Information Quality Improvement as a Measure of Business Intelligence System Benefits

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Abstract: - Since business intelligence systems' impact on performance is first of all long-termed and indirect, most measures of business value are not sufficiently close to immediate influence of such systems and therefore not suitable to justify investments into business intelligence systems in real business environments. Thus, measures related to increased information quality as a result of business intelligence systems introduction are commonly used. The purpose of this study is to test how much does implementation of business intelligence systems actually contribute to solving the major issues regarding information quality. 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. The results of the analysis show that business intelligence systems actually have a positive impact on both 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 higher business value of business intelligence systems. Thus, there is still a gap between available information quality and knowledge workers' needs, in other words – key information quality problems still exist.

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. [1] business intelligence systems have one of the greatest potentials in achieving information asymmetry [2] and differentiation from competitors respectively and thus achieve competitive advantage with IT. When organizations think about introducing business intelligence systems 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. Information goals, such as independent data access, data integration from different (operational) sources, and interactive and comfortable access to data are important, however, they are only the

first step in justifying investments in business intelligence systems [3].
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 [4]. Therefore business intelligence systems allow organizations to access, analyze, and share information and knowledge, which in turn helps them to track, understand, target and manage their business in order to improve enterprise performance [5]. Understanding of business intelligence often differs on its content's focus as well as on several related terms used for referring to business intelligence (including competitive intelligence, competitor intelligence, strategic intelligence etc.). Figure 1 shows what areas the term 'business intelligence' in its broadest meaning relates to.

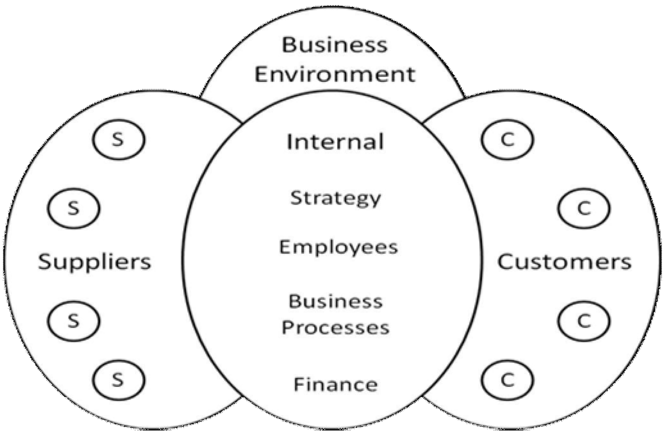

Fig. 1: Broad concept of the term 'business intelligence'

Business intelligence systems are rapidly being adopted to provide enhanced analytical capabilities to previously implemented enterprise resource planning systems, which manage and integrate a very large array of business information [6]. Business intelligence systems have been firstly embraced by those companies for which the customer satisfaction is the key of success, such as banks, financial services, or chains of supermarkets [7]. Nowadays, business intelligence systems are combined with business process management, business rules engines, master data management, complex event processing and other instruments and techniques directly and immediately applied to business decisions [8]. Competitive pressures are forcing companies to react faster and as a consequence, there is now a need to use business intelligence systems to help drive and optimize business processes and operations on a daily basis or even more often [5].

In terms of business intelligence system as an IT investment Chamoni & Gluchowski [9] and Williams [10] suggest that it is important for organizations to strive after mature business intelligence system in order to capture true benefits of business intelligence initiatives. Since business intelligence systems' impact on performance is first of all long-termed and indirect, most measures of business value are not sufficiently close to immediate influence of such systems. However, we can use different measures for benefits of such systems [11, 12, 13]. Benefits, such as time savings and better information, are according to Watson et al. [11] the most tangible and with high local impact, whereas benefits of business process improvement have high potential global impact but are much harder to measure. In fact most of the benefits are strategic benefits, hard to quantify and only appearing several years after the implementation of the solution [8]. When analyzing attainability of information goals of business intelligence systems we have to use information quality criteria [3]. Based on the proposed benefits taxonomy provided by Watson et al. (2002) we can conclude that measuring more direct benefits is simpler, consequently measures generally presenting increased information quality as a result of business intelligence systems introduction are commonly used. A general framework for analyzing benefits of business intelligence systems is presented in [3].
In the view of Davenport & Harris [14] organizations must tackle two important issues in constructing their business intelligence systems architecture: integration of available data and analytics. This is in accordance with the definition of business intelligence systems by English [15], which emphasizes well-designed data stores (integration) and appropriate tools that provide access, analysis and presentation of information (analytics).
Architecturally we can divide business intelligence systems 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 business intelligence is that traditional information support is more application oriented covering the needs of narrow problem areas, whereas business intelligence systems use data integration oriented approach [3, 16].
A state-of-the-art business intelligence system 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. [17].
Information goals of business intelligence 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 the information quality discipline researchers have pondered the question of what can be qualified as "good information". Huang et al. [18] define information quality as "information that is fit for use by information consumers" and similarly Kahn et al. [19] see information quality as the characteristic of information to meet or exceed customer expectations.

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 Conceptualization of the research model

For understanding how much does implementation of business intelligence systems actually contribute to solving issues regarding information it is important to be familiar with these problems. Lesca & Lesca [20] emphasize the following information quality problems that knowledge workers are often faced with: limited usefulness of information due to an overload of information, ambiguity of provided information leading to differing or wrong interpretations due to lacking precision or accuracy, incompleteness of information, information inconsistency, information is not reliable or trustworthy, inadequate presentation, and inaccessible information. Similarly Strong et al. [21] also note problems, such as too much information, subjective production, and changing task needs. Another analysis of knowledge work problems related to information quality can be found in Davenport et al. [22]: knowledge workers struggle with the multitude and insecurity of information inputs and outputs, they often struggle with lacking IT-support, and face unstructured problems. Hence, all these researchers agree that the major problems when providing quality information for knowledge-intensive activities are related to information content.

Several authors have studied various impacts on quality of information for business decision-making [12, 23, 24, 25]. On the other hand, only a few studies have addressed the issue of business intelligence systems maturity [9, 26]. Moreover, we are not aware of any studies that have merged these two fields and evaluated the impact of business intelligence system maturity on information quality.

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.

Early maturity model approaches in the field of information systems emerged from the area of software engineering and were aimed at measuring and controlling processes more closely [27]. The concept of IT/IS maturity has been used in the literature, however we could not rely directly on previous maturity models because they are rather general and their focus is not key technological elements of business intelligence systems as previously broadly defined

In the field of business intelligence systems a maturity model illustrates how business intelligence systems evolve from low-value, cost-centre operations to high-value, strategic utilities that drive performance [28]. In their research Peppard et al. [29] ascertain benefits of business intelligence systems are not simple to quantify. Related to its business value we can view development path of business intelligence systems within organizations through different maturity stages. Chamoni & Gluchowski [9] propose a business intelligence system maturity model with five levels of evolutionary development. Institute TDWI [28] 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 [30] 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 [31] 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.

Based on reviewed business intelligence and business intelligence systems maturity models we found no evidence of unanimous decision about business intelligence systems maturity concept. 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 [6, 32, 33]. Moreover, data orientation is a distinctive characteristic of business intelligence systems compared to older types of decision support systems [16, 33]. 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 [14, 17, 34, 35]. 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 [25, 36, 37, 38, 39, 40, 41, 42, 43]. According to Eppler [25] an information quality framework should provide a systematic and concise set of criteria according to which information can be evaluated, a scheme to solve information quality problems, and the basis for information quality measurement and benchmarking. 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 [25] reviewed frameworks also lack cost dimension of information quality which is very important in evaluating information quality in the field of business intelligence systems.

Table 1: Eppler's Information Quality framework

		Criterion name	**Description**
QUALITY OF INFORMATION CONTENT	Relevance	Comprehensiveness	Is the scope of information adequate? (not too much nor too little)
		Conciseness	Is the information to the point, void of unnecessary elements?
		Clarity	Is the information understandable or comprehensible to the target group?
		Correctness	Is the information free of distortion, bias, or error?
	Soundness	Accuracy	Is the information precise enough and close enough to reality?
		Consistency	Is the information free of contradictions or convention breaks?
		Applicability	Can the information be directly applied? Is it useful?
		Timeliness	Is the information processed and delivered rapidly without delays?
QUALITY OF INFORMATION ACCESS	Process	Traceability	Is the background of the information visible (author, date etc.)?
		Maintainability	Can all of the information be organized and updated on on-going basis?
		Interactivity	Can the information process be adapted by the information consumer?
		Speed	Can the infrastructure match the user's working pace?
	Infrastructure	Security	Is the information protected against loss or unauthorized access?
		Currency	Is the information up-to-date and not obsolete?
		Accessibility	Is there a continuous and unobstructed way to get to the information?
		Convenience	Does the information provision correspond to the user's needs and habits?

The outcome of Eppler's research is a framework of 16 criteria (Table 1) 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 [25]. For end-users, both segments, media and content quality, may be perceived as one final product – information and its various characteristics. For the information producers and administrators however, this difference is crucial, since the information producers usually cannot influence the media quality, and the administrators only have limited possibilities of influencing the content quality. In order to be of practical value, the framework distinguishes between these responsibilities and indicates which areas are the responsibility of information producers (i.e. content quality), and which domain is the responsibility of the support or IT (i.e. media quality). Cartwright et al. [44] conducted an exploratory study on the usefulness of business information produced by formal competitive intelligence systems and found content quality was the highest valued attribute among respondents. Furthermore, respondents felt technical adequacy of competitive intelligence systems might also improve the usefulness of the systems. We thus propose the concept of information quality as two dimensions that are positively influenced 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. We can thus presume business intelligence system maturity affects both dimensions of information quality, each of them in its own way. Our presumption about business intelligence system maturity affecting content and media quality differently is also supported by Eppler [25] who argues technology mainly influences media quality and has limited possibilities influencing the content quality. For example, 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.

In Figure 2 we illustrate the conceptualized research model in which all the main constructs are shown together with the hypothesized relationships among them.

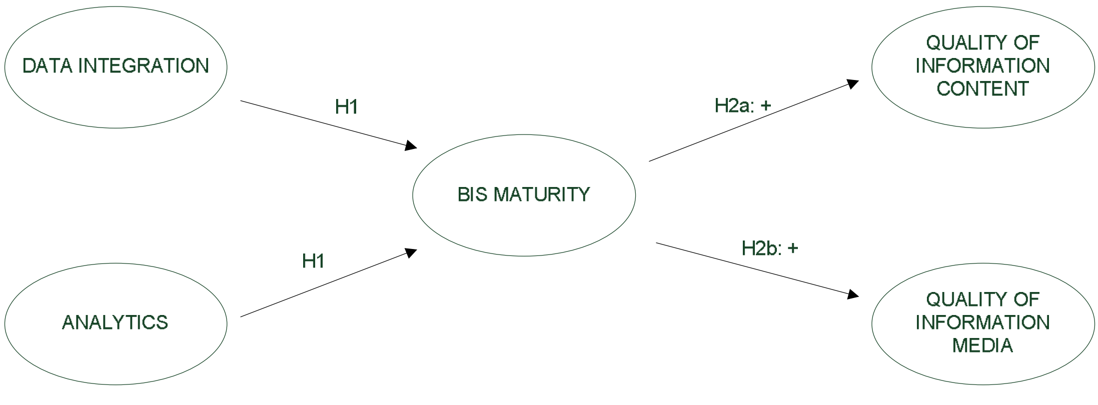

Fig. 2: Conceptualized research model

3 Research framework and methodology

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 [45] 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. Through data integration construct we try to measure the level of data integration for analytical decisions within organizations through 2 indicators: i) how available data is integrated and ii) whether data in data sources is mutually consistent. Our data integration construct is also supported by findings from Lenzerini [46] who argues that for organizations a) the problem of designing data integration systems is important in current real world applications b) data integration aims at combining data residing at different sources, and providing the user with a unified view of these data, and c) since sources are in general autonomous, in many real-world applications the problem arises of mutually inconsistent data sources. Within analytics construct we look at different analysis business intelligence system enables. Although literature refers to many kinds of analytics provided by business intelligence systems, we selected indicators most used in previous works: paper reports [28, 47, 48], ad-hoc reports [49], On-Line Analytical Processing (OLAP) [14, 28], data mining [28] to dashboards, Key Performance Indicators (KPI), and alerts [14, 50].

For measuring quality of information we adopted previously researched and validated indicators provided by Eppler [25]. Out of the 16 information quality criteria from Eppler's [25] 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. According to this framework the infrastructure level contains criteria which relate to the infrastructure on which the content management process runs and through which information is provided. These criteria refer to system's easy and continuous accessibility, its security, its maintainability over time and at reasonable costs, and its high speed or performance.

Table 2 shows a detailed list of indicators used in the measurement model.

Given that non-profit organizations were excluded from the study, the sample is an adequate representation of the population of Slovenian medium and large size organizations by industry type.

3.3 Data analysis

Data analysis was carried out using a form of structural equation modeling (SEM). The PLS methodology 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 [51]. PLS also has the ability to handle relatively small sample size [51, 52], and it copes well with common research issues such as missing values and the presence of multi-collinearity [51, 53]. PLS is considered well suited to explain complex relationships [54].

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 favours the use of PLS. The estimation and data manipulation was done using SmartPLS [55] and SPSS.

Table 2: 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.

4 Results

We first examined the reliability and validity measures for the model constructs. In the initial model not all reliability and convergent validity measures were satisfactory. The loadings of items against the construct being measured were tested against the value .70 [56] on the construct being measured. The manifest variables A1 (paper reports), A2 (interactive reports), CQ2 (information is not precise enough and not close enough to reality), and CQ6 (information is free of distortion, bias, or error) had weak (A1 even negative), though significant (at 1% significance level), loadings on their respective latent constructs and were removed.

Once all the items that did not load satisfactorily had been removed, the model was rerun. Figure 3 shows the results of testing the measurement model in the final run. In the final model all Cronbach’s Alphas exceed the .7 threshold [57]. Without exception, latent variable composite reliabilities are higher than .80, and in general near .90, showing a high internal consistency of indicators measuring each construct and thus confirming construct reliability. The average variance extracted is around or higher than .60, except for Business Intelligence System maturity construct, 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. For Business Intelligence System maturity it would be to expect to 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 Business Intelligence System maturity AVE (.53) is also above the .50 threshold, thus supporting the existence of Business Intelligence System maturity as a second order construct composed by data integration and analytics. Reliability and convergent validity of the measurement model was also confirmed by computing standardized loadings for indicators and bootstrap t-statistics for their significance [58]. 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, the following two procedures were used: 1) a comparison of item cross loadings to construct correlations [59], and 2) determining whether each latent variable shares more variance with its own measurement variables or with other constructs [51, 54, 60]. The first procedure for testing discriminant validity was to assess the indicator loadings on their corresponding construct. All the item loadings met the requirements of the first procedure in the assessment of discriminant validity.

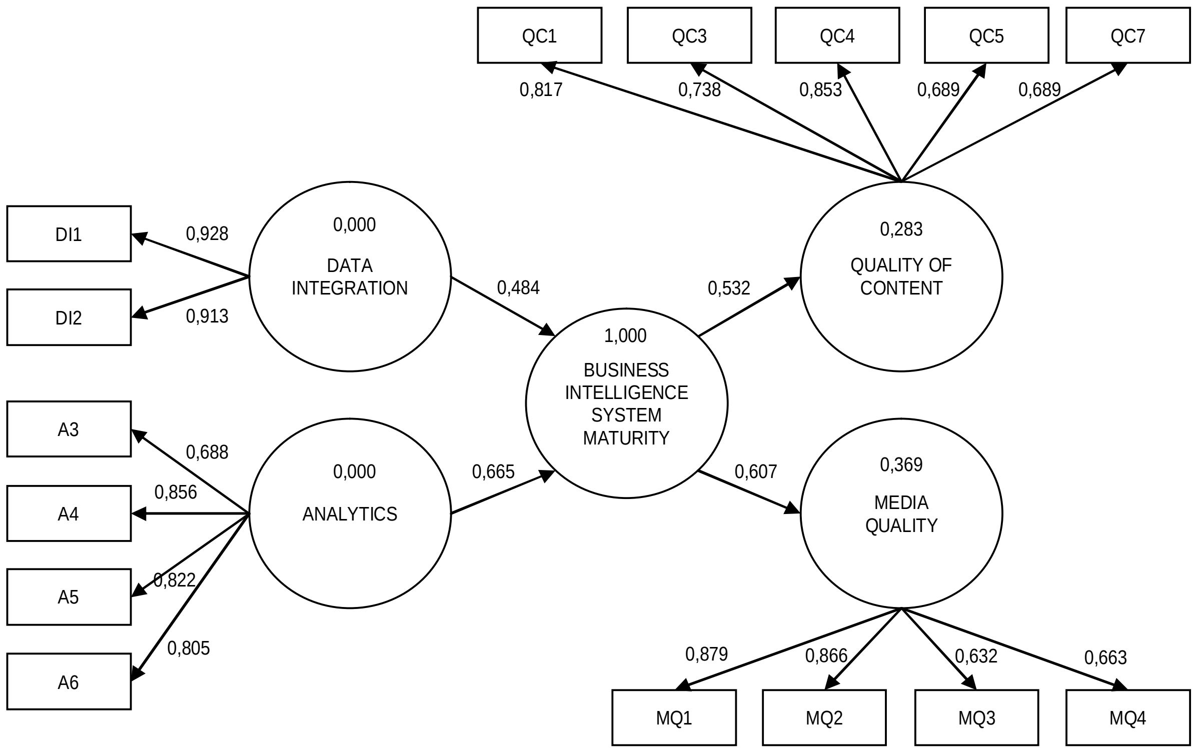

Fig. 3: Final measurement model

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. A correlation between constructs exceeding the square roots of their AVE indicates that they may not be sufficiently discriminable. We observed that the square roots of AVE (shown in bold in the main diagonal) are higher than correlations between constructs, except in the situation where the square root of AVE is smaller than the correlations involving Business Intelligence System maturity and the two constructs contributing to it (data integration and analytics). This is to be expected since Business Intelligence System maturity is a second-order construct. Nevertheless, there is sufficient evidence that data integration and analytics are different constructs (correlation between data integration and analytics is significantly smaller than the respective AVEs). We conclude that all the constructs show evidence for acceptable validity.

After validating the measurement model, the hypothesized relationships between the constructs can be tested. 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 systems 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.

The purpose of business intelligence systems is to let managers get continuous, current information about their business and use this information to make better decisions and move rapidly in response to changes. This study finds that higher level of business intelligence systems maturity has positive impact on information content quality and information media quality, as they were conceptualized in our model. Content quality relates to the actual information itself; to its relevance and soundness. Media quality stresses the channel by which information is provided, and relates to the management of that information and whether the delivery process and infrastructure are of adequate 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.

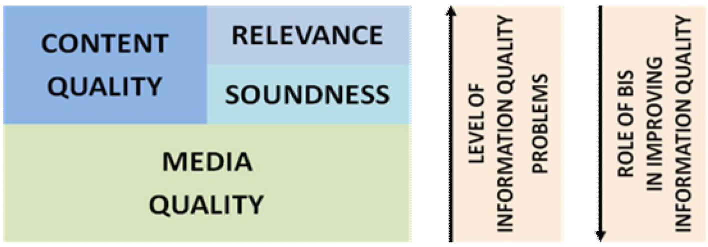

Fig. 4: The information quality gap

Business intelligence systems maturity better explains changes in media quality than in content quality. This has 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, when addressing the problems of information quality media quality (e.g. having fast access to information) problems are less problematic than content quality problems (e.g. gaining relevant and sound information). Yet implementations of business intelligence systems better address media quality problems than content quality problems. It can be concluded from the findings that there is still a gap between available information quality and knowledge workers' needs, in other words – key information quality problems still exist (see Figure 4). 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.

A limitation of this research is the cross-sectional nature of the data gathered. In fact, although our conceptual and measurement model is well supported with theoretical assumptions and previous research findings, the ability to draw conclusions through the model would be strengthened with the availability of longitudinal data.

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