Decision Support Systems 54 (2012) 729–739

Contents lists available at SciVerse ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Towards business intelligence systems success: Effects of maturity and culture on analytical decision making

Aleš Popovič [a], Ray Hackney [b,*], Pedro Simões Coelho [c], Jurij Jaklič [a]

[a] University of Ljubljana, Faculty of Economics, Slovenia, University Nova, ISEGI, Portugal
[b] Brunel University, Business School, UK
[c] University Nova, ISEGI, Portugal

ARTICLE INFO

Article history:
Received 8 August 2011
Received in revised form 27 May 2012
Accepted 19 August 2012
Available online 28 August 2012

Keywords:
Business intelligence system
Information quality
Use of information
Analytical decision-making culture
Success model
Structural equation modeling

ABSTRACT

The information systems (IS) literature has long emphasized the positive impact of information provided by business intelligence systems (BIS) on decision-making, particularly when organizations operate in highly competitive environments. Evaluating the effectiveness of BIS is vital to our understanding of the value and efficacy of management actions and investments. Yet, while IS success has been well-researched, our understanding of how BIS dimensions are interrelated and how they affect BIS use is limited. In response, we conduct a quantitative survey-based study to examine the relationships between maturity, information quality, analytical decision-making culture, and the use of information for decision-making as significant elements of the success of BIS. Statistical analysis of data collected from 181 medium and large organizations is combined with the use of descriptive statistics and structural equation modeling. Empirical results link BIS maturity to two segments of information quality, namely content and access quality. We therefore propose a model that contributes to understanding of the interrelationships between BIS success dimensions. Specifically, we find that BIS maturity has a stronger impact on information access quality. In addition, only information content quality is relevant for the use of information while the impact of the information access quality is non-significant. We find that an analytical decision-making culture necessarily improves the use of information but it may suppress the direct impact of the quality of the information content.

1. Introduction

Evidently the most important research questions in the field of information technology (IT)/information systems (IS) in general involve measuring their business value [54], their success and identifying critical success factors [23]. In a decision-support context, business intelligence systems (BIS) have emerged as a technological solution offering data integration and analytical capabilities to provide stakeholders at various organizational levels with valuable information for their decision-making [76]. In contrast with operational systems, assessing the success of BIS is usually problematic since BIS are as rule enterprise-wide systems where most benefits are long-term, indirect and difficult to measure [69].

The term business intelligence (BI) can refer to various computerized methods and processes of turning data into information and then into knowledge [51], which is eventually used to enhance organizational decision-making [82]. We distinguish the terms BI and BIS and comprehend *BIS* (or the *business intelligence environment* [28]) as *quality information in well-designed data stores, coupled with business-friendly software tools that provide knowledge workers timely access, effective analysis and intuitive presentation of the right information, enabling them to take the right actions or make the right decisions*. We further understand *BI* as *the ability of an organization or business to reason, plan, predict, solve problems, think abstractly, comprehend, innovate and learn in ways that increase organizational knowledge, inform decision processes, enable effective actions, and help to establish and achieve business goals* [80]. Accordingly, processes, technologies, tools, applications, data, databases, dashboards, scorecards and OLAP are all claimed to play a role in enabling the abilities that define BI [80]; however, they are only the means to BI — not the intelligence itself.

Much research has been done in the area of assessing IS success [8] with the McLean & DeLone multidimensional IS Success Model [22,23] being one of the most often used, cited and even criticized works. Categories such as desired characteristics of the IS which produces the information (i.e. system quality), the information product for desired characteristics (i.e. IQ), and the recipients' consumption of the information products (i.e. information use) have been referred to as common IS success dimensions [22]. The model emphasizes the understanding of the connections between the different dimensions of IS success. While value ("net benefits" in the McLean & DeLone success model) is the final success variable, use of the system is fundamental for certain "net benefits" to occur.

* Corresponding author. Tel.: +44 189274000; fax: +44 189274001.
E-mail addresses: ales.popovic@ef.uni-lj.si (A. Popovič), ray.hackney@brunel.ac.uk (R. Hackney), psc@isegi.unl.pt (P.S. Coelho), jurij.jaklic@ef.uni-lj.si (J. Jaklič).

0167-9236/$ – see front matter. Crown Copyright © 2012 Published by Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.dss.2012.08.017

While considerable evidence demonstrates the importance of BI and BIS for organizations, Wixom and Watson suggest the benefits of BIS have not been adequately researched and thus need further attention [84]. Ranjan [65] qualitatively explored the business justifications and requirements for incorporating BI in organizations. Elbashir et al. [27] researched the performance effects of BIS use at the business process and organizational levels. Asserting that the implementation of a BIS is a complex undertaking requiring considerable resources, Yeoh et al. [85] proposed a CSF framework consisting of factors and associated contextual elements crucial for BIS implementation. However, no study has provided an in-depth analysis of BIS success. Consequently, our study's main objective is to provide a comprehensive understanding of the interrelationships between BIS success dimensions, focusing on the variables affecting BIS use.

Different types of IS require specific success models [60] and users prefer different success measures depending on the type of system being evaluated, therefore we adapted the general IS success model to reflect the specifics of BIS. We pay special attention to: a) information quality (IQ); b) the use of information in business processes; and c) the factors affecting the level of use of information, provided by BIS, in business processes and thus the creation of business value. Although IQ is believed to be one of the most important characteristics that determine the degree to which available information is used in organizations, research offers mixed support for the relationship between IQ and its use [60]. IQ generally deals with two main aspects, namely the content of information and its accessibility [29] with different means of BIS impact on the two and with different sets of quality problems that potentially impact information use. Although some of these differences are implicitly recognized in previous IS studies [83], some of the IQ access characteristics have been attributed to antecedents of system quality and the relevance is often not explicitly considered as an IQ dimension. Based on the classification about IS effectiveness provided by Seddon et al. [70], the proposed adaption of the McLean & DeLone IS success model is derived from the managers'/owners' aspect, aiming to provide value for the organization and it focuses on a type of IT or IT application, in this case on a BIS.

This study thus brings novel insights regarding the success of BIS and consequently identifies critical success factors of BIS implementation projects through considering specifics of BIS and the inclusion of different segments of IQ and an analytical decision-making culture in the model. We believe that this work contributes to understanding of the interrelationships between BIS success dimensions. From the aspect of IT development and BIS development, it can be expected that evaluation of such a model and interrelationships between its dimensions enables the understanding of problems and key success factors in implementation.

The structure of the paper is as follows. In the next section, the general IS success model is adapted to reflect the specifics of BIS that justify a separate study on BIS. The research model is then conceptualized. The second part of the paper presents the research design, methodology, and results. Finally, the results are discussed, including the implications for BIS theory and practice, while further possible research directions are outlined.

2. The business intelligence systems success dimensions

It is apparent that successful organizations do not focus solely on the speed and ways information is transmitted, and the amount of information they can process, but mostly on capturing the value of information along the information value chain [35]. A BIS, in its own right, adds value primarily at the beginning of the information value chain where, depending on the implemented technologies, it collects and structures the data transforming it into information.

The implementation of BIS can contribute to improved IQ in many ways, such as: faster access to information, easier querying and analysis, a higher level of interactivity, improved data consistency due to data integration processes and other related data management activities (e.g. data cleansing, unification of definitions of key business terms, master data management). The term *IQ* encompasses traditional indicators of data quality, information relevance, and features related to information access [62]. To understand and analyze the benefits of BIS it is necessary to understand IQ as a broad concept which embraces all of the abovementioned aspects. We expect that addressing the content of information and its accessibility separately can provide better insights into the relationships between IQ and other dimensions of the BIS success model.

Nevertheless, the information that is thereby provided can only be viewed as potentially valuable. If organizations want such information to contribute to their success it must be used within business processes to improve decision-making, process execution or ultimately to fulfill consumer needs [62]. While the need for process orientation is widely recognized in approaches to operational IS development [44], BIS are still mostly understood as data-oriented systems as managerial tasks are less frequently organized by means of well-defined processes [5]. Many approaches do not allow us to associate data with processes [5], yet not relying on business process orientation can lead to BIS deficiencies as the operational process provides the context for data analysis and the interpretation of the analyses' results [5]. For example, in an enterprise where end-to-end operational business processes are not fully understood and managed, data integration is much more difficult if not impossible, and understanding of information needs for BIS is impeded. Understanding of business processes is required in order to find out the relevant indicators [36]. All of this has an impact on all dimensions of BIS success. A lower understanding of business processes, supporting IS, legacy systems, and even hardware infrastructure will be reflected in lower BIS maturity, IQ and, consequently, information use.

Although the improved IQ impacts the level of information use, limits may be expected on the quantity of information an organization can absorb [14] and the related dominant impact of organizational culture on decision-making [57], specifically the attitude to the use of information in decision-making processes. Therefore, we expect that particularly the analytical decision-making culture will affect how much organizations use quality information provided by BIS in their business processes (Fig. 1).

The analyzed BIS success model reflects some specifics of BIS compared to operational information systems. In contrast to operational systems, which focus on the fast and efficient processing of transactions, BIS provides quick access to information for analysis and reporting. They primarily support analytical decision-making [43] and are thus used in knowledge-intensive activities. Due to a more difficult process of identifying information needs as a result of less structured processes in knowledge-intensive activities, the BIS environment faces most challenges in assuring information content quality. It is thus useful to separate the two previously identified aspects of IQ when researching BIS success. Moreover, the use of BIS is in most cases optional. Researchers have previously identified the importance of voluntariness (vs. mandatory use) when studying IS usage behavior [78]. We can therefore expect a stronger impact of IQ and analytical culture on BIS's acceptance, use and consequently its success. Due to the use of BIS especially on strategic and

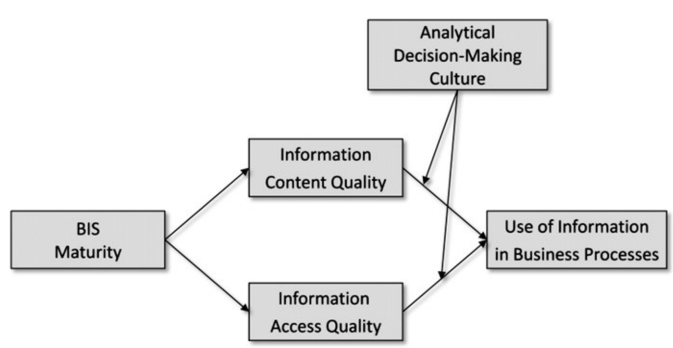

Fig. 1. The BIS success model.

tactical level of decision-making we can expect a greater role of data integration on IQ – especially information content quality – and consequently on use of information. Research into BIS success can partially rely on studies of enterprise IS or decision support systems, although older decision support systems and executive IS were application-oriented, whereas BIS are data-oriented, centered around data warehousing they provide the analytical tools required to integrate and analyze organizational data [33]. Table 1 summarizes the *typical* differences between operational IS and BIS. These specifics of BIS have an impact on all dimensions of BIS success, e.g. data integration on system quality, information relevance problems on information quality and system use.

3. Conceptualization of the research model

3.1. The maturity of business intelligence systems

Organizations' expectations of BIS can be defined according to maturity stages. In its simplest idea, *maturity* refers to the state of being fully developed, and a *maturity stage* refers to a succession of changes that affect an entity (e.g., an organization, an industry, or a society) [47]. Since quality has been characterized as compliance with expectations [45], the assessment of BIS maturity can be considered as a measure of BIS quality.

The successful application of BIS in an organization should use correct, valid, integrated and in-time data, as well as the means which will transform the data into decision information [86]. Data integration is generally recognized as one of the key factors contributing to long-term benefits of enterprise IS [69]. Thus, organizations must tackle two important issues when constructing their BIS architecture: 1) the integration of large amounts of data from disparate heterogeneous sources within BIS [27]; and 2) the provision of analytical capabilities (e.g. querying, online analytical processing, reporting, data mining) for the analysis of business data [75]. On this basis, we pose our first hypothesis:

H1. BIS maturity is determined by data integration and analytical capabilities.

3.2. Business intelligence system maturity and information quality

Although there is no single established definition of IQ [67], there is a common requirement that information is of high value to their users and that it meet users' requirements and expectations [58]. In this paper IQ refers to *information characteristics and dimensions to meet or exceed the expectations, requirements or needs of the knowledge worker* [67].

Table 1
Typical differences between operational IS and BIS.

	Operational IS	BIS
Structuredness of processes in which IS are used	Higher	Lower
Context for identifying information needs	Processes	Processes, performance management
Methods for identifying information needs	Well established	Less established
Data sources employed	Mostly from within the process	Additional data sources required
Level of voluntariness of use	Lower	Higher
Focus of IS	Application- and process-oriented	Data- and process-oriented
Main problems of information quality	Sound data and data access quality	Relevance
IS integration level	Process	Enterprise
Level of required reliability of IS	Higher	Lower

The field of IQ evaluation has been extensively researched and several criteria for assessing IQ have been presented (see [29,64]). IQ is sometimes referred to as richness [1], although this concept is narrower and chiefly relates to the information access quality: bandwidth, customization capabilities, and interactivity. For the purpose of this study we adopted Eppler's IQ framework [29] since it provides one of the broadest and most complete analyses of IQ criteria. His review of 20 selected IQ frameworks suggests that most frameworks are often domain-specific and rarely analyze interdependencies between the IQ criteria. Next, these frameworks do not take specifics of information in knowledge-intensive processes into account. BIS, by definition, support analytical decision-making and thus knowledge-intensive decision processes.

The outcome of Eppler's research is a framework of 16 criteria providing four views on IQ (relevant information, sound information, optimized process, and reliable infrastructure). The first two views, relevance and soundness, relate to actual information itself and hence the term content quality. The remaining views, process and infrastructure, relate to whether the delivery process and infrastructure are of adequate quality and hence the term media quality, which stresses the channel by which information is accessed [29]. In this work we use the terms *information content quality* and *information access quality*. A similar broader understanding of IQ can be found in [69] where both IQ views are discussed (timely, accurate, relevant information), although they are labeled using a narrower term of 'access to information'.

The IS literature has long emphasized the positive impact of an IS investment on the resulting IQ [83]. In terms of BIS investments, Hannula and Pirttimäki [37] argue that the key benefit provided by a BIS is better IQ for decision-making; more specifically, an increase in system quality will cause IQ to increase. Organizations that made commitments to effectively evolve their BIS to higher levels of maturity tended to do so by implementing advanced analytics and assuring data integration across the organization [18], which in turn leads to improved information content quality, and by implementing technology for information access and information sharing [12], which in turn leads to improved information access quality. However, there are different mechanisms for increasing information content and information access quality through higher levels of BIS maturity [29], which therefore call to be researched separately.

A review of the management, IQ, and IT/IS literature on the effects of BIS on information access reveals the greater efficiency of knowledge workers [53], enhanced analytical capabilities [27], and improved timeliness of the input to the decision-making process [85] as *information access quality* features were valued the most by knowledge workers when using BIS.

Despite wide recognition that technology mainly influences information access quality [29], with limited possibilities of influencing *information content quality*, it is believed that through improved interactivity (access quality) knowledge workers do not have information merely delivered but are able to explore it and acquire more relevant information (content quality) [62]. Exploring the usefulness of the business information produced by a BIS, Cartwright et al. [6] found that information content quality was the attribute respondents valued the most. Moreover, a BIS can influence information content quality through a loopback: through a better insight into data it allows a perception of errors during data collection, and consecutively improves data quality control during data collection.

Separating information content quality from information access quality is also important as studies [19,29,73] have long recognized that the most significant problems of providing quality information for knowledge-intensive activities relate to information content. Therefore, it is fair to expect that the separate addressing of the two IQ dimensions and a comprehensive view of IQ will contribute to understanding the relationship between IQ and the use of information. We therefore posit:

H_{2a}. The greater the BIS maturity, the more positive the impact on information content quality.

H_{2b}. The greater the BIS maturity, the more positive the impact on information access quality.

H_{2c}. BIS maturity has different positive impacts on information content quality and information access quality.

3.3. The use of information provided by BIS in business processes

It is widely recognized that information plays a crucial role in the success or failure of organizations [12]. However, the information acquired by decision-makers will bear little impact on an organization's ultimate performance if it is not actually put to use in the making of decisions.

Use of information has been defined as "the application of acquired and transmitted information to organizational decision-making" [49]. It is not surprising that use of information provided by IS has also been recognized as one of the most important measures for IS success with many studies researching its various aspects, such as the motivation to use [24], frequency of use [39], intensity of use [77] and the number of features of the decision support system used as surrogate measures of the success of a decision support system [25].

However, it has been recognized that reach, i.e. the number of the system's users [30], is by itself insufficient; researchers must also consider the nature, extent, quality and appropriateness of use [22,23]. Use of the available quality information can assist organizations when managing business processes [2], managing entire supply chains [75], and making decisions [12,79]. It has been found that the effective use of quality information is positively related to process management [87] and, similarly, process optimization has been identified as one of the key benefits of enterprise systems [69]. The intended goal of embedding analytical information and/or analysis capabilities in the context of business processes is to support and improve process execution [4].

While previous studies mainly suggest a positive relationship between IQ and information use [12,60] we are interested in particular into the relationship of proposed segments of IQ and the use of information. System's output quality, defined as the degree to which the task that the system is capable to match peoples' job goals, indirectly influences intention to use the system via perceived usefulness [78]. In the context of BIS, the output quality refers to information relevance, i.e. information content quality. Jeong et al. [42] emphasize perceived usefulness and perceived accessibility – two attributes of IQ – as antecedent variables of information use. While perceived usefulness mostly reflects information content quality measures, Larcker and Lessig [46] indicate that information will be used if it was perceived as being sufficiently important (relevant, informative, meaningful, helpful or significant) and usable (of unambiguous, clear, or readable format) for users' decision-making process. On the other hand, the challenge is also to implement systems that not only meet users' needs for information [42], but also provide accessible information. Culnan [16], for example, suggests that perceived accessibility of information (reflected through ease of access to information source, its availability, and convenience of information provision) influences the extent of users' use of information. Integrating these arguments, we put forward hypotheses H_{3a} and H_{3b}:

H_{3a}. Information content quality has a positive impact on the use of information.

H_{3b}. Information access quality has a positive impact on the use of information.

Even though researchers asserted the importance of information accessibility for information use [20], Jeong et al. [42] argue that information content attributes are becoming determinants to the use of information. We therefore expect that the two segments of IQ affect the use of information differently and included this expectation in the form of hypothesis H_{3c}:

H_{3c}. Information content quality and information access quality have different positive impacts on the use of information, with the quality of information content impact being stronger.

3.4. Analytical decision-making culture and its impact on the use of information

Although organizations implement decision support systems in order to improve the delivery of information to decision-makers and to support their decision-making activities, the anticipated benefits are not always realized [71], especially if organizations neglect factors affecting how the information these systems provide is used. For effective information use organizations must excel not only in deploying IT, information management practices, information sharing, and information integrity practices, which together will result in a high level of IQ [52]. They must also combine those capabilities by establishing proactive use of an information environment in which decision-making is based on rationality, i.e. on the comprehensive analysis of information. Knowledge workers with analytical decision styles will adopt and use the enterprise's IS and their information to a greater extent than knowledge workers with conceptual decision styles. Hence, an analytical decision-making culture can help with overcoming the well-known trade-off between reach and richness; a larger number of knowledge workers will use more complex BISs and more comprehensive information. Thus, when studying the relationship between IQ and use of information as two dimensions of BIS success, the attitude to the use of information in decision-making processes must be taken into account.

Decision-making models are characterized by the use of resources, mainly information, and specific criteria [56]. The rational or classical decision-making model is based on quantitative disciplines with one of the main characteristics being the comprehensiveness of the analysis, while on the other side of the spectrum the non-rational model assumes that most information is not actually used in decision-making [41]. Clearly, there are several levels between the two extremes, sometimes called the boundedly rational model [41] or the organizational model [56].

The results of several studies reveal several factors that impact the extent of rationality and consequently the use of information in decision-making processes, e.g. junior managers with limited years of service are less likely to use a rational process [56], the strategic decision-making process in large and medium organizations seems to be more rational than in smaller sized organizations [56], established practices of monitoring an organization's performance will make the task of analysis easier [41].

Knowledge workers' choice of using information is therefore likely to be affected by the decision-making style and the decision-making culture in the organization: of whether a decision-making process exists and is understood [21,32], of whether organizations consider the available information regardless of the type of decision to be taken [21] and tend to use such information for each decision process [58,69].

While we expect that BIS maturity positively affects IQ and the latter positively impacts information use as previously hypothesized, this study further aims to provide a better understanding of how an analytical decision-making culture boosts the absorptive capacity of the quality information provided by BIS. More precisely, we investigate the interaction effect of an analytical decision-making culture on the relationship between IQ and the use of information in business processes. We expect analytical decision-making culture to positively influence the use of the quality information provided by BIS in business processes and we thus pose the following two hypotheses:

H_{4a}. The higher the level of analytical decision-making culture in an organization, the stronger the relationship between information content quality and the use of information in business processes.

H_{4b}. The higher the level of analytical decision-making culture in an organization, the stronger the relationship between information access quality and the use of information in business processes.

4. Research design and methodology

4.1. Research instrument

To ensure content validity we developed our questionnaire by building on the previous theoretical basis. To assure face validity pre-testing [15] was conducted using a focus group involving academics from the field and semi-structured interviews with selected participants who were not included in the subsequent research. We used a structured questionnaire with a combination of a seven-point Likert scale and seven-point semantic differentials [13]. The participants were given introduction letters which explained the aims and procedures of the study.

4.2. Measures

Measurement items were developed based on the literature review and supported by expert opinions. All constructs in the proposed model are based on reflective multi-item scales.

Based on the reviewed BI and BIS maturity models [38] we modeled *BIS maturity*, a measure of BIS quality, as a second-order construct formed by two first-order factors: *Data integration* and *Analytical capabilities*. With the *Data integration* construct we measure the level of data integration for analytical decisions within organizations through two indicators [48]: i) how the available data are integrated; and ii) whether the data from different data sources are mutually consistent. Within the *Analytical capabilities* construct we look at a different analysis enabled by a BIS. Although the BIS literature refers to many kinds of analytical capabilities, we selected those indicators most used previously: paper reports, ad-hoc reports, OLAP, data mining, to dashboards, KPIs, and alerts [18,82].

To measure IQ we adopted previously researched and validated indicators provided by the most comprehensive IQ framework found in the literature, i.e. Eppler's framework, which explicitly separates the two aspects *Information content quality* and *Information access quality*. Out of the 16 IQ criteria from Eppler's framework we included 11 of them into two constructs of our research instrument. While we are interested in the quality of available information for decision-making itself we left out those information access quality criteria measuring the infrastructure (e.g. its accessibility, security, maintainability, speed of performance) on which the content management process runs and through which information is provided since these criteria relate to technological characteristics of BIS that we are researching through the *BIS maturity* construct.

Through indicators measuring the *Use of information in business processes* we assessed: a) how the available information is used for managing business processes [2]; b) how the information is used for decision-making in organizations' business processes [11]; and c) which benefits organizations achieve by managing their information [17].

To measure *Analytical decision-making culture* we relied on organizational decision-making characteristics of whether a decision-making process exists and is understood [21,32], of whether organizations consider the available information regardless of the type of decision to be taken [21] and tend to use such information for each decision process [58]. Table 2 provides a detailed list of the indicators used in the measurement model.

4.3. Data collection

The data were collected through a survey of 1329 medium- and large-size business organizations conducted in an EU country, namely Slovenia. Organizations were selected from the official database published by the Agency for Public Legal Records and Related Services (AJPES). AJPES is the primary source of official public and other information on business entities and their subsidiaries which perform profitable or non-profitable activities. Questionnaires were addressed to CIOs and senior managers estimated as having adequate knowledge of BIS and the quality of available information for decision-making. A total of 149 managers responded while, at the same time, 27 questionnaires were returned to the researchers with 'return to sender' messages, indicating that the addresses were no longer valid or the companies had ceased to exist. Subsequently, follow up surveys were sent out, resulting in an additional 32 responses. We followed the approach of Prajogo and McDermott [63] and discounted the number of 'return to sender' mails so the final response rate was 13.6%. The structure of respondents by industry type is presented in Table 3. The distribution of the respondents is an adequate representation of the population of Slovenian medium- and large-sized organizations.

4.4. Development of the measurement model

Our proposed measurement model involved 31 manifest variables loading on to 7 latent constructs: (1) *Data integration*; (2) *Analytical capabilities*; (3) *BIS maturity*; (4) *Information content quality*; (5) *Information access quality*; (6) *Use of information in business processes*; and (7) *Analytical decision-making culture*. Then, the fit of the pre-specified model was assessed to determine its construct validity. The latent construct of *BIS maturity* was conceptualized as a second-order construct derived from *Data integration* and *Analytical capabilities*. The specification of this as a second-order factor followed Chin's [9] suggestion by loading the manifest variables for *Data integration* and *Analytical capabilities* on to the *BIS maturity* factor. The interactions between *Analytical decision-making culture* and both IQ constructs (*Information content quality* and *Information access quality*) were modeled to create new constructs, having as indicators the product of the standardized indicators relative to the constructs involved in the interaction [10].

4.5. Data analysis

The data analysis was carried out using Structural Equation Modeling (SEM). Models were estimated with Partial Least Squares (PLS) that has been widely selected as a tool in the IS/IT field [10].

PLS was chosen for two reasons for our study. First, we have a relatively small sample size for our research. Second, PLS is more appropriate when a research model is in an early stage of development and has not been tested extensively [74]. Further, our data are categorical with an unknown nonnormal frequency distribution which also favors the use of PLS. A review of the literature suggests that empirical tests of BIS, BIS maturity, information asymmetry, and use of information in business processes are still rare. Hence, PLS is the appropriate technique for our research purpose. The estimation and data manipulation were performed using SmartPLS [66] and SPSS.

5. Results

5.1. Measurement of reliability and validity

We first examine the reliability and validity measures for the model constructs (see Table 4). In the initial model not all the reliability and convergent validity measures were satisfactory. The loadings of items were tested against the value 0.7 [40] on the construct being measured. The manifest variables AC1, AC2, CQ6, AQ4, and UI1 had weak (AC1 even a negative), although significant (at the 0.1% significance level), loadings on their respective latent constructs and were removed. Manifest variables AC3, CQ2, CQ5, AQ3, UI8, and UI9 had marginal loadings to 0.7 (0.67, 0.63, 0.64, 0.64, 0.69 and 0.66, respectively) and were retained.

Once the manifest variables that did not load satisfactorily had been removed, the model was rerun. In support of *BIS maturity* hypothesized as a second-order construct we additionally ran the model without a

Table 2
Indicators of the measurement model.

Construct	Lbl	Indicator
		(1 = Statement A best represents the current situation, 7 = Statement B best represents the current situation)
Data integration	DI1	Data are scattered everywhere — on the mainframe, in databases, in spreadsheets, in flat files, in Enterprise Resource Planning (ERP) applications. — Statement AData are completely integrated, enabling real-time reporting and analysis. — Statement B
	DI2	Data in the sources are mutually inconsistent. — Statement AData in the sources are mutually consistent. — Statement B
		(1 = Not existent … 7 = Very much present)
Analytical capabilities	AC1	Paper reports
	AC2	Interactive reports (Ad-hoc)
	AC3	On-line analytical processing (OLAP)
	AC4	Analytical applications, including Trend analysis, "What-if" scenarios
	AC5	Data mining
	AC6	Dashboards, including metrics, key performance indicators (KPI), alerts
		(1 = Strongly disagree … 7 = Strongly agree)
Information content quality	CQ1	The scope of information is adequate (neither too much nor too little).
	CQ2	The information is not precise enough and not close enough to reality.
	CQ3	The information is easily understandable by the target group.
	CQ4	The information is to the point, void of unnecessary elements.
	CQ5	The information is contradictory.
	CQ6	The information is free of distortion, bias, or error.
	CQ7	The information is up-to-date and not obsolete.
Information access quality	AQ1	The provision of information corresponds to users' needs and habits.
	AQ2	The information is processed and delivered rapidly without delay.
	AQ3	The background of the information is not visible (author, date etc.).
	AQ4	Information consumers cannot interactively access the information.
		(1 = Strongly disagree … 7 = Strongly agree)
Use of information in business processes		The available information within our organization's business processes …
	UI1	… exposes the problematic aspects of current business processes and makes stakeholders aware of them.
	UI2	… provides a valuable input for assessing business processes against standards, for continuous process improvement programs, and for business process change projects.
	UI3	… stimulates innovation in internal business processes and external service delivery.
	UI4	The information reduces uncertainty in the decision-making process, enhances confidence and improves operational effectiveness.
	UI5	The information enables us to rapidly react to business events and perform proactive business planning.
	UI6	We are using the information provided to make changes to corporate strategies and plans, modify existing KPIs and analyze newer KPIs.
		Through managing the organization's information, we are …
	UI7	… adding value to the services delivered to customers.
	UI8	… reducing risks in the business.
	UI9	… reducing the costs of business processes and service delivery.
		(1 = Strongly disagree … 7 = Strongly agree)
Analytical decision-making culture	AD1	The decision-making process is well established and known to its stakeholders.
	AD2	It is our organization's policy to incorporate available information within any decision-making process.
	AD3	We consider the information provided regardless of the type of decision to be taken.

Table 3
Structure of respondents by industry type compared to the whole population structure.

Industry	Share of respondents (in %)	Population share (in %)
Agriculture, hunting and forestry	1.1	1.5
Manufacturing	46.2	50.7
Electricity, gas and water supply	5.5	3.8
Construction	12.2	11
Wholesale and retail trade	12.3	14
Hotels and restaurants	4.4	4.1
Transport, storage and communication	9.1	5.7
Financial intermediation	4.9	5.1
Real estate, renting and business activities	2.4	3.1
Not given	1.9	

second-order construct. Compared to the results for this model our second-order construct model had R^2 values only marginally smaller than those in the first-order construct model, and the indicator loadings were very similar in both models. Further, other measures used for reliability and convergent validity also tended to support our second-order construct hypothesis.

In the final model all Cronbach's Alphas exceed the 0.7 threshold [77]. Without exception, the latent variable composite reliabilities [81] are higher than 0.8, and in general near 0.9, showing the high internal consistency of indicators measuring each construct and thus confirming construct reliability. The average variance extracted (AVE) [31] is around or higher than 0.6, except for the *BIS maturity* construct, indicating that the variance captured by each latent variable is significantly larger than the variance due to measurement error, and thus demonstrating the convergent validity of the constructs. It was expected that *BIS maturity* would have a smaller AVE since this is a second-order construct and its AVE is lower than the AVE of the two contributing constructs. Nevertheless, it should be noted that *BIS maturity* AVE is also above the 0.5 threshold, thus supporting the existence of *BIS maturity* as a second-order construct. The reliability and convergent validity of the measurement model were also confirmed by computing standardized loadings for the indicators and Bootstrap t-statistics for their significance (see Table 4). All standardized loadings exceed (or were very marginal to) the 0.7 threshold and they were found, without exception, to be significant at the 0.1% significance level, thus confirming the high convergent validity of the measurement model.

To assess discriminant validity we have determined whether each latent variable shares more variance with its own measurement variables or with other constructs [9,31]. We compared the square root of the AVE for each construct with the correlations with all other constructs in the model (Table 5). A correlation between constructs exceeding the square roots of their AVE indicates that they may not be sufficiently discriminable. We can observe that the square roots of AVE (shown in bold in the main diagonal) are higher than the correlations between the constructs, except in the situation where the square root of AVE for *BIS maturity* is smaller than the correlations involving this construct and the two constructs contributing to it. This was expected since *BIS maturity* is a second-order construct. Nevertheless, there is sufficient evidence that *Data integration* and *Analytical capabilities* are different constructs (the correlation between them is significantly smaller than the respective AVEs). Additionally, we have compared individual item cross loadings with construct correlations [34]. All construct loadings are larger than the corresponding cross-loadings, thus reinforcing discriminant validity. We conclude that all the constructs show evidence of acceptable validity.

We conducted two different tests in order to examine the existence of common method bias. One is Harmon's single-factor analysis [61]. The analysis produced 4 factors with eigenvalues higher than 1. Taken together, these factors explained 59.3% of the variance of the

Table 4
Reliability and validity measures of the research model.

Constructs	Indicators	Final model					Estimates		
		Mean	Mode	Std. Dev.	Loadings	t-Values	Cronbach's Alpha	Composite reliability	Average variance extracted
Analytical capabilities	AC3	4.27	5	1.729	0.6611	10.3521	0.7614	0.8492	0.5864
	AC4	3.04	3	1.523	0.8380	33.2443			
	AC5	2.69	2	1.850	0.7791	20.2111			
	AC6	2.67	1	1.722	0.7741	19.6246			
BIS maturity	DI1				0.7483	19.7937	0.7913	0.8515	0.5096
	DI2				0.6794	10.6746			
	AC3				0.6641	10.0212			
	AC4				0.7696	21.2654			
	AC5				0.6496	11.8984			
	AC6				0.6790	14.8742			
Data integration	DI1	5.04	6	1.441	0.9076	55.6216	0.7581	0.8919	0.8049
	DI2	5.19	6	1.396	0.8866	29.8855			
Information content quality	CQ1	4.67	5	1.252	0.7859	30.6543	0.8330	0.8751	0.5413
	CQ2	4.95	6	1.666	0.6314	10.0259			
	CQ3	5.07	5	1.239	0.7207	16.1724			
	CQ4	4.79	5	1.323	0.8362	30.8903			
	CQ5	5.73	6	1.334	0.6447	10.7001			
	CQ7	5.48	6	1.305	0.7730	22.4736			
Information access quality	AQ1	4.62	5	1.503	0.9120	42.5162	0.7747	0.8669	0.6896
	AQ2	4.79	6	1.413	0.9085	50.9490			
	AQ3	5.53	7	1.541	0.6417	8.5053			
Use of information in business processes	UI2	5.12	6	1.401	0.7324	19.9828	0.8717	0.8983	0.5254
	UI3	4.36	5	1.456	0.7569	26.1751			
	UI4	5.71	6	1.142	0.6950	8.7854			
	UI5	5.35	6	1.262	0.7857	21.2314			
	UI6	4.97	5	1.368	0.7472	20.3849			
	UI7	5.00	6	1.491	0.7209	19.3724			
	UI8	5.42	6	1.340	0.6936	10.0572			
	UI9	5.27	6	1.445	0.6593	14.4200			
Analytical decision-making culture	AD1	4.81	6	1.428	0.7474	14.0462	0.7794	0.8203	0.6049
	AD2	4.76	4	1.411	0.8606	44.7272			
	AD3	4.68	5	1.363	0.7180	9.5499			

Note: All t-values significant at the 0.1% significance level (N = 181, t critical value = 3.291).

data, with the first extracted factor accounting for 35% of that variance. Given that more than one factor was extracted from the analysis and the first factor accounted for much less than 50% of the variance, common method bias is unlikely to be a significant issue with the collected data. For the second test we used Lindell and Whitney's method [50] which employs a theoretically unrelated construct (marker variable) to adjust the correlations among the principal constructs. *Job satisfaction* was used as the marker variable. Since the average correlation among *Job satisfaction* and the principal constructs was r = 0.16 (average t-value = 2.03), this test showed no evidence of common method bias. In summary, these tests suggest that common method bias is not involved in the study's results.

5.2. Results of the model estimation

After validating the measurement model, the hypothesized relationships between the constructs were tested. A bootstrapping with 1000 samples was conducted. The structural model was then assessed by examining the determination coefficients, the path coefficients and their significance levels.

As shown in Fig. 2 the influence of *BIS maturity* explains about 30% of the variance in *Information access quality* and about 20% of the variance in *Information content quality*. Moreover, the influence of *Information content quality* and *Analytical decision-making culture* explains more than 50% of the variance in the *Use of information in business processes* (as *Information access quality* was found to play no significant role). It is again worth noting that *BIS maturity* is a second-order construct, so its R^2 is obviously 1.

The standardized path coefficients range from 0.071 (the non-significant impact of *Information access quality* on *Use of information in business processes*) to 0.682 (the impact of *Analytical capabilities* on *BIS maturity*). Globally, hypotheses H1 through H_2 (H_{2a}, H_{2b} and H_{2c}) are fully supported. All the path coefficients associated to H_1, H_{2a}, and H_{2b} are significant at the 0.1% significance level. As indicated by the path loadings, *BIS maturity* has significant direct and different positive influences on *Information content quality* (H_{2a};

Table 5
Correlations between the latent variables and square roots of the average variance extracted.

	Analytical capabilities	BIS maturity	Data integration	Information content quality	Information access quality	Use of information in business processes	Analytical decision-making culture
Analytical capabilities	**0.7658**						
BIS maturity	0.9058	**0.6997**					
Data integration	0.4664	0.7972	**0.8972**				
Information content quality	0.3491	0.4523	0.4465	**0.7357**			
Information access quality	0.4103	0.5471	0.5550	0.6716	**0.8304**		
Use of information in business processes	0.4531	0.4683	0.3325	0.5658	0.4870	**0.7248**	
Analytical decision-making culture	0.4349	0.4554	0.3304	0.4335	0.4533	0.6104	**0.7777**

Note: Numbers shown in bold indicate the square root of AVE.

$\hat{\beta}=0.452$) and *Information access quality* (H_{2b};$\hat{\beta}=0.547$). To confirm H_{2c} we tested whether $\hat{\beta}_{(\text{BIS maturity impact on information content quality})}=\hat{\beta}_{(\text{BIS maturity impact on information access quality})}$. The *t*-statistic for the difference of the two impacts is 2.3 with $p<0.05$, hence confirming that the two hypothesized impacts are indeed different. To derive additional relevant information, the sub-dimensions of the second-order construct (*BIS maturity*) were also examined. As evident from the path loadings of *Data integration* and *Analytical capabilities*, the effects of each of these two dimensions of *BIS maturity* are significant ($p<0.001$) and of a moderate to high magnitude ($\hat{\beta}=0.479$ and $\hat{\beta}=0.682$, respectively), supporting H_1 as a conceptualization of the dependent construct as a second-order structure [16,9]. The support for H_1 is also reinforced by results showing the validity of the constructs *Data integration*, *Analytical capabilities*, and *BIS maturity*.

The path loadings for the remainder of the model indicate *Information content quality* ($\hat{\beta}=0.313$, $p<0.001$) have a direct and positive impact on the *Use of information in business processes*, (H_{3a}). However, the impact of *Information access quality* ($\hat{\beta}=0.071$) on the *Use of information in business processes* (H_{3b}) was found to be non significant.

Note that the effect of BIS maturity on IQ was found to be larger on the access component (H_{2b}) than on the content component (H_{2a}). Nevertheless, *Information content quality* had a greater effect on *Use of information in business processes* than *Information access quality* (which was found to be non-significant) does (H_{3c}). The consequences of this gap will be discussed in the next section.

Finally, the interaction effect of *Analytical decision-making culture* on the relationship between *Information content quality* and the *Use of informationv in business processes* (H_{4a}) is significant, but negative ($\hat{\beta}=-0.139$, $p<0.05$). Further, the instrumental impact of *Analytical decision-making culture* on the *Use of information in business processes* was found to be significant and positive ($\hat{\beta}=0.421$, $p<0.001$). Note that hypothesis H_{4a} is thus not supported because, although significant, the effect has the opposite sign of what was expected. This means that the relationship between information content quality and the use of information in business processes is weaker the higher the level of the analytical decision-making culture. Although with the opposite sign of what was hypothesized, the impact of information content quality on the use of information in business processes is found contingent on the analytical decision-making culture. IQ seems to be less important for the use of information in the business processes of organizations with a stronger analytical decision-making culture. In fact, this effect is about 0.31 when the level of *Analytical decision-making culture* is average, but can vary between a non-existing effect of about zero (when *Analytical decision-making culture* is about 2 standard-deviations above average) to a high magnitude effect of 0.68 (when *Analytical decision-making culture* is about 2 standard-deviations below average).

To confirm the validity of our results we re-estimated the model controlling some additional variables. We included in the model both industry (10 classes) and sales volume (3 classes) as explanatory (control) variables. The results show that both variables are non-significant when explaining the dependent variable (Industry: F value = 0.52, p = 0.8952; Sales: F value = 2.45, p = 0.0894), therefore confirming that the previously found relationships are not induced by profile variables.

6. Discussion and conclusion

6.1. Discussion

Our findings provide some interesting insights into the interrelationships between BIS success dimensions and the effects of BIS maturity and analytical decision-making culture on use of information (see Fig. 2). Survey data linked *Data integration* and *Analytical capabilities* as two dimensions of BIS maturity. Specifically, it appears that both dimensions are significant yet analytical capabilities are considerably more important for achieving higher BIS maturity. Decision support systems literature provides supporting evidence. Studies suggest that data integration is a starting point for implementing BIS [69] and for organizations striving to reach higher levels of BIS maturity it is imperative that they first solve data integration issues (e.g. data quality and security issues, metadata management issues, lack of IT data integration skills, and data transformation and aggregation issues) that are frequently preventing them to get results to users in a timely manner [86].

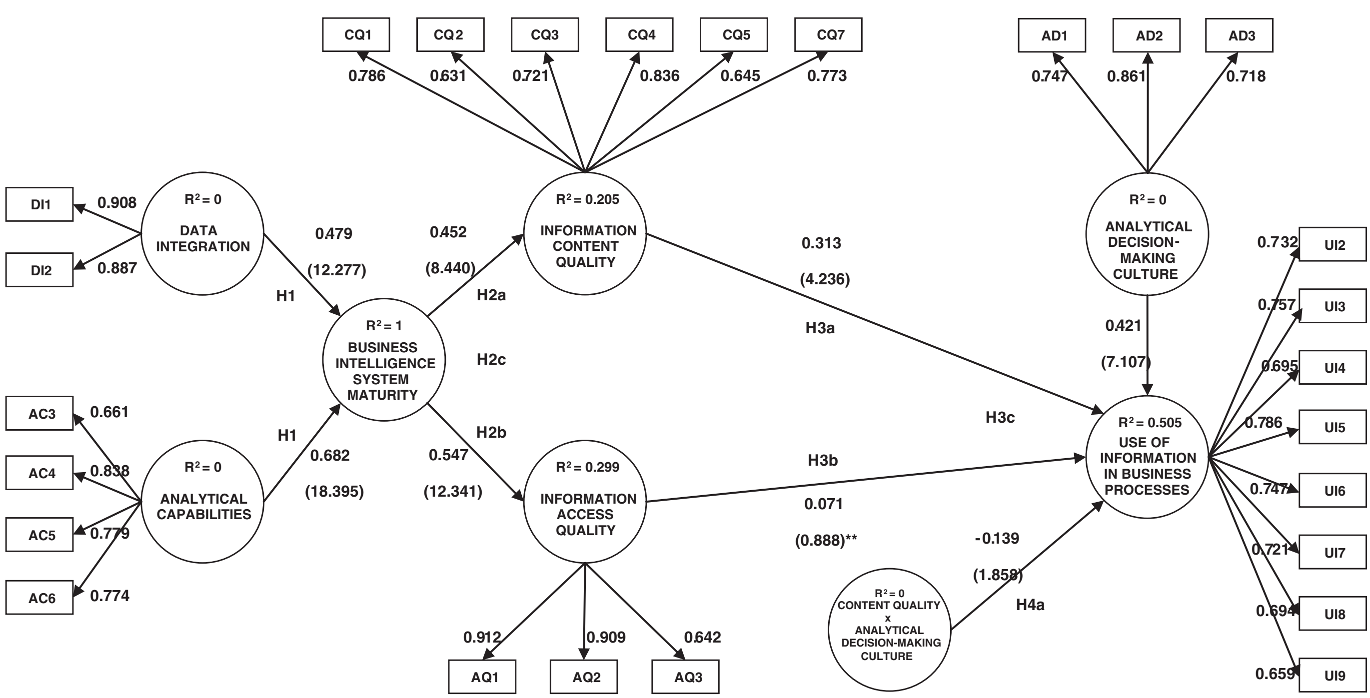

Fig. 2. The final measurement mode.

However, it is the introduction of advanced analytical technologies, such as OLAP, data mining, and dashboards that enable reaching higher levels of maturity which significantly contribute in advancing BIS from low-value operations to strategic tool.

BIS maturity encourages better IQ. Hannula et al. [37] argue that an increase in BIS quality will cause IQ to increase. Our results reveal that BIS maturity has a significant positive impact on both segments of IQ, namely *Information content quality* and *Information access quality*, as they were conceptualized in our model. Even if both IQ segments are obviously addressed through the implementation of BIS, IQ literature proposes that implementation projects should focus more on issues related to the main IQ concerns in knowledge-intensive activities, i.e. content quality issues ([19,29,73]), which means that the implementation of BIS should affect information content quality more than information access quality. In our case, the results demonstrate that the implementation of BIS indeed has different impacts on the two dimensions of IQ. It appears as if organizations implementing BIS give less emphasis to information content quality and instead call attention to information access quality. Relatively high costs in seeking information content quality that is not readily available [29], prevalence of mostly technologically-oriented BIS implementation projects [85], the shift in focus of BIS projects from knowledge workers' actual needs to addressing technical issues of providing the rapid processing and delivery of information, and lack of appropriate managerial methods (e.g. business performance management) to enable knowledge workers to more clearly define their information needs and consequently to address information content quality issues are a few possible reasons for this.

In addition, these dimensions of IQ appear to endorse information use. Information of higher perceived quality will be used more frequently than information of lower perceived quality, and information sources that are more accessible will be used more frequently than those that are less accessible [64]. The results of this study offer additional important insights into the impact of the two IQ dimensions on the *Use of information in business processes*, as they were conceptualized in our model. Specifically, we found that only *Information content quality* is relevant; the impact of *Information access quality* is non-significant. While this conforms to IQ literature it further emphasizes the gap between the information access quality provided by BIS and the IQ needs of knowledge workers when using information. Although the decision support literature proposes that the implementation of BIS contributes above all to faster access to information, easier querying and analysis, along with a higher level of interactivity [62], it is essential to draw attention to the problems of IQ in knowledge-intensive activities that knowledge workers most often encounter. The unsuitability of content quality affects future uses of information and can easily lead to a less suitable business decision (e.g. analyzing poor quality data does not provide the right understanding of business issues which, in turn, affect decisions and actions). Hence, such approaches and focuses of BI projects result in dissatisfaction with BIS and ultimately in the non-use of these systems, bringing a lower success rate for BIS projects. Even though information access quality, as perceived by the user, is important, lower access quality is less likely to be used for excluding criterion when information is needed.

Lastly, analytical decision-making culture appears to diminish the decision-makers' perception about the relevance of content quality for the use of information in business processes. The decision-making literature proposes that decision-makers' choice of using information is likely to be affected by decision-making culture in the organization [26,72]. Although not considered in our hypotheses we a posteriori found that *Analytical decision-making culture* directly and positively affects the *Use of information in business processes*. Yet, the impact of *Analytical decision-making culture* on the relationship between *Information content quality* and the *Use of information in business processes* is negative; it suppresses the direct impact of information content quality on the use of information. Once organizations reach higher levels of analytical decision-making culture decision-makers tend to use the available information in organizations' business processes regardless of its content quality. This implies that improving information content quality will have a stronger effect on information use in organizations with low levels of an analytical decision-making culture. The shift towards higher analytical decision-making culture enables organizations to use information even though the information is not of the best quality. On the other hand, IQ contributes to information use in spite of analytical decision-making culture reaching relatively low levels.

It is apparent that few previous studies in the field have explored BIS success dimensions and investigated the links among them. Cavalcanti [7] researched how different BI practices (e.g. environmental, market, and consumer intelligence) relate to perceived business success but provide no insights into what are the success dimensions of these BI practices. To this body of knowledge Ranjan [65] added guidelines for successfully implementing BIS in organizations in terms of users, technology and desired firm goals; however, the research is still lacking the interconnections between these dimensions. Acknowledging the role of organizational obstacles (e.g. the prevailing socio-cultural milieu), Seah et al. [68] researched the effects of leadership style on the success of BIS implementation. Our work expands those efforts by including analytical decision-making culture as a relevant dimension of BIS success research. Wixom and Watson [84] proposed data quality (analyzed through common measures of data quality for IS), system quality (studied through flexibility and integration), and perceived net benefits (as perceived by an organization's data suppliers) as the three dimensions of data warehousing success, although the authors suggested that "more work is needed, however, to examine exactly how the dimensions of success interrelate." In our work we expanded the focus from data warehousing to broad BIS, employed IQ (rather than data quality) measures, expanded the study of BIS quality by adding the analytical capabilities of the system, suggested the use of information in organizations' processes as a dependent variable, and established links among these success dimensions. In their critical success factor framework for the implementation of BIS, Yeoh et al. [85] identified system quality, IQ, and system use as BIS implementation success measures but provided no additional information about the relationships among these measures. Upgrading their work, we proposed BIS maturity as a system quality measure, analyzed the resulting IQ through two different dimensions, we further established and tested interrelationships among the success measures, included information use as a relevant success measure, and added analytical decision-making culture as an organizational measure importantly affecting the relationships between IQ and use. Focusing on the success of adopting data warehousing, Nelson et al. [55] studied the determinants of system quality and IQ. While their work adds important insights into indicators that are important for data warehousing, we expanded this by providing a more comprehensive view of IQ dimensions and system quality (measured through BIS maturity) in the context of BIS. Lastly, based on seminal works on IS success models [23] and technology acceptance [83] where a conceptual gap between system/information satisfaction and use has been identified, we tried to bridge this gap in the BIS context by proposing and testing the interrelationships among previously identified success dimensions and the newly added analytical decision-making culture effect.

Leveraging the quantitative research and blending the decision-making and IS literature enabled the development of a model allowing a comprehensive understanding of the interrelationships among BIS success dimensions and research hypotheses that explicate these relationships. The model of these interrelationships was designed and empirically validated. By studying the interactions, as well as the components themselves, it identifies specifics and provides a more comprehensive view of BIS success than previous studies. Although several studies exist about various impacts of IQ on business decision-making (e.g. [3,23,29]), to our knowledge this is the first study to directly establish the effects of BIS maturity on the use of information in business processes through the inclusion of different segments of IQ and the interacting effect of an analytical decision-making culture. Studying the two IQ segments separately and considering an analytical decision-making culture as the interacting variable enables a better understanding of the impact of IQ on the use of information than previous studies which provided discordant results [59]. This facilitates understanding of an organization's ability to recognize the value of the available information (i.e. the absorbability of information) provided by BIS for applying it to emerging business process requirements.

We encourage practitioners involved in BIS implementation projects to focus more on knowledge workers' actual needs (i.e. providing content quality), and not merely on providing the rapid processing and delivery of information (i.e. access quality), since a clearer definition of their needs would ensure the comprehensiveness and conciseness of the information. This emphasizes the need for the simultaneous implementation of contemporary managerial concepts that better define information needs in managerial processes by connecting business strategies with business process management. The latter includes setting organizational goals, measuring them, monitoring and taking corrective actions, and goes further to cascading organizational goals and monitoring performance down to levels of individual business activities. Moreover, this study provides insights for managers regarding the factors that affect the use of information in business processes, an awareness of the actual business value of BIS, and it also sets the grounds for organizations to assess their readiness for future BIS initiatives. An analytical decision-making culture appears to be a critical factor in ensuring BIS success. Given our goal of studying the relationships among the BIS success dimensions that might spur more comprehensive empirical research, we now intend to examine opportunities for testing and extending our research.

6.2. Conclusion

Our research sought to learn from organizations that have implemented a BIS where we examined the interrelationships of BIS success dimensions through cross-sectional data. However, whether and how our hypotheses apply to longitudinal designs raise important questions. Future studies may extend our work to settings with different information behavior [52] and also to study these phenomena in organizations with different organizational cultures [48]. The analysis presented and resulting model offer insights into BIS success dimensions and their interrelationships. We believe that our outline success model captures the interrelationship dimensions for BIS success and will be of value to both the academic and practitioner communities.

References

[1] H. Altarawneh, S. Allahawiah, Electronic Markets has Weakened the "Tradeoff between Reach and Richness" in the Internet, World Academy of Science, Engineering and Technology, 62(2010).
[2] N. Berente, B. Vandenbosch, B. Aubert, Information flows and business process integration, Business Process Management Journal 15 (1) (2009) 119–141.
[3] P. Bharati, A. Chaudhury, An empirical investigation of decision-making satisfaction in web-based decision support systems, Decision Support Systems 37 (2) (2004) 187–197.
[4] T. Bucher, B. Dinter, Process orientation of information logistics — an empirical analysis to assess benefits, design factors, and realization approaches, in: 41st Hawaii International Conference on System Sciences, (Hawaii, 2008).
[5] T. Bucher, A. Gericke, S. Sigg, Process-centric business intelligence, Business Process Management Journal 15 (3) (2009) 408–429.
[6] D.L. Cartwright, P.D. Boughton, S.W. Miller, Competitive intelligence systems: relationships to strategic orientation and perceived usefulness, Journal of Managerial Issues 7 (4) (1995).
[7] E.P. Cavalcanti, The relationship between business intelligence and business success, Journal of Competitive Intelligence and Management 3 (1) (2005) 6–15.
[8] P.Y.K. Chau, K.K.Y. Kuan, T.-P. Liang, Research on IT value: what we have done in Asia and Europe, European Journal of Information Systems 16 (3) (2007) 196–201.
[9] W.W. Chin, Issues and opinion on structure equation modeling, MIS Quarterly, 22(1) (1998) vii-xvi.
[10] W.W. Chin, B.L. Marcolin, P.R. Newsted, A partial least squares latent variable modeling approach for measuring interaction effects: results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study, Information Systems Research 14 (2) (2003) 189–217.
[11] C.W. Choo, The knowing organization: how organizations use information to construct meaning, create knowledge and make decisions, International Journal of Information Management 16 (5) (1996) 329–340.
[12] C.L. Citroen, The role of information in strategic decision-making, International Journal of Information Management 31 (6) (2011) 493–501.
[13] P.S. Coelho, S.P. Esteves, The choice between a 5-point and a 10-point scale in the framework of customer satisfaction measurement, International Journal of Market Research 49 (3) (2007) 313–345.
[14] W.M. Cohen, D.A. Levinthal, Absorptive capacity: a new perspective on learning and innovation, Administrative Science Quarterly 35 (1) (1990) 128–152.
[15] D.R. Cooper, P.S. Schindler, Business Research Methods, 8th ed. McGraw-Hill/Irwin, Boston, 2003.
[16] M.J. Culnan, The dimensions of perceived accessibility to information: implications for the delivery of information systems and services, Journal of the American Society for Information Science 36 (5) (1985) 302–308.
[17] T.H. Davenport, M.C. Beers, Managing information about processes, Journal of Management Information Systems 12 (1) (1995) 57.
[18] T.H. Davenport, J.G. Harris, Competing on analytics: the new science of winning, (Harvard Business School Press, 2007).
[19] T.H. Davenport, S.L. Jarvenpaa, M.C. Beers, Improving knowledge work processes, Sloan Management Review 37 (1996) 53–66.
[20] F.D. Davis, R.P. Bagozzi, P.R. Warshaw, User acceptance of computer technology: a comparison of two theoretical models, Management Science 35 (8) (1989) 982–1003.
[21] S.M. de Alwis, S.E. Higgins, Information as a tool for management decision-making: a case study of Singapore, in: Information Research, (2001).
[22] W.H. DeLone, E.R. McLean, Information systems success: the quest for the dependent variable, Information Systems Research 3 (1) (1992) 60–95.
[23] W.H. DeLone, E.R. McLean, The DeLone and McLean model of information systems success: a ten-year update, Journal of Management Information Systems 19 (4) (2003) 9–30.
[24] G. DeSanctis, R.B. Gallupe, A foundation for the study of group decision support systems, Management Science 33 (5) (1987) 589–609.
[25] G. Dodson, D. Arnott, G. Pervan, The Use of Business Intelligence Systems in Australia, in: ACIS 2008: 19th Australasian Conference on Information Systems, Christchurch, New Zealand, 2008. pp. 260–271.
[26] J.J. Elam, D.G. Leidner, EIS adoption, use, and impact: the executive perspective, Decision Support Systems 14 (2) (1995) 89–103.
[27] M.Z. Elbashir, P.A. Collier, M.J. Davern, Measuring the effects of business intelligence systems: the relationship between business process and organizational performance, International Journal of Accounting Information Systems 9 (3) (2008) 135–153.
[28] L.P. English, Business Intelligence Defined, in, Business Intelligence, Network, 2005.
[29] M.J. Eppler, Managing Information Quality: Increasing the Value of Information in Knowledge-Intensive Products and Processes, 2nd ed., (Springer, 2006).
[30] P.B. Evans, T.S. Wurster, Strategy and the new economics of information, Harvard Business Review 75 (5) (1997) 70–82.
[31] C. Fornell, D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, Journal of Marketing Research 18 (1) (1981) 39–50.
[32] J. Frishammar, Information use in strategic decision-making, Management Decision 41 (4) (2003) 318–326.
[33] M.N. Frolick, T.R. Ariyachandra, Business performance management: one truth, Information Systems Management 23 (1) (2006) 41–48.
[34] D. Gefen, D. Straub, A practical guide to factorial validity using PLS-graph: tutorial and annotated example, Communications of the Association for Information Systems 16 (2005) 91–109.
[35] R. Glazer, Measuring the value of information: the information-intensive organization, IBM Systems Journal 32 (1) (1993) 99–110.
[36] M. Golfarelli, S. Rizzi, I. Cella, Beyond data warehousing: what's next in business intelligence?, in: proceedings of the 7th ACM international workshop on Data warehousing and OLAP, ACM, Washington, DC, USA, 2004. pp. 1–6.
[37] M. Hannula, V. Pirttimäki, Business intelligence — empirical study on the top 50 Finnish companies, Journal of American Academy of Business 2 (2) (2003) 593–600.
[38] I. Hribar Rajterič, Overview of business intelligence maturity models, Management 15 (1) (2010) 47–67.
[39] C.-c. Hsieh, M.-t. Lu, C.-c. Pan, Current status of DSS use in Taiwan, Information & Management, 22(4) (1992) 199–206.
[40] J. Hulland, Use of partial least squares (PLS) in strategic management research: a review of four recent studies, Strategic Management Journal 20 (2) (1999) 195–204.
[41] E. Hyyryläinen, O.-P. Viinamäki, The implications of the rationality of decision-makers on the utilization of evaluation findings, International Journal of Public Administration 31 (10–11) (2008) 1223–1240.
[42] M. Jeong, C.U. Lambert, Adaptation of an information quality framework to measure customers' behavioral intentions to use lodging Web sites, International Journal of Hospitality Management 20 (2) (2001) 129–146.
[43] Z. Jourdan, R.K. Rainer, T.E. Marshall, Business intelligence: an analysis of the literature, Information Systems Management 25 (2) (2008) 121–131.
[44] B. Jukic, N. Jukic, M. Velasco, Enterprise information systems change, Adaptation and Adoption: A Qualitative Study and Conceptualization Framework, Information Resources Management Journal 22 (1) (2009) 63–87.
[45] B.K. Kahn, D.M. Strong, R.Y. Wang, Information quality benchmarks: product and service performance, Communications of the ACM 45 (4) (2002) 184–192.
[46] D.F. Larcker, V.P. Lessig, Perceived usefulness of information: a psychometric examination, Decision Sciences 11 (1) (1980) 121–134.

[47] C.S. Leem, B.W. Kim, E.J. Yu, M.H. Paek, Information technology maturity stages and enterprise benchmarking: an empirical study, Industrial Management & Data Systems 108 (9) (2008) 1200–1218.
[48] M. Lenzerini, Data integration: a theoretical perspective, in: L. Popa, S. Abiteboul, P.G. Kolaitis (Eds.), Proceedings of the 21st ACM SIGMOD-SIGACT-SIGART Symposium on Principles of Database Systems, (ACM), NY, USA, New York, 2002, pp. 233–246.
[49] D. Leonard-Barton, I. Deschamps, Managerial influence in the implementation of new technology, Management Science 34 (10) (1988) 1252–1265.
[50] M.K. Lindell, D.J. Whitney, Accounting for common method variance in cross-sectional research designs, Journal of Applied Psychology 86 (1) (2001) 114–121.
[51] A. Lönnqvist, V. Pirttimäki, The measurement of business intelligence, Information Systems Management 23 (1) (2006) 32–40.
[52] D.A. Marchand, W.J. Kettinger, J.D. Rollins, Information orientation: people, technology and the bottom line, Sloan Management Review 41 (4) (2000) 69–80.
[53] G. Matei, A collaborative approach of business intelligence system, Journal of Applied Collaborative Systems 2 (2) (2010) 91–101.
[54] N. Melville, K. Kraemer, V. Gurbaxani, Information technology and organizational performance: an integrative model of IT business value, MIS Quarterly 28 (2) (2004) 283–322.
[55] R.R. Nelson, P.A. Todd, B.H. Wixom, Antecedents of Information and System Quality: An Empirical Examination Within the Context of Data Warehousing, in: Journal of Management Information Systems, (M.E. Sharpe Inc., 2005), pp. 199–235.
[56] M. Nooraie, Decision magnitude of impact and strategic decision-making process output: the mediating impact of rationality of the decision-making process, Management Decision 46 (4) (2008) 640–655.
[57] P.C. Nutt, The effects of culture on decision-making, Omega 16 (6) (1988) 553–567.
[58] P.C. Nutt, The formulation process and tactics used in organizational decision-making, Organization Science 4 (2) (1993) 226–251.
[59] G. Peters, S. Poon, Analyzing IT business values — A Dominance based Rough Sets Approach perspective, Expert Systems with Applications 38 (9) (2011) 11120–11128.
[60] S. Petter, W.H. DeLone, E.R. McLean, Measuring information systems success: models, dimensions, measures, and interrelationships, European Journal of Information Systems 17 (3) (2008) 236–263.
[61] P.M. Podsakoff, S.B. MacKenzie, J.Y. Lee, N.P. Podsakoff, Common method biases in behavioral research: a critical review of the literature and recommended remedies, Journal of Applied Psychology 88 (5) (2003) 879–903.
[62] A. Popovič, P.S. Coelho, J. Jaklič, The impact of business intelligence system maturity on information quality, Information Research 14 (4) (2009).
[63] D.I. Prajogo, C.M. McDermott, The relationship between total quality management practices and organizational culture, International Journal of Operations & Production Management 25 (11) (2005) 1101–1122.
[64] S. Raghunathan, Impact of information quality and decision-maker quality on decision quality: a theoretical model and simulation analysis, Decision Support Systems 26 (4) (1999) 275–286.
[65] J. Ranjan, Business justification with business intelligence, VINE 38 (4) (2008) 461–475.
[66] C.M. Ringle, S. Wende, A. Will, SmartPLS 2.0 M3, in, (University of Hamburg, 2007).
[67] J. Ruževičius, A. Gedminaitė, Business information quality and its assessment, Engineering Economics 52 (2) (2007) 18–25.
[68] M. Seah, M.H. Hsieh, P.-D. Weng, A case analysis of Savecom: the role of indigenous leadership in implementing a business intelligence system, International Journal of Information Management 30 (4) (2010) 368–373.
[69] P.B. Seddon, C. Calvert, S. Yang, A multi-project model of key factors affecting organizational benefits from enterprise systems, MIS Quarterly 34 (2) (2010) 305–328.
[70] P.B. Seddon, S. Staples, R. Patnayakuni, M. Bowtell, Dimensions of information systems success, Communications of AIS 2 (3) (1999).
[71] R. Sharma, P. Yetton, The contingent effects of management support and task interdependence on successful information systems implementation, MIS Quarterly 27 (4) (2003) 533–555.
[72] S.K. Singh, H.J. Watson, R.T. Watson, EIS support for the strategic management process, Decision Support Systems 33 (1) (2002) 71–85.
[73] D.M. Strong, Y.W. Lee, R.Y. Wang, Data quality in context, Communications of the ACM 40 (5) (1997) 103–110.
[74] H.H. Teo, K.K. Wei, I. Benbasat, Predicting intention to adopt interorganizational linkages: an institutional perspective, MIS Quarterly 27 (1) (2003) 19–49.
[75] P. Trkman, K. McCormack, M.P.V. de Oliveira, M.B. Ladeira, The impact of business analytics on supply chain performance, Decision Support Systems 49 (3) (2010) 318–327.
[76] E. Turban, R. Sharda, D. Delen, Decision Support and Business Intelligence Systems, 9th ed. Prentice Hall Press, Upper Saddle River, NJ, 2010.
[77] V. Venkatesh, S.A. Brown, L.M. Maruping, Predicting different conceptualizations of system use: the competing roles of behavioral intention, Facilitating Conditions, and Behavioral Expectation, MIS Quarterly 32 (3) (2008) 483–502.
[78] V. Venkatesh, F.D. Davis, A theoretical extension of the technology acceptance model: four longitudinal field studies, Management Science 46 (2) (2000) 186–204.
[79] H.J. Watson, D.L. Goodhue, B.H. Wixom, The benefits of data warehousing: why some organizations realize exceptional payoffs, Information & Management 39 (2002) 491–502.
[80] D. Wells, Business Analytics — Getting the Point, in, (BeyeNETWORK, 2008).
[81] C.E. Werts, R.L. Linn, K.G. Jöreskog, Intraclass reliability estimates: testing structural assumptions, Educational and Psychological Measurement 34 (1) (1974) 25–34.
[82] S. Williams, N. Williams, The Profit Impact of Business Intelligence, Morgan Kaufmann, 2007.
[83] B.H. Wixom, P.A. Todd, A theoretical integration of user satisfaction and technology acceptance, Information Systems Research 16 (1) (2005) 85–102.
[84] B.H. Wixom, H.J. Watson, An empirical investigation of the factors affecting data warehousing success, MIS Quarterly 25 (1) (2001) 17–41.
[85] W. Yeoh, A. Koronios, J. Gao, Managing the implementation of business intelligence systems: a critical success factors framework, International Journal of Enterprise Information Systems 4 (3) (2008) 79–94.
[86] L. Zeng, L. Xu, Z. Shi, M. Wang, W. Wu, Techniques, Process, and Enterprise Solutions of Business Intelligence, in: 2006 IEEE International Conference on Systems, Man, and Cybernetics, (Taipei, 2006).
[87] X. Zu, L.D. Fredendall, T.J. Douglas, The evolving theory of quality management: the role of six sigma, Journal of Operations Management 26 (2008) 630–650.

Aleš Popovič is an Assistant Professor of Information Management at the Faculty of Economics at the University of Ljubljana and visiting professor at ISEGI — University Nova in Lisbon. He holds BS, MSC and Ph.D. degrees from the University of Ljubljana. His research focuses on business intelligence, information management, and business process management. He is the (co)author of numerous papers in national and international professional and scientific journals. He has collaborated in many applied projects in the areas of business process modeling, analysis, renovation and informatization and in the area of business intelligence.

Ray Hackney holds the Chair in Business Systems at Brunel University. He has contributed extensively to research in the field with numerous international publications. He has taught and examined in a number of doctoral and MBA programs including the Manchester Business School and the Open University. Professor Hackney is currently Associate Editor of the JGIM, JEUC, JEIM, ACITM and case editor for IJIM. His research interests include the strategic management of information systems within a variety of eBusiness and eGovernment contexts. He is also the Head of the Information Systems Integration and Evaluation (ISEing) research group with the Brunel Business School, UK. Professor Hackney was President of the Information Resource Management Association (IRMA) during 2001/2002 and now serves on the Executive Committee of the European Doctoral Association for Management and Business (EDAMBA).

Pedro Simões Coelho is a Professor at the New University of Lisbon, Institute for Statistics and Information Management, Portugal and a Visiting Professor at the Faculty of Economics, University of Ljubljana, Slovenia. He is researcher in the Center for Statistics and Information Management (CEGI) of the same university, President of the General Assembly of the Portuguese Association for Classification and Data Analysis (CLAD). He is also member of the scientific quality committee in UNL. He is former member of the Portuguese High Council for Statistics (CSE), President of the Fiscal Board of the European Center of Statistics for the Developing Countries (CESD-Lisboa), member of the UNL senate and Dean of ISEGI-UNL. His main research interests are centered in sampling, survey methodology, marketing research, customer satisfaction measurement and structural equation modeling. He is author of more than 100 studies and projects in the field of statistics, marketing research and information management, resulting in more than 300 research reports. He is presently referee of several scientific publications, namely of the European Journal of Marketing. Prof. Coelho has been consultant of several organizations, namely Eurostat, the Portuguese Statistical Office and the Portuguese Central Bank.

Jurij Jaklič is a Professor of Information Management at the Faculty of Economics of the University of Ljubljana and an invited professor at the ISEGI-UNL. He holds a bachelor degree in applied mathematics from the University of Ljubljana, an MSc in Computer Science from Houston University (USA) and a PhD in Information Management from the Faculty of Economics of the University of Ljubljana. His current main research interests encompass the fields of information quality, business intelligence and business process management. He is the (co)author of around 100 papers and research reports; many of them have been published in international scientific journals such as Journal of Information Technology Management, Supply Chain Management, Information Science, and Simulation. He is the Editor-in-Chief of the journal Applied Informatics. He has been involved in several research and consulting projects in the areas of business intelligence, business process renovation and IS strategic planning.