Do Business Intelligence Systems Actually Improve Information Quality?

JURIJ JAKLIC
Department of Information management
University of Ljubljana, Faculty of Economics
Kardeljeva pl. 17, 1000 Ljubljana
SLOVENIA
jurij.jaklic@ef.uni-lj.si http://www.ef.uni-lj.si

PEDRO SIMÕES COELHO
Institute for Statistics and Information Management
University NOVA
Campus de Campolide, 1070-312 Lisboa
PORTUGAL
psc@isegi.unl.pt http://www.isegi.unl.pt

ALES POPOVIC
Department of Information management
University of Ljubljana, Faculty of Economics
Kardeljeva pl. 17, 1000 Ljubljana
SLOVENIA
ales.popovic@ef.uni-lj.si http://www.ef.uni-lj.si

Abstract: - Technology and solution providers in the field of business intelligence usually claim that implementation of business intelligence technologies and systems will lead to easier, more flexible, and rapid access to information. Shortly, they promise improved information quality. The aim of this study is to test the declared impact of business intelligence systems on improved information quality and to further investigate this relationship. Empirical data were collected through a survey of Slovenian medium and large size organizations. Quantitative analysis was carried out on the data, which related to 181 medium and large size organizations. Data analysis was carried out using PLS Path Modelling. From the study it appears data integration and analytics are important components when defining business intelligence systems maturity. The results of the analysis show that business intelligence systems actually have a positive impact on two segments of information quality, namely content quality and media quality. However, the impact of business intelligence systems on media quality is stronger, while the quality of content is more important for making better business decisions and providing high business value of business intelligence systems. Thus, implementation of business intelligence systems must be complemented with other activities for advancing information quality.

Key-Words: Analytics, Business intelligence, Business intelligence systems maturity, Data integration, Information quality, PLS methodology

1 Introduction

According to a research by IT Strategies, Inc. [16] business intelligence systems (BIS) have one of the greatest potentials in achieving information asymmetry and differentiation from competitors respectively and thus achieve competitive advantage with IT. When organizations think about introducing BIS the key factor is improvement of information processes – a different way for providing information, i.e. improvement of information quality, such as increased self-service access to data, data integration from different sources, and interactive and convenient access to data.

Business intelligence systems refer to an important class of systems for data analysis and reporting that provide managers at various levels of the organization with timely, relevant, and easy to use information, which enable them to make better decisions [14].

Architecturally we can divide BIS into two parts: a) data warehousing and b) access to data, data analysis, reporting and delivery. The main difference between traditional information support (e.g. decision support systems, executive information systems etc.) and BIS is that traditional information support is more application oriented, whereas BIS use data integration oriented approach [10]. A state-of-the-art BIS thus includes infrastructure (data warehouse) and analytical tools, such as powerful analytical capabilities, including OLAP, data mining, predictive analytics, scorecards and dashboards, alerts and notifications, querying and reporting, data vizualization etc. [24].

Information goals of BIS aim at reducing the gap between the amount and quality of *data* organizations collect and the amount and *quality of information* available to users on tactical and strategic level of business decisions. In business practice this gap comes in different forms: inconsistent data sources, organizations possess data they are unaware of, data owners are too protective of information, data within operational databases is not properly arranged to support management's decision, analysts take too much time to gather the required information instead of its analysis, management gets extensive reports that are rarely used or inappropriate, due to increased need for information in analytical decision processes IS staff plays a role of data steward, there is lack of external and/or competitive information to support decision-making, and there are limitations of incompatible software/hardware systems.

In this study we aim to analyze relationship between business intelligence systems and information quality, and to investigate into more details the impact of business intelligence systems' maturity on two segments of information quality, namely content quality and media quality.

The outline of the paper is as follows: Section 2 conceptualizes the research model leading to the development of suitable hypotheses. Section 3 aims to present a methodological framework for the study, while Section 4 provides results of data analysis. Section 5 concludes with a summary of the main findings.

2 The research model

Business intelligence systems maturity should describe the evolution of organizations' business intelligence system capabilities. Most models include technological and usage components, however, this study is only focused on technological components that can potentially improve information quality that can be deployed for improving business processes.

A business intelligence maturity model illustrates how business intelligence systems evolve from low-value, cost-centre operations to high-value, strategic utilities that drive performance [23]. Chamoni & Gluchowski [2] propose a business intelligence system maturity model with five levels of evolutionary development. Institute TDWI [23] proposes a six-stage business intelligence maturity model where maturity is defined through system's architecture, attainment of the system, its users, and to what problems business intelligence system provides answers to. Moss & Atre [19] point out the importance of data integration, choosing the right data sources and providing analytics to suit user's information needs. In the same context Gangadharan & Swami [11] propose effective data integration process, integrated enterprise portal infrastructure, and delivery of answers to all key business questions as criteria for evaluation of completeness and adequacy of business intelligence systems infrastructure.

Not taking into account non-technological components we can derive two main emphasizes from the reviewed models. First, there is awareness for importance of aggregating large amounts of data from disparate sources within business intelligence systems [13; 17]. Moreover, data orientation is a distinctive characteristic of business intelligence systems compared to older types of decision support systems [10]. Second, organizations are focusing on technologies (e.g. querying, online analytical processing, reporting, data mining) for analysis of business data integrated from heterogeneous source systems [6; 24]. On this basis we propose our first hypothesis:

H1: *Business intelligence system maturity is determined by data integration and analytics.*

The field of information quality evaluation has been previously extensively researched [7; 8; 18; 22; 25]. We adopted Eppler's information quality framework since it provided one of the broadest and thorough analyses by reviewing relevant literature on information quality where 70 criteria for quality were identified with some of them partially or fully overlapping. His review of selected 20 information quality frameworks showed that most of the frameworks are often domain-specific and they rarely analyze interdependencies between the information quality criteria. Next, these frameworks do not take into account specifics of information in knowledge-intensive processes. Business intelligence systems by definition support analytical decision-making, thus knowledge-intensive decision processes. Furthermore, Eppler's [8] reviewed frameworks also do not deal with cost dimension of information quality which is very important in evaluating information quality in the field of business intelligence systems.

The outcome of Eppler's research is a framework of 16 criteria providing four views on information quality (relevant information, sound information, optimized process, and reliable infrastructure). The upper two levels of the framework are labeled content quality, while the lower two are referred to as media quality. The first two views, relevance and soundness, relate to actual information itself, hence the term content quality. The second two categories, process and infrastructure, relate to whether delivery process and infrastructure are of adequate quality, hence the term media quality, which stresses the channel by which information is transported [8]. However, for end-users, both segments, media and content quality, may be perceived as one final product – information and its various characteristics. We thus propose the concept of information quality as two dimensions that are positively impacted by business intelligence systems maturity. In this context, hypotheses 2a and 2b are put forward:

H2a: *Business intelligence system maturity has positive impact on content quality.*

H2b: *Business intelligence system maturity has positive impact on media quality.*

The purpose of business intelligence systems is improving both segments of information quality. For example, data warehousing can imply an increase of content quality from comprehensiveness and consistency criteria point of view but it can also improve media quality since users don't have to search for data within different data sources and combine it in information. Through improved interactivity (media quality) users don't get information just delivered but are able to explore it and get more relevant information (content quality) for appropriate decisions. Moreover, business intelligence system maturity can influence content quality through a loopback: through a better insight into data it allows perception of errors at data collection, and consecutively it improves data quality control at data collection. We decided to include our expectation in the model in the form of hypothesis 3:

H3: *Business intelligence system maturity has different positive impact on content quality and media quality.*

3 Research instrument and data analysis

3.1 Research instrument

The questionnaire was developed by building on the previous theoretical basis in order to ensure content validity. Pre-testing was conducted using a focus group involving 3 academics interested in the field and 7 semi-structured interviews with selected CIOs who were later not interviewed. This was also used to assure face validity. We used a structured questionnaire with 7-point Likert scales for the information quality items and a combination of 7-point Likert scales and 7-point semantic differentials for those items measuring business intelligence system maturity. According to Coelho & Esteves [5] an above 5-point scale generally shows higher convergent and discriminant validity than the 5-point scale, and a higher explanatory power thus confirming a higher nomological validity.

3.2 Measures

Based on the reviewed business intelligence and business intelligence systems maturity models we modeled business intelligence system maturity concept as a second-order construct formed by two first-order factors: data integration and analytics. Within analytics construct we look at different analysis business intelligence system enables. Although there are many kinds of analytics provided by business intelligence system literature refers to we selected indicators most used in previous works: paper reports [23], ad-hoc reports [4], OLAP [6; 23], data mining [23] to dashboards, KPIs, and alerts [6].

For measuring quality of information we adopted previously researched and validated indicators provided by Eppler [8]. Out of the 16 information quality criteria framework we included in our research instrument 11 of them. Since we are interested in the quality of available information for decision-making itself we left out those media quality criteria measuring infrastructure through which the information is actually provided (i.e. accessibility, security, maintainability, and speed) since they relate to technological characteristics of business intelligence systems that we research through business intelligence system maturity construct.

To assess discriminant validity we used two procedures: 1) a comparison of item cross loadings to construct correlations [12], and 2) determining whether each latent variable shares more variance with its own measurement variables or with other constructs [3]. All item loadings met the requirements of the first procedure in the assessment of discriminant validity. For the second procedure we compared the square root of the AVE for each construct with the correlations with all other constructs in the model. Our analysis returned higher square roots of AVE than correlations between constructs, thus showing evidence for acceptable validity.

Table 1 shows a detailed list of indicators used in the measurement model.

3.3 Data analysis

The PLS methodology, a form of structural equation modeling (SEM), was chosen to conduct data analysis in this study. Unlike SEM-ML, which is based on the covariance structure of the latent variables, SEM-PLS is a component-based approach. Thus, PLS is suitable for predictive applications and theory building because it aims to examine the significance of the relationships between research constructs and the predictive power of

the dependent variable [3]. PLS also has the ability to handle relatively small sample size [3], and it copes well with common research issues such as missing values and the presence of multi-collinearity [3]. PLS is considered well suited to explain complex relationships [9].
PLS was chosen for two reasons. First, we have a relatively small sample size for our research. Second, our data has an unknown nonnormal frequency distribution which also favors the use of PLS. The estimation and data manipulation was done using SmartPLS [21] and SPSS.

4 Results

We first examined the reliability and validity measures for the model constructs. The loadings of items against the construct being measured were tested against the value .7 [15] on the construct being measured. Once all the items that did not load satisfactorily had been removed, the model was rerun. Figure 1 shows the results of testing the measurement model in the final run. In the final model all Cronbach's Alphas exceed the .7 threshold [20]. Latent variable composite reliabilities are in general near .90, showing a high internal consistency of indicators measuring each construct and thus confirming construct reliability. The average variance extracted (AVE) is around or higher than .60, indicating that the variance captured by each latent variable is significantly larger than variance due to measurement error, and thus demonstrating a convergent validity of the constructs. Since business intelligence system maturity is a second-order construct has a lower AVE – though still above the .50 threshold – than the AVE of the two contributing constructs. Reliability and convergent validity of the measurement model was also confirmed by computing standardized loadings for indicators and Bootstrap t-statistics for their significance [1]. All standardized loadings exceed (or were very marginal to) the .7 threshold and they were found, without exception, significant at 1% significance level, thus confirming a high convergent validity of the measurement model.
To assess discriminant validity we used two procedures: 1) a comparison of item cross loadings to construct correlations [12], and 2) determining whether each latent variable shares more variance with its own measurement variables or with other constructs [3]. All item loadings met the requirements of the first procedure in the assessment of discriminant validity. For the second procedure we compared the square root of the AVE for each construct with the correlations with all other constructs in the model. Our analysis returned higher square roots of AVE than correlations between constructs, thus showing evidence for acceptable validity.

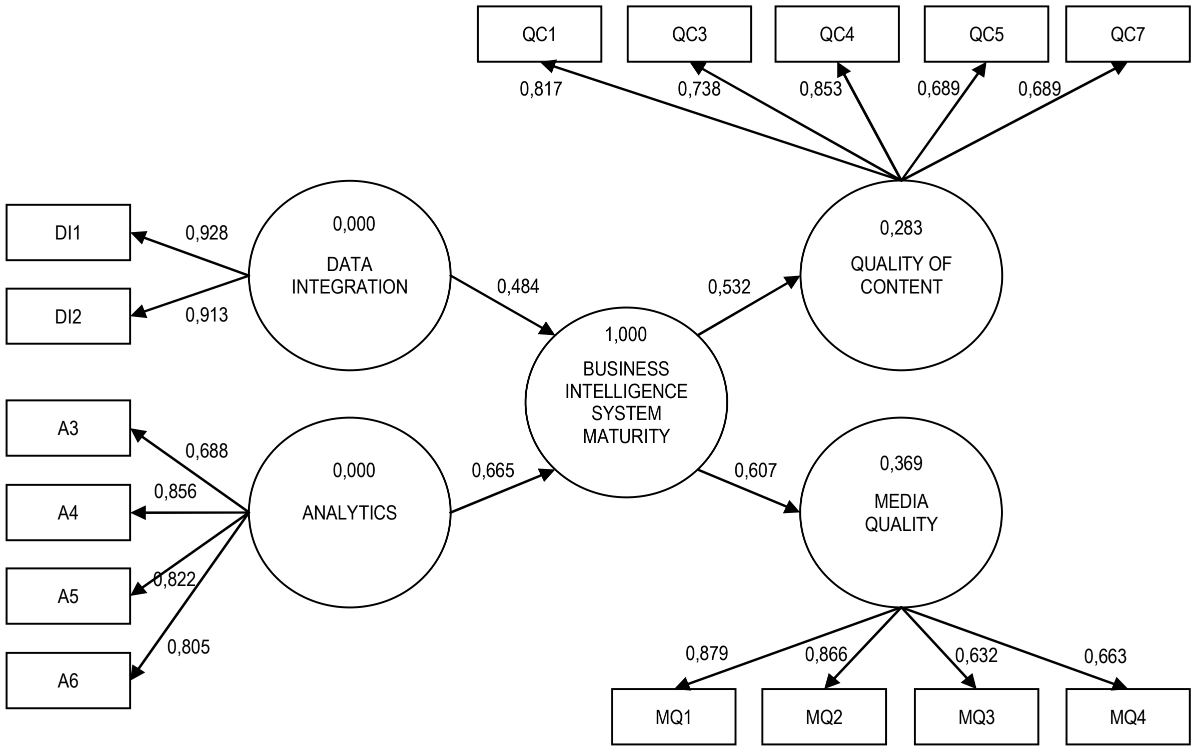
Table 1: Indicators of the measurement model

Construct	*Label*	*Indicator*
Data integration	DI1	Data is scattered everywhere - on the mainframe, in databases, in spreadsheets, in flat files, in Enterprise Resource Planning (ERP) applications. – Statement A Data is completely integrated, enabling real-time reporting and analysis. – Statement B
	DI2	Data in the sources are mutually inconsistent. – Statement A Data in the sources are mutually consistent. – Statement B
Analytics	A1	Paper Reports
	A2	Interactive Reports (Ad-hoc)
	A3	On-Line Analytical Processing (OLAP)
	A4	Analytical Applications, including Trend analysis, "What-if" scenarios
	A5	Data Mining
	A6	Dashboards, including Metrics, Key Performance Indicators (KPI), Alerts
Content Quality	CQ1	The scope of information is adequate (not too much nor too little).
	CQ2	The information is not precise enough and not close enough to reality.
	CQ3	The information is easily understandable to 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.
Media Quality	MQ1	The information provision corresponds to the user's needs and habits.
	MQ2	The information is processed and delivered rapidly without delays.
	MQ3	The background of the information is not visible (author, date etc.).
	MQ4	Information consumers cannot interactively access the information.

ISSN: 1790-2769

ISBN: 978-960-474-124-3

Fig. 1: Final measurement model



After validating the measurement model a bootstrapping with 1,000 samples has been conducted which showed that all of the hypotheses are supported with an error probability of less than .001. The structural model was assessed by examining path coefficients and their significance levels.

5 Conclusions

Our analysis confirmed the conceptualization and operationalization of business intelligence maturity as a second-order construct. The results also indicate the relative importance of these dimensions regarding business intelligence systems maturity. According to this study both dimensions are important, yet analytics have considerably higher importance than data integration. This could be explained with data integration being a prerequisite for business intelligence systems. On the other hand, higher levels of business intelligence maturity require introduction of advanced analytical technologies, such as OLAP, data mining, and dashboards. Based on the results from our research, basic analytical technologies, such as paper reports and interactive (ad-hoc) reports, have no significant effect on business intelligence systems maturity.

This study finds that higher level of business intelligence systems maturity has positive impact on information content quality and information media quality. Moreover, the results show business intelligence system maturity impact on media quality is stronger than the impact on content quality. This is expected since the purpose of introducing such technology is first of all to provide managers with easier access to data, providing data from multiple sources, autonomous data analysis, exception reporting etc. Introduction of business intelligence technology contributes to information media quality in many ways, for example, OLAP increases interactivity, data warehouse and OLAP provide timely access to information, and dashboards increase convenience. Changes in content quality, on the other hand, are partially due to the introduction of new technology (integration and cleansing with ETL), and partially due to the process changes because of the introduction of business intelligence.

The results have an important implication in introducing business intelligence systems, as the quality of content is more important for making better business decisions and providing high business value of business intelligence systems. Thus technology does not solve all problems associated with quality of information, a common misunderstanding in professional field. The consequence of such misunderstanding results in dissatisfaction with business intelligence systems, no use of business intelligence systems, and with this lower success rate of business intelligence systems projects.

References:

[1] J. C. Anderson and D. W. Gerbing, Structural equation modeling in practice: A review and recommended two-step approach, *Psychological Bulletin*, Vol. 103, No. 3, 1988, pp. 411-423.

[2] P. Chamoni and P. Gluchowski, Integration trends in business intelligence systems - An empirical study based on the business intelligence maturity model, *Wirtschaftsinformatik*, Vol. 46, No. 2, 2004, pp. 119-128.

[3] W. W. Chin, Issues and opinion on structure equation modeling, *MIS Quarterly*, Vol. 22, No. 1, 1998, pp. vii-xvi.

[4] Claraview (2005). *Business Intelligence Maturity Model* Retrieved January 20, 2006, from http://www.claraview.com

[5] P. S. Coelho and S. P. Esteves, The choice between a 5-point and a 10-point scale in the framework of customer satisfaction measurement, I*nternational Journal of Market Research*, Vol. 49, No. 3, 2007, pp. 313-345.

[6] T. H. Davenport and J. G. Harris, *Competing on analytics: the new science of winning*, Harvard Business School Press, 2007.

[7] L. P. English (2007). *Information Quality and Management Transformation* Retrieved January 5, 2008, from http://www.b-eye-network.com/view/5679

[8] M. J. Eppler, *Managing Information Quality: Increasing the Value of Information in Knowledge-Intensive Products and Processes*, Springer, 2006.

[9] C. Fornell and D. F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, *Journal of Marketing Research*, Vol. 18, No. 1, 1981, pp. 39-50.

[10] M. N. Frolick and T. R. Ariyachandra, Business Performance Management: One Truth, *Information Systems Management*, Vol. 23, No. 1, 2006, pp. 41-48.

[11] G. R. Gangadharan and S. N. Swami (2004). Business intelligence systems: design and implementation strategies. Paper presented at the *26th International Conference on Information Technology Interfaces* (ITI 2004).

[12] D. Gefen and D. Straub, A practical guide to factorial validity using PLS-graph: tutorial and annotated example, *Communications of the Association for Information Systems*, Vol. 16, No. 2005, pp. 91-109.

[13] M. Golfarelli, S. Rizzi, and I. Cella (2004). Beyond data warehousing: what's next in business intelligence? *Proceedings of the 7th ACM international workshop on Data warehousing and OLAP*.

[14] M. Hannula and V. Pirttimäki, Business Intelligence - Empirical Study on the Top 50 Finnish Companies, *Journal of American Academy of Business*, Vol. 2, No. 2, 2003, pp. 593-600.

[15] J. Hulland, Use of partial least squares (PLS) in strategic management research: a review of four recent studies, *Strategic Management Journal*, Vol. 20, No. 2, 1999, pp. 195-204.

[16] IT_Strategies (2008). *Fact Gap Fuels ERP Investments and Invites Printer Vendors to Ride the Wave* Retrieved January 28, 2008, from http://www.techexchange.com/thelibrary/RideTheWave.html

[17] A. D. Jhingran, N. Mattos, and H. Pirahesh, Information integration: A research agenda, IBM Systems Journal, Vol. 41, No. 4, 2002, pp. 555-562.

[18] Y. W. Lee, D. M. Strong, B. K. Kahn, and R. Y. Wang, AIMQ: a methodology for information quality assessment, *Information & Management*, Vol. 40, No. 2, 2002, pp. 133-146.

[19] L. T. Moss and S. Atre, *Business Intelligence Roadmap: The Complete Project Lifecycle for Decision-Support Applications*, Addison-Wesley Professional, 2003.

[20] J. C. Nunnally, *Psychometric Theory*, McGraw-Hill, 1978.

[21] C. M. Ringle, S. Wende, and A. Will (2007). *SmartPLS 2.0 M3*. University of Hamburg.

[22] Y. Salaun and K. Flores, Information quality: Meeting the needs of the consumer, International *Journal of Information Management*, Vol. 21, No. 1, 2001, pp. 21-37.

[23] TDWI (2005). 2005 *TDWI Poster: Business Intelligence Maturity Model* Retrieved January 20, 2006, from http://tdwi.org/Publications/display.aspx?ID=7288

[24] E. Turban, R. Sharda, J. E. Aronson, and D. King, *Business Intelligence: A Managerial Approach*, Prentice Hall, 2008.

[25] R. Y. Wang, V. C. Storey, and C. P. Firth, A framework for analysis of data quality research, *IEEE Transactions on Knowledge and Data Engineering*, Vol. 7, No. 4, 1995, pp. 623-640.