities of its BI system. Although many companies currently utilize BI primarily for structured decision making based on internal quantitative data, there is a rapidly increasing movement toward using BI as a foundation to support less structured decision making based on a variety of data [77]. The ability to shift to this environment depends on BI capabilities, such as the sources from which the data are obtained, data types, data reliability, user access, system flexibility, integration with other systems, and the level of risk the system supports. As organizations move beyond structured decision environments in their BI use, the importance of certain BI capabilities is likely to increase. In this study, we examine five technological and organizational BI capabilities—data quality, integration of BI with other systems, user access, the flexibility of the BI, and risk support—and these capabilities' importance to organizations with different information needs and decision environments.

2.2.1. Data quality

Traditionally, BI has largely relied on structured and/or numerical data, which can be measured on a numerical scale and analyzed with statistical methods and computing equipment [87]. However, in an increasing number of BI application areas, the collection and analysis of qualitative and/or unstructured data are critical [8]. This type of data cannot be used in mathematical calculations; it refers to data in a text, image or sound format that requires interpretation. Although research suggests that data quality is a critical success factor for BI [97], less attention has been paid to the quality of qualitative data than to the quality of quantitative data. The rise in qualitative data means that many companies are storing and managing increasingly large data sets for their BI. Data in many sectors range from a few dozen terabytes to many petabytes. For example, it is estimated that there are over 30 million networked sensor nodes in the transportation, automotive, industrial, utilities, and retail sectors today, and the amount of data collected from these nodes is growing at a pace of more than 30% annually [59]. Companies today grapple with higher data volume, velocity, and variety—i.e., bigger data—than ever before [77]. Although some sectors, such as retail, wholesale, and financial, are more likely than others to realize value from 'big data,' almost all sectors currently grapple with the problem of realizing value from their data. In a recent study, data problems are cited as the most common challenge companies face in managing high-performing BI systems [78].

Data quality refers to the consistency and comprehensiveness of the data [33]. It is estimated that more than half of BI projects fail due to data quality issues and that customer data quality issues cost U.S. businesses over $600 billion dollars a year [35]. Poor data handling processes, poor data maintenance procedures, and errors in the migration process from one system to another can cause poor data reliability. If the information being analyzed is not accurate or consistent, organizations cannot satisfy their customers' expectations nor keep up with new information-centric regulations. The technological ability of BI to deliver accurate, consistent and timely information across its users can enable an organization to improve its business agility [67].

Another aspect of data quality arises from its source. Data may be internal or external to the organization. Internal data sources are generally integrated and managed within a traditional BI application information management infrastructure, such as a data warehouse, a data mart, or an online analytical processing (OLAP) cube. External data include the data that organizations exchange with customers, suppliers and vendors. This is rarely inserted into a data warehouse. Often, external data are retrieved from web sites, spreadsheets, audio files, and video files. This further complicates the issues surrounding data quality because the quality of data from all sources is critical to BI success. Clean and relevant data are one of the most important factors of BI success [27]. As companies incorporate data from a wider variety of sources, they will continue to face new and ever-increasing issues surrounding the quality of the data on which they rely. Therefore, we propose the following hypothesis:

H1a. The better the data quality in an organization, the greater its BI success.

2.2.2. Integration with other systems

The integration between BI and other systems in the organization is another critical factor for BI success [93]. Integration involves linking various systems and their applications or data together, either physically or functionally, so that value can be created above and beyond that provided by each individual system. While much of the discussion of integration in BI specifically on data integration and its associated tools, the integration of both related systems and data stores presents a significant challenge in many sectors. For example, a recent survey of the energy utility sector found that this integration was one of the top two challenges they faced in moving forward with BI [53].

For organizations that use data from multiple sources and feed the data into multiple information systems, the quality of the communication between these systems directly affects the overall performance. The level and quality of integration between BI and other systems is becoming increasingly critical to managing BI performance and ensuring reliable results. For example, evolving technologies that enable in-database analytics and in-memory databases often require faster data refresh than ever before, particularly for sectors that utilize real-time practices such as operational BI and analytics. Some sectors require a higher level of integration between systems than others, such as those that engage in financial trading, utility grid monitoring, e-commerce product recommendations, commodity price optimization, or the capture and analysis of streaming data in real or near-real time [78]. The growing number and variety of data sources for BI in many organizations place increasing pressure on the integration between the systems from which the data are sourced.

Many organizations prefer to have their information systems' applications interact at multiple levels so that enterprise business integration can occur. This integration can be at the data level, the application level, the business process level, or the user level; however, these four levels are not isolated from each other. Organizations must find ways to successfully manage integration within BI systems and between BI and other information systems. Although data integration provides a unified view of business data, application integration unifies business applications by managing the flow of events [56]. Various technologies are available for these types of integration. For example, enterprise information integration (EII) enables applications to view dispersed data as though it resided in a single database, and enterprise application integration (EAI) allows applications to communicate with one another using standard interfaces [88]. These technologies also provide benefits to the end users, such as reducing the time spent on management changes and training issues [13]. Therefore, we propose the following hypothesis:

H1b. The higher the quality of integration of BI with other systems in an organization, the greater the BI success.

2.2.3. User access

One size does not fit all with BI; different BI tools have different capabilities and serve different purposes. Because organizations have multiple purposes for and user groups within BI, they may need to employ different BI applications with different access methods [43]. Some organizations deploy a BI that provides unlimited access to data analysis and reporting tools to all its users, while others offer relatively restricted access [38]. Although most web-centric applications are relatively easy to use, especially for non-technical users, desktop applications are mainly dedicated to specific users and provide specialized functionalities for more effective analysis [47]. The former may increase BI success by providing faster analysis, while the latter may increase it by facilitating more effective decision making. Because user access depends on the characteristics of the BI infrastructure and applications, it is considered a technological BI capability. For example, mobile BI, which is becoming more widely used in some sectors, could utilize many types of devices simultaneously in one organization [70]. Building, supporting, and managing multiple vehicles for a variety of user access methods and to support a variety of analyses is a critical BI capability. User access needs vary within an organization. For example, at the operational level, users may need to track core operational processes and have access to near-real time data, while upper-level managers may need to monitor the execution of strategic objectives throughout the organization and will, therefore, require a different level of access from the operational users [26]. Even within a single level, user access needs may differ across sectors. For example, in the financial services sector, users may need access that enables real-time market stress tests or intra-day profit and loss analyses across markets, while users in the manufacturing sectors may need access to manage operational efficiency and provide plant visibility.

Whether the organization prefers to use best-of-breed applications or a single BI suite, it is important to match tool capabilities with user types [44]. While some organizations limit user access through practicing authorization/authentication and access control, others prefer to allow full access to all types of users through a web-centric approach. It is critical that organizations achieve the necessary balance to allow the way BI users access information to fit the types of decisions they make using BI. In this study, we define user access according to users' perceptions of their access to their BI, including such factors as the overall quality, scope, and support of their decision making. Therefore, we propose the following hypothesis:

H1c. The higher the quality of user access to BI in an organization, the greater its BI success.

2.2.4. Flexibility

Flexibility is the organizational capability of BI to provide decision support when variations exist in business processes, technology or the business environment in general [31]. To achieve the competitive advantages provided by BI, organizations must select the underlying technology to support the BI operations carefully; flexibility is one of the most important factors to consider. Ideally, the system must be compatible with the existing tools and applications to minimize cost and complexity [24].

The strictness of the business process rules and regulations supported by the BI directly affects the flexibility of BI. If strict sets of policies and rules are embedded in the applications, BI will have a relatively low flexibility: as regulations become stricter, dealing with exceptions and urgencies becomes more difficult. Technology does not always support exceptional situations, although organizations need flexibility and robust functionality to experience the optimal potential of BI [3]. When the assessment of problems about which decisions must be made requires flexibility, this capability is key to BI success. Therefore, we propose the following hypothesis:

H2a. The level of BI flexibility positively influences BI success.

2.2.5. Risk management support

Risk management support refers to the organizational BI ability to support decisions under conditions of uncertainty when not all the facts are known [37]. People, processes, technology and external events can present risks to an organization [46]. Risk management is crucial to organizational success, and risk management support by BI applications is important, especially for organizations operating in high-risk environments. For example, innovative organizations, which are typically considered risk-tolerant, rely on BI to make entrepreneurial decisions motivated by the exploration and discovery of new opportunities and new risks [23]. However, risk and uncertainty exist in every business decision, and organizations may use BI to minimize uncertainty and make better decisions. The degree to which BI has decision support capabilities may significantly affect BI success. Therefore, BI may be more successful if it has the ability to address risk in the decision making environment. Therefore, we propose the following hypothesis:

H2b. The risk management support offered by BI positively influences BI success.

In summary, BI provides both technological and organizational capabilities to organizations. These capabilities impact the way an organization processes information and the performance of the organization [12,71,99]. Thus, it is critical that these capabilities match the decision environment in which the BI is deployed.

2.3. Decision environment

The decision environment is defined as the combination of different types of decisions made and the information-processing requirements of the decision maker when making those decisions [65]. The theory suggests that the match between the decision environment and the support a system such as BI provides is key to the organization's ability to leverage that system to achieve success [5]. Furthermore, the complexity of the decisions being made impacts the level of this match [20]. We posit, therefore, that a key requirement of BI success is the presence of the right BI capabilities, which must be related to the decision environment in which the BI is used.

A decision environment comprises many factors, but two of its most widely studied dimensions are decision types and information processing needs. Decision types are part of the decision environment because the extent to which decisions within an environment are structured or unstructured influences the performance of the analytical methods used in decision making. The types of decisions supported in a decision environment should be considered when selecting methods of determining the information requirements of that decision. The decision maker's information needs are also part of the decision environment because decision making involves processing and applying the gathered information [98]. Because appropriate information depends on the characteristics of the decision making context, it is difficult to separate information processing needs from decision making [98].

Gorry and Scott Morton's [34] framework of management information systems is a well-established, theoretically grounded representation of the decision environment. The framework identifies decisions ranging from unstructured to structured, based on Simon's [85] decision types. A decision is structured if it is repetitive and routine; it is unstructured if there is no fixed method of handling it and it is made on a non-repetitive basis [85]. Decisions that fall between these two types are classified as semi-structured [51].

The second dimension of Gorry and Scott Morton's framework groups decisions according to their information requirements and is based on Anthony's [4] framework of managerial activities. The activities are grouped into three categories: strategic planning, management control, and operational control. The *strategic planning* category involves activities related to long-term plans, which are typically non-routine and require creativity [84]. The *management control* category includes both planning and control, and it involves making decisions about what to do in the future based on the guidelines established during strategic planning [66]. The *operational control* category involves decisions related to "the process of assuring that specific tasks are carried out effectively and efficiently" [4] (p. 69). The differences between Anthony's information requirements categories are attributed to the fundamental characteristics of the information needed in the different categories. Thus, the categories can also represent the different information processing needs of the decision makers.

The Gorry and Scott Morton framework [34] allows nine combinations of the three decision types and the three information processing needs. However, we focus on the two extreme ends of the decision environment spectrum to best identify any differences between the BI capabilities' impact on the level of success attributable to the decision environment. The two decision environments we focus on are (1) structured decision types and the predominant characteristics of the information needed for operational control decisions and (2) unstructured decision types and the information processing needs of strategic planning decisions. *Structured operational control* requires a high level of detailed data on a frequent, repetitive basis, and the decisions are usually short-term in nature. Examples of decisions in this environment include inventory reordering and daily production scheduling, which can be accomplished using a computer-based system and involve limited uncertainty, low risk, and limited levels of human judgment or intervention. *Unstructured strategic planning* typically addresses a longer period of time and a broader range of data from variety of sources. Examples include research and development planning and new market assessment, which involve more uncertainty, higher risk, and greater levels of human judgment.

2.3.1. Moderating effect of the decision environment

This section provides the development of the hypotheses surrounding the moderating effect of the decision environment on the relationships discussed in Hypotheses 1 and 2. The full research model is presented in Fig. 1.

The impact of poor data quality may differ across decision environments. Although providing the right information for the decision making process is critical, the impact of poor data quality may be different for operational control activities than for strategic planning activities. Operational control activities requiring structured decisions are carried out more frequently and require more detailed structured information [4]. Research has shown that poor data quality in this decision environment can cause customer dissatisfaction, an increased cost of operations and employees' job dissatisfaction [72]. Poor data quality may manifest more immediately at a detailed level due to the short-term nature of the operational control decision environment. Furthermore, the short-term nature of operational control decisions does not often allow time to change the decision if errors are identified in the data.

Although data quality is important in the unstructured strategic planning environment, the impact of poor data quality may be subtler due to the longer term nature of strategic decisions [75]. Because strategic decisions also frequently require data from outside the organization that may be harder to validate, a lower quality of data may be assumed and, therefore, incorporated into the decision making process. Finally, poor data quality may be less

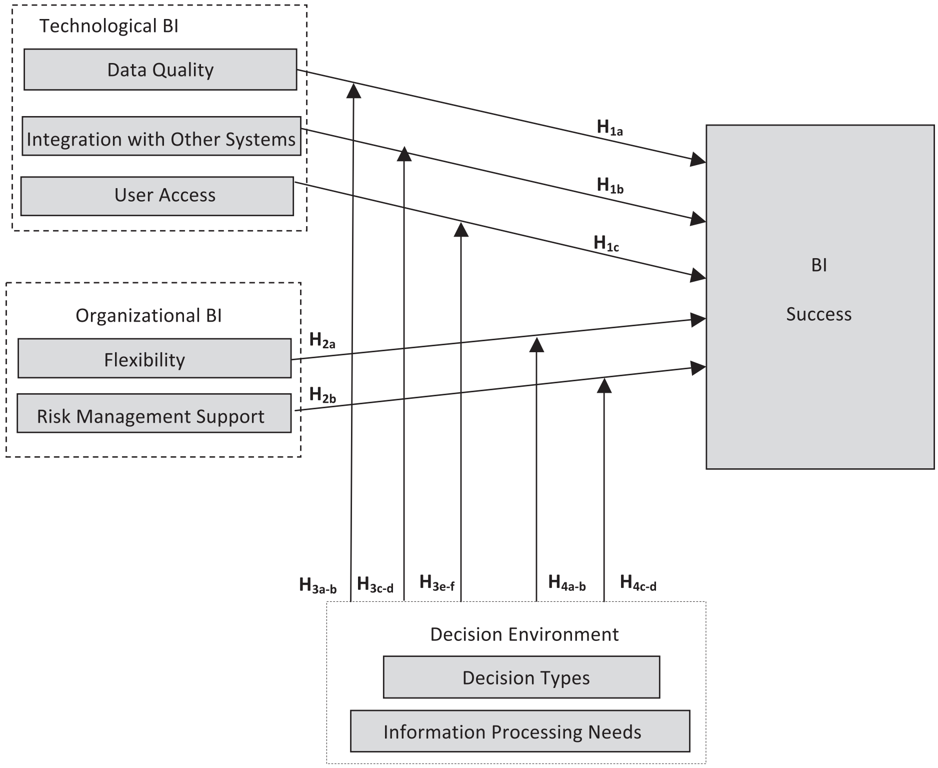

Fig. 1. Research model.

apparent when the data are aggregated for strategic decisions. Therefore, we propose the following hypothesis about the structured operational decision environment:

H3a. The positive influence of data quality on BI success is stronger for structured decisions.

H3b. The positive influence of data quality on BI success is stronger for operational information processing needs.

Many organizations implement multiple information systems or multiple applications for different purposes. These applications often need to interact at multiple levels for enterprise business integration and data integration to occur. The integration of BI with other systems is especially critical to unstructured decision making and strategic planning activities because these processes collect data from multiple data sources [88]. Thus, we propose the following hypothesis for the unstructured strategic decision environment:

H3c. The positive influence that the high-quality integration of BI with other systems exerts on BI success is stronger for unstructured decisions.

H3d. The positive influence that the high-quality integration of BI with other systems exerts on BI success is stronger for strategic information processing needs.

How users access BI is another factor that may influence BI success differently in different decision environments. Decision makers in the operational environment need access to real-time and transaction-level details to support their day-to-day activities. A satisfactory and well-performing user interface to access the data eliminates the burden of accessing multiple applications and saves valuable time for the decision maker, which is vital to operational activities [58]. Thus, we propose the following hypothesis for the operational decision environment:

H3e. The positive influence that high-quality user access to BI exerts on BI success is stronger for structured decisions.

H3f. The positive influence that high-quality user access to BI exerts on BI success is stronger for operational information processing needs.

Different decision environments are also likely to require different levels of flexibility. Strategic decisions are often unique, requiring novel approaches to decision making and the use of new information sources and decision support tools and techniques. Thus, a higher level of BI flexibility in terms of adjusting to the needs of an individual decision maker and incorporating new information sources and decision support tools and techniques is necessary. For operational decisions that are frequently bound by strict rules and regulations, a high level of flexibility may be counterproductive by complicating decision making, and a BI with a low flexibility capability may be more successful [42]. Thus, we propose the following hypothesis for the strategic decision environment:

H4a. The positive influence that BI flexibility exerts on BI success is stronger for unstructured decisions.

H4b. The positive influence that BI flexibility exerts on BI success is stronger for strategic information processing needs.

The level of risk taken by the decision maker may also differ in different decision environments. Therefore, BI applications may need to provide different levels of risk management capabilities for different decision environments. In the strategic environment, decisions are long term and are made in response to (or in anticipation of) changes in the external environment. Both the long-term planning horizon and the turbulence of the external environment increase the uncertainty facing the decision maker [48]. Therefore, risk management support is likely to be more essential in the strategic decision environment. On the other hand, operational decisions tend to have a short-term time horizon and involve well-defined problems related to the organization's internal environment. As such, they are likely to involve less uncertainty and require less risk management support. Thus, we propose the following hypothesis for the strategic planning environment:

H4c. The positive influence that risk management support capabilities exert on BI success is stronger for unstructured decisions.

H4d. The positive influence that risk management support capabilities exert on BI success is stronger for strategic information processing needs.

3. Methodology

3.1. Instrument design and development

A survey was undertaken to verify the proposed hypotheses. This survey consists of four parts. The first contains items used to collect demographic information from the respondents. The second measures the dependent variable, BI success, using items measuring the respondents' perceptions of achieved benefits, adapted from Gartner Group's BI adoption survey [41]. The third part includes items measuring the independent variable, BI capabilities, and the fourth includes items used to measure the moderator variable, the decision environment. The BI capabilities were operationalized with questions developed based on the Gartner Group reports and other practitioner-oriented publications from the Data Warehousing Institute (TDWI) related to BI capabilities [22]. The decision environment was operationalized as strategic versus operational and was measured using questions adapted from Gorry and Scott Morton [34], Kirs et al. [54], Klein et al. [55] and Shim et al. [84]. A 5-point Likert scale was used for all the items in the survey except the demographic information.

The survey was refined in several steps. First, several academic experts reviewed the survey. Based on their suggestions, we addressed the ambiguity, sequencing and flow of the questions. Second, a pilot study was conducted with 24 BI professionals who have experience with BI implementation and use. These participants were all operational managers. The appropriateness of the questions based on the results of the pilot study indicated that no further changes to the instrument were necessary.

3.2. Data collection

The research population of this study is composed of business managers who use BI for strategic and operational decision making across a range of organizations and industries. Data were collected from a sampling frame of randomly selected organizations located in the United States through a web-based survey. Random sampling helps ensure that the respondents are representative of the population of interest and reduces the chances of bias toward a particular industry or specific organizational or respondent characteristics [52]. The names and contact information of the decision makers were obtained from the publicly available mailing list of a market research company that maintains a list focusing on BI professionals. Three weeks after the survey link was sent out, a reminder was sent to improve the response rate. In all, the survey link was delivered to more than 3000 recipients.

A total of 97 responses was gathered during the data collection process. This corresponds to a response rate of lower than 1%. This result is not necessarily surprising for web-based surveys [10]. Of the 97 responses, five were incomplete and were, therefore, dropped from subsequent analyses, yielding 92 usable responses. *T*-tests were used to assess the non-response bias, and the early respondents ($N = 53$) were compared to the late respondents ($N = 39$); there were no significant differences at the 0.05 significance level. Unfortunately, there were only five operational managers among these respondents. Because we are interested in comparisons between strategic and operational decision environments and because we made no changes to the survey after the pilot test, we merged the responses from this collection with those from the operational managers in the pilot study. This provided us with 116 usable responses.

Before proceeding with the data analysis, however, *t*-tests were used to examine whether a response bias existed between the pilot group and the survey group. As expected, there were significant differences in terms of the moderator, decision environment. The first set of respondents belonged to a SAS Users Group composed of operational managers who are responsible for generating and using advanced BI applications, while the mailing list comprised a broader segment of BI users and managers. Therefore, including this set of respondents does increase the representation of the operational decision environment. Further analysis using *t*-tests was conducted to determine whether significant differences could be observed in the independent or dependent variables between the two groups. None were found. Finally, we compared the two groups in terms of their demographics. The survey group from the mailing list is more representative of larger organizations than the pilot study group, which is not surprising, as the list tapped a broader segment of industries and companies than the pilot study. As expected, the pilot study group contains more operational-level managers. Therefore, merging the two groups provides a broader representation of organizations and decision makers than the mailing list group alone. Therefore, the responses of all 116 respondents were used.

4. Analysis and results

The survey respondent pool was made up of 90.4% male and 9.6% female professionals. While 47.8% of the respondents had a graduate degree, the highest education level was post-graduate (25.2%). The respondents represent a broad sample with respect to organizational size, annual total revenue, and the organizational industry (Table 1). Almost 50% of the respondents indicated information technology as their functional area in the organization, while the rest belonged to various other functional areas. The respondents also represent a broad sample with respect to their levels in the organization and their experience with BI. Twenty-five percent of the respondents were operational-level managers, 40 were middle managers and 18% were executive-level managers. We are examining decision environments at two extremes—operational structured and strategic unstructured—and, therefore, managers at the operational and executive levels are key to our understanding of these two environments. Although middle managers may be expected to work in a decision environment that can be characterized as tactical and semi-structured decision making, we include them to capture where their use of BI might overlap with the two extremes. The boundaries between the different decision environments are not always clear-cut in practice; therefore, we capture information from all three levels of decision makers [4,34,84]. The respondents were asked to indicate whether they were new to BI, intermediate BI users, or advanced BI users. Fifty-one percent of the respondents identified themselves as advanced BI users, and 12% viewed themselves as new to BI. A statistical summary of the responses to specific survey questions for each of the BI capabilities and BI success in general is presented in Ref. [49].

Table 1
Profile of respondents.

Category	Percent of respondents
Functional area	
Information technology	46.6
Management	9.5
Finance	7.8
Marketing	7.8
Sales	5.2
Supply chain	2.6
Operations research	0.9
Other	19.8
Level in organization	
Executive	18.1
Middle	40.5
Operational	25.0
BI experience	
New BI user	12.1
Intermediate BI user	37.1
Advanced BI user	50.9
Industry	
Manufacturing	10.3
Insurance/real estate/legal	9.5
Medical/health	8.6
Transportation/utilities	7.8
Wholesale/retail/distribution	7.8
Banking	5.2
Data processing services	4.3
Education	11.2
Business service/consultant	14.7
Number of company employees	
Less than 100	23.3
100–499	9.5
500–999	8.6
1000–4999	23.3
5000–9999	9.5
10,000 or more	25.9
Company's total annual revenue (U.S. Dollars)	
Less than $100 million	32.8
$100 million to $499 million	12.9
$500 million to $1 billion	9.5
$1 billion or greater	34.5

4.1. PLS analysis

PLS path modeling was used to analyze and assess the proposed research model and test the hypotheses. PLS has several advantages over other statistical techniques such as regression and analysis of variance. It is able to concurrently test the measurement and structural model and is robust to violations of homogeneity and the normal distribution of the data set [18]. PLS can also handle smaller sample sizes better than other techniques, although it is not a panacea for unacceptably low sample sizes [60]. PLS requires a minimum sample size that is 10 times greater than either the number of independent constructs influencing a single dependent construct or the number of items comprising the most formative construct [96]. Our model examines five BI capabilities as independent variables; therefore, it requires a minimum sample size of 50. Thus, our sample size of 116 satisfies the requirement. However, the generalizability of our findings should be interpreted in light of this relatively small sample size. SmartPLS version 2.0.M3 [73] was used to analyze the research model.

4.1.1. Reliability and validity tests

The acceptability of the measurement model was assessed according to the model's construct validity and the internal consistency between the items [6]. Internal consistency, a widely used indicator of reliability, was assessed using Cronbach's alpha, and exploratory factor analysis was used to assess dimensionality [11]. All the Cronbach's alpha values were satisfactory after item purifications. For constructs that were measured with only two items (two dimensions of the decision environment), reliability was assessed by measuring the inter-item correlations. All the assessed correlations were significant at the 0.001 level ($r = 0.335$ for Decision Type and $r = 0.411$ for information processing needs).

The independent and dependent variables were assessed for construct validity through convergent and discriminant validity, as well as composite reliability [36]. Convergent validity was assessed according to the average variance extracted (AVE) and communality. Both communality and the AVE values for all the constructs are suggested to be at least 0.5 or higher [30,76]. The results indicated that all the constructs satisfy the condition (Table 2).

Discriminant validity was assessed by comparing the square root of AVE associated with each construct with the correlations among the constructs and observing whether that square root was a greater value [19]. As suggested for discriminant validity, the values on the diagonal were all larger than the off-diagonal values. The values of composite reliability, which measures "the internal consistency of the constructs and the extent to which each item indicates the underlying construct" [63] (p. 173), were above the recommended level (0.70) for most of the constructs and acceptable for the decision types construct [9]. Table 2 presents the composite reliability, average variance extracted (AVE), the square root of AVE, and the correlations between constructs. We also conducted Harman's single factor test, as suggested by Podsakoff and Organ [69], to examine the potential for common method bias; the resulting single factor accounted for less than 50 percent of the variance (35%), indicating that common method bias is not an issue in this data set.

4.1.2. Hypotheses 1 and 2

H1a–c are concerned with the relationships between technological BI capabilities and BI success. H2a–d are concerned with the relationships between organizational BI capabilities and BI

Table 2
Construct level measurement statistics and correlation of constructs.

Construct	Composite reliability	AVE[a]	Risk Mgmt	Flexibility	Data quality	Integration	User access quality	Decision types	Information characteristics	BI success
Risk management	0.87	0.69	**0.831**							
Flexibility	0.94	0.81	0.586	**0.900**						
Data quality	0.85	0.49	0.410	0.546	**0.700**					
Integration	0.87	0.63	0.594	0.533	0.520	**0.794**				
User access quality	0.87	0.69	0.619	0.583	0.629	0.558	**0.831**			
decision type	0.47	0.45	0.066	0.262	0.200	0.085	0.110	**0.671**		
Information characteristics	0.83	0.70	0.176	0.051	0.101	0.111	0.196	0.041	**0.837**	
BI success	0.93	0.59	0.441	0.464	0.356	0.560	0.550	0.103	0.142	**0.768**

The shaded numbers in bold on the diagonal are the square roots of the variance shared between the constructs and their measures.
Off-diagonal elements are correlations among constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements.
[a] Average variance extract.

Table 3
Path coefficients and t values for BI capabilities (H1 and H2).

Hypothesis	Constructs	Path coefficients	t value
H1a	Data quality	−0.132	1.420*
H1b	Integration with other systems	0.368	2.943***
H1c	User access quality	0.355	2.305**
H2a	Flexibility	0.148	1.408*
H2b	Risk	−0.039	0.340

* Significant at 0.1 level.
** Significant at 0.05 level.
*** Significant at 0.01 level.

success. To obtain reliable results and t-values, 500 random samples of 116 responses were generated using the bootstrapping procedure available in the SmartPLS software. The significance of the hypotheses was evaluated by assessing the significance and the sign of the inner model path coefficients using t-tests. To evaluate the predictive validity of the relationships between the constructs, R-square values were assessed. Four of the five hypotheses were statistically significant, and the overall model has good explanatory relevance. The total variance, explained by the five constructs, is 41.4 percent. In addition to the R-square, we performed the Stone–Geisser test of predictive relevance and calculated the Q-square to assess the model fit in the PLS analysis [32,86]. The Q-square measures how well the missing data can be restored by the PLS model, and a Q-square greater than zero implies that the model has predictive relevance [14,39]. In our primary PLS model, the Q-square for BI success is 0.2240. Table 3 presents the path coefficients between BI capabilities and BI success and the t-values associated with these paths.

BI success is significantly and positively related to BI capabilities, such as integration with other systems (H1b), user access quality (H1c), and flexibility (H2a). Interestingly, however, although data quality is significantly related to BI success, the sign of the path coefficient is negative; thus, the relationships are the opposite of those hypothesized. One possible explanation for this is multicollinearity. Therefore, the tolerance and variance inflation factor (VIF) values of the BI capabilities were examined [45]. However, the results were all below the recommended cut-off points (tolerance values are greater than 0.3 and VIF values are less than 3), indicating little or no multicollinearity among the constructs.

In addition, we examined the correlations among the constructs. However, the correlations between data quality and some of the other constructs are moderately high (.51–.62); this indicates that a multicollinearity effect may be present. In addition, there is low to moderate correlation among several of the other constructs. Cohen et al. [21] suggest that findings be interpreted using the sign of the correlation coefficient rather than the path coefficient when low to moderate multicollinearity is suspected. Therefore, the values of the t statistics are used together with the sign of the correlation coefficients to interpret the significance and direction of the paths.

4.1.3. Hypotheses 3 and 4

Hypotheses 3 and 4 posit that the decision environment moderates the relationship between the BI capabilities and the BI success. Testing interaction effects with PLS is a relatively new approach, and few academic publications illustrate how to model and estimate moderating effects in PLS path models [28,40]. We adopted the product indicator approach to test the moderating effects. All the constructs in our research model are reflective. Thus, the indicator variables of the predictor and moderator constructs were used to generate new product indicators to measure the interaction terms. As suggested by Chin et al. [18], the product indicators were standardized. The significance of the moderating effects was evaluated by assessing the significance and the sign of the inner model path coefficients of the interaction terms after a bootstrapping technique with 500 samples was applied. All the interaction effects were tested simultaneously [82]. Table 4 shows the path coefficients and t values.

The R-square indicates that this model explains 55.7% of the variance in BI success. Using the method suggested by Tabachnick and Fidell [89], we calculated that the R-square increase attributable to the moderating effects is significant at $p = 0.01$ ($F10{,}98 = 3.16 > Fcritical = 2.51$). The Stone–Geisser test calculated the Q-square as 0.2979, which also indicates predictive relevance. Therefore, the interaction effects model has adequate explanatory capabilities. These findings are interpreted in light of both the t statistics and the correlations between BI success and the interaction terms.

Three of the interaction effects were statistically significant. The relationship between BI success and flexibility is significantly moderated by decision types ($\alpha = 0.1$) and information processing needs ($\alpha = 0.05$). Therefore, both H4a and H4b are supported. The degree of flexibility supported by the BI is more strongly related to BI success in the decision environments of unstructured decisions and strategic planning. The relationship between BI success and risk management support is significantly moderated by information processing needs ($\alpha = 0.05$) but not decision types. However, the relationship is in the opposite direction of that hypothesized. The degree of risk supported by the BI is more strongly related to BI success regarding operational information processing needs. However, this interaction effect is difficult to interpret because the direct effect of risk management support on BI success is found to be insignificant. There is no significant moderator effect from the decision environment on the relationship between any of the other BI capabilities and BI success.

Table 4
Path coefficients and t values for moderating effects (H3 and H4).

Hypotheses	Constructs	Path coefficients[a]	t value
H3a	Data quality × decision type	0.159	1.177
H3b	Data quality × information characteristics	−0.017	0.142
H3c	Integration with other systems × decision type	0.093	0.506
H3d	Integration with other systems × information characteristics	0.021	0.161
H3e	User access quality × decision type	0.119	0.677
H3f	User access quality × information characteristics	0.022	0.190
H4a	Flexibility × decision type	−0.334	1.812**
H4b	Flexibility × information characteristics	−0.255	2.110**
H4c	Risk × decision type	0.254	1.455*
H4d	Risk × information characteristics	0.308	2.068**

[a] Negative path coefficients correspond to unstructured decision types and strategic information processing needs.
* Significant at 0.1 level.
** Significant at 0.05 level.

5. Discussion of findings and implications

As predicted by our research model, user access quality, flexibility, and integration with other systems positively affect BI success. While these results are not surprising, they further emphasize the importance of paying attention to both technical and organizational BI capabilities. Our results indicate that organizations must pay attention to providing appropriate user access to BI resources and ensuring the seamless integration of BI with other systems. Organizations should also consider incorporating the necessary flexibility in decision making processes supported by BI, even for structured operational decisions.

Perhaps the most surprising finding is that data quality is negatively related to BI success, regardless of the decision environment. One possible explanation for this is that the importance of data quality is a given in many organizations today, so the data quality provided by most BI is perceived to be "good enough," and additional improvements to data quality may come at the expense of lower flexibility or other BI capabilities. As organizations emphasize data quality to the exclusion of other capabilities, they impair BI success. Therefore, data quality may be a capability that is necessary but not sufficient to achieve BI success. The findings also indicate that data quality is not as strongly correlated with BI success as many of the other capabilities (Table 2). This may indicate that variability in data quality among the surveyed organizations is relatively low, which is consistent with our assumption that the current data quality of the BI applications is perceived as "good enough."

This finding is somewhat disturbing, given the evidence that companies in many sectors continue to grapple with the quality of the data that underlie their BI systems. Ironically, the increasing potential for companies to manage the ever-increasing data volume, velocity and variety may lead some companies to downplay the importance of the underlying processes that help insure clean, valid, and reliable data. For example, open-source systems such as Apache Hadoop are well suited to sectors such as transportation, automotive, utilities, or retail that address data sets that are too large for traditional relational or multidimensional data structures [2]. Hadoop can be utilized to work with traditional data warehouses and even to augment traditional ETL processes [7]. Large data warehouse vendors now provide the tools to facilitate this process. However, some companies are tempted to use this open-source technology to facilitate a massive 'dumping ground' for their big data without a cogent data management plan [83]. Organizations' failure to continually place a high priority on the quality of the data underlying their BI systems could easily lead to a situation in which they fail to recognize that their decisions are being undermined by erroneous data.

Our study also found no support for the hypothesized relationship between risk management support capabilities and BI success. This leads us to one of two possible interpretations: either organizations are using BI for decisions that involve risk management (perhaps because risk management capabilities are not yet present), or the level of risk support provided by most BI applications is sufficient and, therefore, does not explain variations in the level of BI success. In addition, the support of risk may be more relevant in some sectors than others. For example, companies in the financial sectors require BI to support decisions that are tightly coupled with risk management. Research that is more focused on the role of risk management support in BI success in specific sectors or with a finer grained decision environment lens may be useful.

The results of the tests of H3 and H4 provide additional information about the importance of BI capabilities when considered in light of the decision types and information processing needs the BI is utilized to support. Interestingly, none of the interactions between these decision environment constructs and the technological BI capabilities (H3a–f) were significantly related to BI success, although all the capabilities were directly related to BI success. This suggests that technological capabilities may be a necessary foundation of BI success, regardless of the decision environment. For BI to successfully support decision making, it should be usable, and decision makers should feel that they can rely on it. Thus, it should be grounded in high-quality data, interact seamlessly with the other systems with which it is related, and be accessible to its users in any decision environment.

The results of the tests of H4 suggest that the extent to which organizational BI capabilities are related to BI success does differ between decision environments. Specifically, the extent to which BI supports flexibility in the decision process is more strongly related to BI success in decision environments characterized by unstructured decision types and strategic information processing needs. Finally, and somewhat counterintuitively, the extent to which BI supports risk is more strongly related to BI success regarding operational information processing needs. One possible explanation for this finding about risk is that while risk may be greater in strategic decision environments, it is not absent from the operational environment. Because a BI system enables many types of analyses of a greater amount of data than was traditionally possible, by its very nature, it helps mitigate some of the uncertainty that comes from not having—or not being able to adequately grapple with—quantities of data. Furthermore, a BI may provide updates and exception reports that may not be as readily accessible through the vehicles traditionally used in operational decision environments, thereby minimizing risk. Regardless, this finding needs to be treated with caution because the interaction effect was found significant in the absence of risk management capabilities' direct effect on the decision environment.

In summary, our findings provide support for the role of the decision environment in BI success. They are consistent with prior research that suggests that technological capabilities directly impact BI success regardless of the decision environment and are, therefore, foundational capabilities that are the necessary "price of entry" of achieving success with BI. On the other hand, our findings suggest that organizational BI capabilities that support such factors as flexibility and risk in decision making should be managed in light of the decision environment in which the BI is employed. The type of decision and/or the information processing needs of the decision maker may be critical determinants of the extent to which such factors should be built into the BI. This is consistent with prior work suggesting that BI systems are not "one size fits all" [95]. This has implications for both the breadth and depth of BI usage.

As an organization seeks to expand its BI deployment to include a wider network of uses and users across functional areas of the firm and between various levels in the firm, it should be mindful of the decision environments into which the BI is being extended and the variety of capabilities the BI provides to support decision making in these environments. Furthermore, as an organization moves up the ladder of BI maturity, the types of questions it seeks to answer shift from looking back—"what happened?"—to looking forward—"what will happen?" or "how can we change what happens?" This may expand the decision environment from one of structured decision types for operational information processing to one of more unstructured decision types and more strategically oriented information processing needs. Therefore, it is critical both to have the right BI capabilities in place for the initial implementation and to be aware of the need for—and the ability to—manage these capabilities as the organization's BI usage grows and matures.

6. Conclusions

In this study, we examined the relationship between technological and organizational BI capabilities, decision environment characteristics and BI success. The results of the study paint an insightful yet occasionally surprising picture of the factors influencing BI success. Although some BI capabilities are found to be important for BI success regardless of the decision environment, other capabilities' effects are moderated by the decision environment's characteristics. Still other BI capabilities, such as data quality, appear to have reached an acceptable level, and further improvements to such capabilities may not translate into greater BI success. These findings have important implications for both researchers and practitioners.

From the research point of view, this study brings the BI research and the information processing literature together. While this study focused only on two types of decision environments, future research is necessary to incorporate the additional decision environments in the nine cells of the Gorry and Scott Morton framework. Including intermediary decision environments could provide more insight into where the inflection points are located. For example, at what point along the continuum of decision environments do technological capabilities enhance BI success the most? Future research could also draw on a sample taken from specifically targeted organizations to allow more in-depth comparisons of decision environments and information requirements from applications in different business sectors. While this study focused on decision environments, future research could incorporate other factors, such as decision makers' roles, preferences and interests in organizational decision making or decision hierarchies and networks to examine decision propagation and consensus in an organization.

From the practitioner's point of view, this study suggests that utilizing the right BI capabilities within the proper decision environment is important to allow an organization to realize maximum benefits from its BI investment. While user access and seamless integration with other systems is critical regardless of the decision environment, as organizations shift to using BI in less structured decision environments, they should pay additional attention to ensuring the adequate flexibility of their BI applications.

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