The Impact of Business Intelligence Tools on Performance: A User Satisfaction Paradox?

Bernhard Wieder[1], Maria-Luise Ossimitz[2] and Peter Chamoni[3]

Abstract

While Business Intelligence (BI) initiatives have been a top-priority of CIOs around the world for several years, accounting for billions of USD of IT investments per annum (IDC), academic research on the actual benefits derived from BI tools and the drivers of these benefits remain sparse.

This paper reports the findings of an exploratory, cross-sectional field study investigating the factors that define and drive benefits associated with the deployment of dedicated BI tools.

BI is broadly defined as an analytical process which transforms fragmented data of enterprises and markets into action-oriented information or knowledge about objectives, opportunities and positions of an organization; BI tools are software products primarily designed and deployed to support this analytical process (e.g. data warehouse software, data mining software, digital dashboards applications).

Building upon DeLoneand McLean's (1992; 2002; 2003) information systems success model, we develop, test and refine a BI quality and performance model adapted for the specific purpose, application, user group and technology of BI tools. The ultimate performance predictors in this model are user satisfaction and the impact of BI tools on managerial decision quality, both of which are determined by data quality.

Partial Least Square (PLS) modeling is used to analyze data collected in a survey administered to IT executives of large Australian Stock Exchange (ASX) listed companies.

The results confirm some of the theoretical relationships established in – especially the original – DeLone-McLean model in the specific context of BI. More importantly, the results also confirm the important role of explicit BI management as antecedent of benefits derived from BI tools, and the key impact of data quality on managerial decision making and organizational performance.

However, the results also reveal a 'user satisfaction paradox': In contrast to the predictions derived from the DeLone-McLean model, organizational performance is negatively associated with user satisfaction with BI tools. Financial performance data collected for

[1] UTS Business School - Accounting, University of Technology, Sydney, Australia, bwieder@uts.edu.au

[2] UTS Business School - Accounting, University of Technology, Sydney, Australia, maria.ossimitz@uts.edu.au

[3] Mercator School of Management, University Duisburg-Essen, Germany, peter.chamoni@uni-due.de

ex-post verification of this unexpected result confirm this paradox. We discuss BI-specific interpretations of these unexpected findings and provide avenues for future research.

Keywords: Business Intelligence (BI), information systems success, data quality, user satisfaction, IT impact analysis

JEL Classification: M10, M15, M40

1. Introduction

`Business Intelligence (BI) has been a top priority of IT executives for several years and this trend is expected to continue (Gartner Research, 2011). While both the basic concept and also the term 'business intelligence' date back many decades[1], the emergence of the data warehouse as new infrastructure for reporting and analysis combined with OLAP and new of fact-based support decision support systems (DSS) (Power 2003)leveraged interest in BI in the past decade, and what was initially considered another 'consulting fad', is now considered a potential source of competitive advantage (Wixom et al., 2008; Hocevar and Jaklic, 2010; Gonzales, 2011).

The academic research community only gradually embraced the topic of BI, and today research on BI is still fragmented and sparse. While a research time lag on emerging IS concepts or innovations is a generally observable phenomenon[2], which can be explained by e.g. academic caution, risk aversion and publication time lags, we assume that the absence of a generally accepted definition of the term BI contributed and still contributes to this time lag. And while there is some convergence in the most widely used definitions of BI, the rapid developments of new 'BI tools' and technologies increasingly blurs the practical understanding and meaning of the term BI. It is therefore particularly important to operationalize the meaning of BI (and related terms) for the purpose of our research.

For Foley and Manon (2010), for example, 'business intelligence (BI) is a combination of processes, policies, culture, and technologies for gathering, manipulating, storing, and analysing data collected from internal and external sources, in order to communicate information, create knowledge, and inform decision making', while Watson and Wixom (2010) provide a narrower definition, focusing more on technology aspects of BI, which they define as 'umbrella term that is commonly used to describe the technologies, applications and processes for gathering, storing, accessing and analyzing data to help users make better

[1] Both the academic and practitioner literatures on BI often ignore the fact that the term 'Business Intelligence' was not 'invented' by the Gartner Group, but rather emerged in 1958 in a visionary article by Luhn (1958), in which he presents a 'Business Intelligence System' as an 'automatic system … to disseminate information to the various sections of any industrial, scientific or government organization' (Luhn, 1958). His description of such a system very closely resembles current state-of-the-art BI systems – approximately half a decade ahead of its time.

[2] In the case of enterprise resource planning (ERP) the time lag was more than 15, if not 20, years.

decisions'. Following their definition, BI could also be described as *'special purpose' information system*, the purpose being decision support[3]. The Data Warehouse Institute (TDWI) uses a similar definition, but ads that 'BI programs usually combine an enterprise data warehouse and a BI platform or tool set to transform data into usable, actionable business information' (TDWI, 2012).

Merging these definitions, we understand BI as an analytical process which transforms fragmented data of enterprises and markets into action-oriented information or knowledge about objectives, opportunities and positions of an organization.*BI software* describes software products primarily designed to support this analytical process (e.g. data warehouse software, data mining software, digital dashboards software), *BI tools* are BI software products *deployed* in an organization, and a *BI system* is a collective of BI tools and related technologies, applications and processes used in support of BI.

Early research related to BI was largely descriptive or normative and focused on either on the emerging data warehouse concept (Gardner, 1998; Inmon, 2000; Rekom, 2000; Watson, 2001; Wixom and Watson, 2001; Watson et al., 2002; Sammon et al., 2003; Zeng et al., 2003; Hugh et al., 2004; Inmon, 2004; Shankaranarayanan and Even, 2004; Williams, 2004; Wixom, 2004; Sammon and Adam, 2005; Solomon, 2005; Tseng and Chou, 2006), or adapted the established stream of research on decision support systems (DSS) to the new data warehouse environment (e.g. Ellis, 2004; March and Hevner, 2007; Baars and Kemper, 2008)[4].

Earlier empirical research on BI or data warehousing (DW) explored *user satisfaction* with DW (Chen et al., 2000), factors affecting *DW success* (Wixom and Watson, 2001) and factors influencing the adoption of DW (Hwang et al., 2004). More recently, studies emerged investigating the determinants of *information and systems quality* in the context of DW (Nelson et al., 2005), the effects of DW on *decision performance* (Yong-Tae, 2006), the *measurement of BI* (Lönnqvist and Pirttimäki, 2006), the *effects of BI on performance* (Elbashir et al., 2008), the status of BI in certain countries, e.g. Australia (Foster et al., 2005; Dodson et al., 2008), DW success factors (Hwang and Xu, 2008), the impact of BI on orga*nizational decisions* (Davenport, 2010) and *costs and benefits associated with BI* (Hocevar and Jaklic, 2010).

The *purpose of this research* is to integrate and extend the findings of previous DW/BI research by developing, testing and refining an information systems success model for the specific purpose, application, target group and technology of BI.

The remainder of this paper is organized as follows: Section 2 identifies the drivers of BI success and establishes predicted relationships between the constructs (path model). Section 3 reports on the research design and method used in our study, and reports the

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[3] Definitions of 'information system' typically refer to interaction between people, procedures and technology in the process of capturing, transmitting, storing, retrieving, manipulating and displaying data and information for a specific purpose.

[4] Watson (2010) provides an analysis of the development of DSS in the context of data warehousing and Clark et al. (2007) provide a comprehensive literature analysis of research on management support systems (MSS), including BI.

results of our statistical analysis. The results and limitations of our study are discussed in section 4.

2. Theory development

What all the above-mentioned definitions of BI have in common is that BI is a broad concept of managing and providing data for improved (managerial) decision making[5]. This implies that BI success or BI quality is to be measured around the *quality or quality increase of data* provided and the *quality or quality increase of decisions* made in an organization.

Data/Information Quality and Quality of Managerial Decision Making

Data or information[6] quality research has a long history in the IS discipline, with DeLone and McLean's (1992; 2002; 2003) information systems success model receiving most attention and attracting many followers in the past two decades (Petter and McLean, 2009). Data quality is undoubtedly a key aspect of every information system, but considering the very nature and purpose of BI systems, maintaining and providing high quality data appears to be a relatively more important concern in BI systems than in other business information systems, in particular OLTP systems (e.g. ERPS), which typically have a very large non-managerial user base and often provide high levels of transaction automation and control. The importance of data quality for BI was already confirmed in Wixom and Watson's (2001) first comprehensive empirical investigation of the factors affecting data warehousing success.

Partial Least Squares analysis of the data identified significant relationships between the system quality and data quality factors and perceived net benefits.

Many attempts have been made to operationalize data or information quality substantially[7]. Nelson et al. (2005) provided the first and so far only comprehensive analysis of information quality in the specific context of data warehousing. Following a comprehensive literature review, they aggregate the large number of quality attributes into the following four dimensions of information quality: *Accuracy* (intrinsic), *completeness, currency* and *format* (all extrinsic). Their measurement model validation using PLS modeling reveals, however, that *currency* does not load significantly on information quality. They provide a possible explanation for the insignificance of currency, but our alternative interpretation is in increasingly real time data environments, currency has become a minor data quality concern. We build on their work with minor variations (see measurement model below).

[5] This notion is also reflected BI software vendor promises and selling lines.

[6] While we are aware of the differences between data and information, research on those constructs does not usually draw a clear line and research on the antecedents or determinants of data quality and information quality overlap substantially (see Nelson et al. 2005, in particular their analysis of prior literature). We therefore use the terms data and information as de facto synonyma for the purpose of this research.

[7] See Nelson et al. (2005), in particular their systematic analysis of prior literature.

Data quality is not an aim in itself, but rather a means to the key aim of BI: Providing (better) support for decision making, resulting in faster, better informed and more accurate decisions. This leads to our first hypothesis:

H1: BI data quality impacts positively on managerial decision quality.

Good (or better) decisions are decisions which create competitive advantage, be it in the form of entrepreneurial rents (Schumpeter, 1950; Rumelt, 1987), or a sustained competitive position. The widely accepted short-term operationalization of competitive position is performance *relative to rival firms* (Arend, 2003). Accordingly, we predict as follows:

H2: Managerial decision quality impacts positively on relative organisational performance.

User Satisfaction and BI System Use

In all versions of DeLone and McLean's (1992; 2002; 2003) information systems success model, user satisfaction and system use are key links between information quality and individual impacts or net benefits respectively. Considering that BI systems are discretionary 'informational' systems in a sense that they are not required for business process execution or other forms of transaction processing, the particular importance of addressing *user satisfaction* and (the relationship with)*actual use* of the system is obvious. Further to that, BI systems are often deployed as alternatives to 'islands of spreadsheets', with the latter often remaining in place as some form of shadow systems. We therefore expect a large variation in BI system *use* across organizations, even if they deploy similar BI solutions, and we concur with DeLone and McLean's assessment of the important role of IS use in terms of achieving benefits associated with the system. Finally, Cox's (2010) recent research confirms the positive association between frequent BI use and quality and speed of decisions. We therefore predict as follows:

H3: The scope of use of a BI system impacts positively on managerial decision quality.

While improving decision support is the main purpose of BI, there are also other benefits associated with BI, including reductions in total cost of ownership (TOC), efficiency and quality increases in information processing, improved customer satisfaction, improving internal communication and collaboration (Hocevar and Jaklic, 2010; Imhoff and White, 2010; Watson and Wixom, 2010). Those benefits can only be realized, if the BI tools implemented are actually used. Accordingly, we predict a direct impact of BI use on performance:

H4: The scope of use of a BI system impacts positively on organisational performance.

In line with DeLone and McLean (1992; 2002; 2003) we argue that user satisfaction with a system is likely to increase usage, even more so with discretionary systems.

H5: User satisfaction with a BI system impacts positively on the scope of use of the system.

Scope of BI System

As mentioned in the introduction, BI 'is an umbrella term that is commonly used to describe the technologies, applications and processes for gathering, storing, accessing and analyzing data to help users make better decisions' (Watson and Wixom, 2010). The range of software products offered in support of BI is broad and varies significantly in terms of purpose or role within a BI architecture, detailed functionality, functional scope and level of sophistication. Examples of BI software include data warehouse (management) software, extraction transformation and loading (ETL) tools, simple query tools, OLAP engines, data mining software and visualization tools such as digital dashboards (Turban and Volonino, 2011).

Many BI software products are either by functional design or by deployment subject oriented, i.e. they have a functional focus (e.g. market analysis or sales forecasting). Enterprise data warehouses, however, can potentially support a broad range of business functions in an organization. Accordingly, BI systems deployed in organizations will have a great level of variation in terms of functional scope, which will have a direct impact on the scope of use of the BI system.

H6: The scope of a BI system impacts positively on the scope of use of the system

Quality of BI Management

The importance of proper management was already emphasized in early studies on critical success factors of data warehouse projects (Wixom and Watson, 2001), and still remains a critical dimension of BI maturity (TDWI-Research, 2008).

Wixom and Watson (2001) found that management support and resources help to address organizational issues that arise during warehouse implementations, and that adequate resources, user participation and highly-skilled project team members increase the likelihood that warehousing projects finish on-time, on-budget and with the right functionality. Standard development and implementation methodologies are also commonly cited as critical success factors of BI projects (Hwang and Xu, 2008). Managing BI systems 'scalable' has been a major quality aspect of BI management from the earlier days of data warehousing (Gardner, 1998) to the area of BI (Imhoff, 2005), and is still considered to be an ongoing and future trend in BI (Watson, 2009).

Finally, TDWI (2008) emphasizes the importance of standards for developing, testing, and deploying BI/DW functionality to be defined, documented, and implemented.

While the early literature focused on quality as aspects of DW/BI project management, the more recent – especially practitioner oriented – literature increasingly deals with BI management (and governance) as an ongoing process (BI management as a sub-function of IT management).

Following from the above, we expect that high quality BI management has a positive impact on various aspects of BI: Through end user involvement, timely completion of BI projects and provision of adequate resources and support, we expect a positive impact on user satisfaction and a steady increase in BI scope in an organization. Adherence to standards and the provision of adequate resources and scalable solutions is expected to result in higher levels of data quality, which is expected to indirectly contribute to user satisfaction.

H7: BI management quality impacts positively on BI data quality.

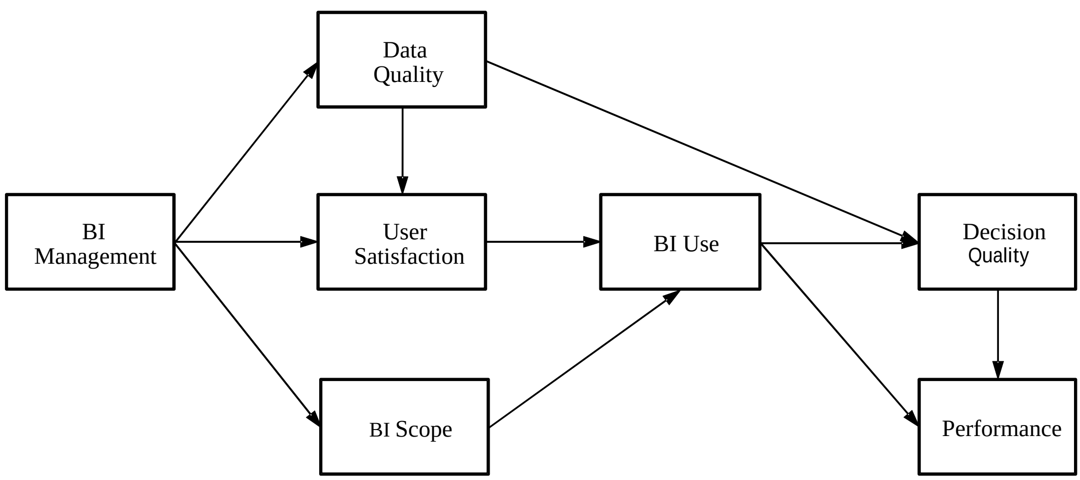
H8: BI management quality impacts positively on the scope of the BI system.

H9a: BI management quality impacts positively on user satisfaction with a BI system.

H9b: This relationship is mediated by data quality.

Figure 1 provides a graphical summary of our hypotheses (path-model).

Figure 1: Research Model



3. Research Design and Method

Sample Selection and Data Collection

A cross-sectional research design was employed with a survey administered to the 500 largest Australian Stock Exchange (ASX) listed companies in terms of capitalization. Target respondents were the most senior IT managers (CIO or equivalent), because they were considered best suited to answer questions about both their management domain and firm performance. Contact details of the managers including email addresses were obtained from a private data provider.

In June 2009, an email invitation was sent to the target respondents inviting them to participate in the survey by completing a comprehensive web-based online questionnaire. The initial invitation was followed up by an invitation letter accompanied by a hard-copy of the survey. With many invitation emails not reaching their addressees ('bounce backs') and an almost equal number of invitation letters being returned to sender because of the addressees having left the company, a contact details review was performed in September 2009, and email and hard-copy invitations were sent out to the corrected contacts. Despite this review and follow-up, 69 of the 500 firms could not be reached, reducing the effective sample size to 431.

44 firms (10.21%) responded to the survey, but 11 had to be removed from the sample, because they failed to either complete all questions in the questionnaire or meet the minimum size criteria[8] of $50 million AUD annual revenue and 50 full-time equivalent (FTE) employees. A non-response bias was inherent to the study insofar as only firms which deployed BI software (as defined above) were encouraged to participate. In the absence of publicly available data on the use of BI software in the target group, the impact of this exclusion cannot be determined.

Table 1 provides a breakdown of the 33 use able responses by industry and firm size. The largest industry groups represented in the sample are mining and real estate with the rest of the respondents representing a broad cross-sectional sample of Australia's private sector industry.

[8] Some of the respondents of the top-500 ASX listed companies completed the survey for their respective business units, and not all of them met the minimum size criteria for inclusion in the survey.

Table 1: Respondents by Industry and Firm Size

Industry	**N**	**%**
Materials – Mining	*5*	*15.2%*
Real Estate	*4*	*12.1%*
Capital Goods	*3*	*9.1%*
Food, Beverage & Tobacco	*3*	*9.1%*
Transportation	*3*	*9.1%*
Diversified Financials – Banks	*3*	*9.1%*
Commercial & Professional Services	*3*	*9.1%*
Consumer Services	*2*	*6.1%*
Retailing and Wholesale	*2*	*6.1%*
Media	*1*	*3.0%*
Energy	*1*	*3.0%*
Insurance	*1*	*3.0%*
Pharmaceuticals, Biotechnology & Life Sciences	*1*	*3.0%*
Software & Services	*1*	*3.0%*
Total	*33*	*100.0%*

Annual Revenue (in Millions)		**%**	**Employees (FTE)**		**%**
	< 50	*0.0%*		*< 50*	*0.0%*
50	*< 100*	*9.1%*	*50*	*< 100*	*3.0%*
100	*< 500*	*36.4%*	*100*	*< 500*	*21.2%*
500	*< 2,500*	*21.2%*	*500*	*< 1,000*	*27.3%*
2,500	*< 10,000*	*24.2%*	*1,000*	*< 3,000*	*9.1%*
10,000	*< 50,000*	*9.1%*	*3,000*	*< 10,000*	*21.2%*
> 50,000		*0%*	*> 10,000*		*18.2%*

Table 2 depicts the positions/roles of the respondents. Two thirds of the respondents were heads of IT, either in an explicit 'CIO' role or as heads of IT at the group or business unit level. The other respondents were managers of IT in general or BI in particular.

Table 2: Respondents' Positions/Roles

Position	**%**
Head of IT – Group	*33.3*
Other IT Manager	*24.2*
CIO	*21.2*
Manager Business Intelligence	*9.1*
Head of IT Business Unit/Division	*6.1*
Other	*6.1*

Measurement Model

BI Management Quality

In the absence of an established measurement for *BI management quality*, reflective indicators were derived from the BI Maturity Model (BIMM), developed and used by the TDWI (Chamoni and Gluchowski, 2004; TDWI-Research, 2008). After the exclusion of some indicators used in this reference model but not loading on the construct of BI Management Quality in our survey, the following four indicators were used for analysis: (1) BI development standardization, (2) BI project management success (as evidenced by BI projects being delivered in time and within budget), (3) BI resources (the availability of resources in IT required for BI), and the scalability of BI solutions.

Respondents were asked to rate their firm's performance in terms of achieving the above-mentioned objectives on a five point Likert type scale (1 = not achieved at all; 5 = 'fully achieved').

Scope of BI

The measurement model for *Scope of BI* was also developed primarily based on technical practitioner literatures on BI or data warehousing.

The first dimension of *Scope of BI* refers to the number of BI tools available in an organisation. Respondents were asked to select or list commercial OLAP software, querying and frontend reporting software, digital dashboards anddata mining software (see Appendix) used in their organization. The count of software products deployed in each organization was used to measure '*BI tools available*'.

The second dimension of Scope of BI was '*BI functional scope'*, which refers to business functions or processes typically supported by BI solutions. The questionnaire items were derived from practitioner literature combined with our own software functionality analysis (see Appendix for items).We allowed for additional functions to be added as open items. The count of business functions or processes supported by BI solutions in each organization was used to measure *BI functional scope.*

Data Quality

The measurement model for data quality built on the extensive IS research on data or information quality, in particular the fundamental research provided by Nelson et al. (2005), who adapted general IS quality theory to the specific context of data warehousing.

We build on Nelson's et al. (2005) findings adopting elements of their broad definition of completeness, but refine the concept insofar as we emphasize the importance of avoiding information overload. The resulting dimension used in our study is *adequacy of data volume*, with *data relevance* – which is included in their definition of data completeness – measured separate in our study. We also adopt the dimension *accuracy or correctness* and *format* (*presentation*) of data, but extend the concept of format by also explicitly addressing transparency of data. The latter addition reflects concerns raised by traditional spreadsheet users that data warehouse based BI tools are black boxes which lack transparency. Related to those concerns is the question of trust in data, which has been raised in data quality literature before and appears to be particularly relevant for BI.

Following exploratory factor analysis and initial PLS testing, the following items scored significant loadings on the data quality construct used in our research: (1) Adequacy of data volume[9], (2) data relevance, (3) data transparency, and (4) trust in data. Accuracy/correctness and format/presentation had to be excluded from the measurement model.

Respondents were asked to rate their firm's performance in terms of achieving the above-mentioned information-related objectives on a five point Likert type scale (1 = 'not achieved' at all; 5 = 'fully achieved').

User Satisfaction

Considering the research method (survey) used in our study, we were unable to measure user satisfaction directly at the user level, e.g. by interviewing or surveying a sample of users within each organisation. Instead we asked our survey respondents about their assessment of user satisfaction with the BI system. While this is a limitation of our study, we argue that (most) senior IT managers in an organisation would have a reasonably good understanding of how satisfied users are with the BI solutions deployed in an organisation, even more so as BI solutions typically have a relatively small and more senior user group than large scale operational systems such as ERPS.

Exploratory factor analysis and initial PLS testing revealed that the following four (out of initially seven) items revealed highly significant loadings on the user satisfaction construct: Users' perceptions about (1)the effectiveness and efficiency of the BI system, (2) the suitability/task relevance of information provided by the BI system, (3) the extent to which the BI system meets user requirements and (4) general user satisfaction with BI system.

Respondents were asked to rate the user satisfaction with the BI system on a five point Likert type scale (1 = 'very negative'; 3 = 'neutral'; 5 = 'very positive').

BI System Use

In the absence of an established measurement model for *BI system use*, reflective indicators were – once again – derived from the BI Maturity Model (BIMM), developed and used by the TDWI (Chamoni and Gluchowski 2004, TDWI-Research 2008). Based on this reference, two aspects of BI system use were captured: (a) the functional scope of BI, and (b) level of sophistication of BI use (see Appendix). For the measurement of the latter aspect, we distinguished between the following usage levels: Passive use, ad-hoc reporting, OLAP use and analytics expert use. While we argue there is an implicit rank in this measurement in terms of level of sophistication, we acknowledge that it does not reflect an ordinal scale for statistical purposes. We therefore generated a separate score

[9] 'Adequacy' captures both the notion of *having enough data* and *not experiencing data overload*.

for each level of use across each function. Out of the resulting four diffusion scores, only 'passive use' and 'ad-hoc reporting use' were included in our analysis, because OLAP use and analytic use were negligible across the sample and therefore did not load significantly on our construct of BI system use.

Quality of Managerial Decision Making

Considering the research method (survey) used in our study, we were unable to measure user satisfaction directly at the user level, e.g. by interviewing or surveying a sample of users within each organisation. Instead we asked our survey respondents about their assessment of user satisfaction with the BI system.

Like in the case of user satisfaction, the research method used only allowed us to measure the impact of the deployment of BI solutions at a very aggregate level and only indirectly by asking respondents about their perceptions about the said impact; another limitation of our study.

The indicators used to measure this construct were derived from decision science (Yong-Tae, 2006) and comprised five aspects of decision making quality, four of which loaded significantly on our 'impact' construct: (1) Effectiveness of decision making, (2) accuracy/correctness of decision making, (3) timeliness/speed of decision making, and making rationale/informed decisions.

Respondents were asked to rate the impact of the BI system on the quality of managerial decision making along the five aspects mentioned above on a five point Likert type scale (1 = 'very negative'; 3 = 'neutral'; 5 = 'very positive').

Relative Performance (Competitive Advantage)

Respondents were asked to rate their firm's performance relative to their main competitors. One of the advantages of using relative measures it that they control for differences in performance that are due to industry, environment, and strategy effects (Govindarajan and Fisher, 1990; Garg et al., 2003).

Profitability, *revenue growth* and *market share* are well established indicators of financial performance (e.g. Kaplan and Norton, 1996; Slater and Olson, 2000) and were therefore adopted in our study. Following a balance scorecard approach (Kaplan and Norton, 1996), leading performance indicator closest[10] to financial performance were also included in the form of relative *customer satisfaction* and *customer loyalty*.

Considering the mix of leading and lagging performance indicators used, the measurement model was also specified as reflective, following Tippins and Sohi (2003) and Johansson and Yip (1994).

[10] The other antecedents of firm performance (business process performance and learning and growth) were not included acknowledging the static nature of our research.

Financial Performance (ROA)

To overcome some of the weaknesses inherent to perception based measures of firm performance and to increase the reliability of our performance measures, we collected publicly available financial data of the firms in our sample to determine the return-on-assets (ROA) in the financial year prior to the completion of the survey.

This additional financial performance variable was not considered a main testing variable for two reasons: First, we could only derive the ROA at the company level (as listed at the ASX), but not at the business unit level (some of the respondents referred to). The second reason is that ROA is a directly observable and well established performance construct in itself, and therefore strictly speaking not a *latent* variable. In spite of these limitations, the inclusion of an 'ROA-based firm performance indicator' allowed us to establish a link between perceived performance and traditional archival financial performance indicators.

Partial Least Square Modeling (PLS)

Structural equation models (SEM) are strongly suited to testing both theories and measurement models (Bagozzi, 1980). The partial least squares (PLS) procedure was used, because it is most appropriate for the non-normal datasets and small sample sizes in the current research (Wold, 1982; Chin, 1998). PLS uses very general soft distributional assumptions and non-parametric prediction-orientated model evaluation measures (Wold, 1982; Chin, 1998).

The next section herein evaluates the measurement models, and then the following section assesses the structural model to determine the results. Chin and Dibbern's (2010) guidelines for reporting on PLS analyses were followed[11].

Evaluation of the Measurement Model

The adequacy of reflective measurement models is examined via; (1) individual item reliability, (2) convergent validity, and (3) discriminant validity (Chin, 1998; Hulland, 1999). First, individual item reliability is assessed by examining the item's loading on its construct as opposed to the other latent variable constructs in the model. As shown in Table 3, all construct-specific loadings are above 0.60, with many in the 0.80 and 0.90 'high' range (Chin, 1998; Hulland, 1999). Table 3 also confirms that each indicator's load is highest for the relevant latent variable construct.

[11] SmartPLS version 2.00 M3 was used (Ringle et al., 2005).

Table 3: Measurement Model – Discriminant Validity

	BI Mgt	BI Scope	Data Quality	User Satisf.	BI Use	Decision Quality	Perf. Ind.	Perf. ROA
BI development standardisation	**0.8553**	0.2358	0.7238	0.6212	0.0392	0.2558	-0.2210	0.0840
BI projects on time	**0.8668**	0.3796	0.6673	0.5111	0.1356	0.2717	-0.2301	-0.3579
BI resources	**0.7964**	0.3514	0.5586	0.5354	0.0000	0.3485	-0.1179	-0.1895
BI scalability	**0.9209**	0.2831	0.7115	0.6471	0.0453	0.2541	-0.2772	-0.1754
BI tools available	0.2027	**0.9140**	0.0616	-0.2077	0.6837	0.1184	0.3353	0.0225
BI functional scope	0.4607	**0.8912**	0.2999	0.2842	0.4538	0.3219	0.1809	-0.0827
Data volume adequacy	0.7124	0.2129	**0.9138**	0.6512	0.0418	0.3567	-0.1556	0.1333
Data relevance	0.6528	0.1499	**0.8916**	0.6528	0.0268	0.5137	-0.0976	0.0225
Data transparency	0.6714	0.1145	**0.8875**	0.5902	-0.0610	0.4626	-0.1828	-0.0392
Data trusted	0.7517	0.2134	**0.9021**	0.5897	0.0655	0.5047	-0.0539	-0.1337
Effectiveness & efficiency of BI system	0.6940	0.0442	0.6469	**0.9486**	-0.1788	0.3423	-0.4717	-0.2979
Suitability/task relevance of BI info.	0.5007	0.0113	0.6165	**0.9265**	-0.1327	0.3350	-0.3764	-0.2721
BI system meeting user requirements	0.6583	0.0481	0.6670	**0.9395**	-0.0878	0.3754	-0.3713	-0.1287
General end-user satisfaction	0.6674	-0.0020	0.6676	**0.9512**	-0.2606	0.3052	-0.4405	-0.2634
Scope of passive use	0.0356	0.4896	-0.0468	-0.3134	**0.8573**	-0.0204	0.2287	0.0467
Scope of ad-hoc reporting	0.0749	0.6136	0.0784	-0.0105	**0.8829**	0.1491	0.2589	0.0016
Decision effectiveness	0.3459	0.3532	0.4996	0.4232	0.1085	**0.8432**	0.0787	-0.0465
Accuracy/correctness of dec. making	0.2914	0.1622	0.4389	0.1768	0.0796	**0.7724**	0.2193	-0.0693
Timeliness/speed of decision making	0.2285	0.0711	0.3618	0.3221	-0.1060	**0.8099**	0.1364	-0.2080
Making rationale/informed decisions	0.1403	0.1290	0.3067	0.2249	0.1453	**0.7818**	0.2210	0.0212
Customer loyalty	-0.1736	0.0294	-0.2169	-0.3481	0.2243	-0.0305	**0.6053**	0.1063
Market share	-0.2129	0.1892	-0.2327	-0.4102	0.1054	-0.0199	**0.6094**	0.4983
Profitability	-0.2822	0.1747	-0.1539	-0.4411	0.3443	0.1801	**0.8278**	0.3272
Quality management	-0.0050	0.3503	0.1670	-0.0759	0.2999	0.3909	**0.7272**	0.1865
Revenue growth	-0.2196	0.2206	-0.1074	-0.3308	0.0082	0.1105	**0.8106**	0.3793
ROA	-0.1803	-0.0301	-0.0063	-0.2552	0.0265	-0.0902	0.4447	**1.0000**

Table 4 reports the measurement indicators' means and standard deviations along with other standard measurement model quality indicators, as well as the bootstrapped error terms, t-statistics and significance levels.

All *composite reliability* measures (0.84 to 0.97) comfortably exceed the recommended threshold of 0.70 (Fornell and Larcker 1981, Chin 1998). Cronbach's Alphas (α) are slightly lower, but still greater or very close to 0.70 (Nunnally 1978, Chin 1998), indicating strong reliability of the measurement model. All average variances extracted (AVE) are higher than 0.50 (Fornell and Larcker, 1981), ranging from 0.52 to 0.89. Hence, there is no concern with *convergent validity* either.

Table 4: Measurement Model – Descriptive Statistics and Quality Indicators

Constructs and Indicators:	Mean	Std. dev.	Loadings	Composite reliability rc	Cronbach's Alpha α	AVE	Bootstrapping	
							SE	t-statistic
A. BI Management				**0.92**	**0.88**	**0.74**		
BI development standardization	*3.03*	*1.287*	*0.86****				*0.05*	*15.66*
BI projects on time	*2.94*	*1.298*	*0.87****				*0.04*	*22.10*
BI resources	*3.00*	*1.000*	*0.80****				*0.10*	*8.03*
BI scalability	*3.36*	*1.168*	*0.92****				*0.03*	*27.92*
B. Scope of BI				**0.90**	**0.77**	**0.81**		
BI tools available	*3.82*	*1.911*	*0.91****				*0.03*	*36.00*
BI functional scope	*4.91*	*2.708*	*0.89****				*0.09*	*10.18*
C. Data Quality				**0.94**	**0.92**	**0.81**		
Data volume adequacy	*3.42*	*0.936*	*0.91****				*0.04*	*22.71*
Data relevance	*3.42*	*0.867*	*0.89****				*0.05*	*19.13*
Data transparency	*3.39*	*0.966*	*0.89****				*0.06*	*14.66*
Data trusted	*3.36*	*0.929*	*0.90****				*0.04*	*22.21*
D. User Satisfaction				**0.97**	**0.96**	**0.89**		
Effectiveness & efficiency of BI system	*3.27*	*1.008*	*0.95****				*0.02*	*45.98*
Suitability/task relevance of BI info.	*3.64*	*0.859*	*0.93****				*0.03*	*35.92*
BI system meeting user requirements	*3.33*	*1.051*	*0.94****				*0.03*	*31.22*
General end-user satisfaction with BI system	*3.21*	*0.927*	*0.95****				*0.02*	*52.28*
E. BI Use				**0.86**	**0.68**	**0.76**		
Scope of passive use	*2.88*	*2.147*	*0.86****				*0.16*	*5.50*
Scope of ad-hoc reporting	*2.36*	*1.765*	*0.88****				*0.05*	*18.16*
F. Decision Quality				**0.88**	**0.82**	**0.64**		
Decision effectiveness	*3.70*	*0.684*	*0.84****				*0.13*	*6.67*
Accuracy/correctness of decision making	*3.53*	*0.671*	*0.77****				*0.14*	*5.67*
Timeliness/speed of decision making	*3.67*	*0.777*	*0.81****				*0.15*	*5.31*
Making rationale/informed decisions	*3.52*	*0.667*	*0.78****				*0.19*	*4.09*
G1. Performance (indicators)				**0.84**	**0.77**	**0.52**		
Customer loyalty	*3.73*	*0.839*	*0.61****				*0.19*	*3.11*
Market share	*3.48*	*0.972*	*0.61***				*0.24*	*2.52*
Profitability	*3.79*	*0.893*	*0.83****				*0.12*	*6.67*
Quality management	*3.76*	*1.062*	*0.73****				*0.21*	*3.48*
Revenue growth	*3.79*	*0.857*	*0.81****				*0.11*	*7.43*
G2. Performance (ROA)				**1.00**	**1.00**	**1.00**		
ROA	*0.051*	*0.0458*	*1.00*				-	-

*** significant at $p < 0.01$; ** significant at $p < 0.05$ (two-tailed)

Table 4 also reports on the bootstrapping results (SE, t-statistic and p-values) for the indicator variables. With the exception of performance indicator ‘market share’, which is significant at $p < 0.05$, all other indicator loadings are highly significant at $p < 0.01$.

As for the assessing of *discriminant validity*, Chin (1998) outlined two procedures for: (1) cross-loadings (see Table 3 above) and (2) the AVE-PHI matrix. The diagonal elements in the Table 5 show the square roots of the AVE of each construct, whereas the off-diagonal elements show the PHI matrix of latent variable (LV) correlations. The cross-loading test requirements are fully met: No indicator has a higher correlation on a LV other than the one it is intended to measure, and each block of indicators does not load higher on its respective LV than indicators for other LVs (Fornell and Larcker, 1981; Chin, 1998)[12].

Table 5: Measurement Model: Discriminant Validity

	A	B	C	D	E	F	G1	G2
A. BI Management	**0.861**							
B. Scope of BI	0.359	**0.903**						
C. Data Quality	0.776	0.193	**0.899**					
D. User Satisfaction	0.675	0.027	0.691	**0.941**				
E. BI Use	0.065	0.637	0.022	-0.178	**0.870**			
F. Decision Quality	0.325	0.237	0.512	0.360	0.078	**0.802**		
G1.Performance (indic.)	-0.249	0.291	-0.135	-0.443	0.281	0.201	**0.722**	
G2.Performance (ROA)	-0.180	-0.030	-0.006	-0.255	0.027	-0.090	0.445	**1.000**

An interesting detail shown in Table 5 is the negative correlations, in particular between the performance constructs and BI management, data quality and user satisfaction. This observation will be further explored below.

Evaluation of the Structural Model

The results of the structural model are summarised in Table 6 and Figure 2.

The model provides strong support for hypotheses 1, 6, 7 and 8, and some (week) support for hypotheses 4, 9a and 9b. Hypotheses 2, 3 and 5 were rejected, and most notably, the relationship between user satisfaction and BI use was negative *and* significant. Possible explanations and implications are discussed below.

The amount of variance in the endogenous constructs explained by the model (R^2) is indicative of the predictive power of the exogenous latent variables. The explained variance of most of the variables was substantial to moderate (Chin, 1998). As expected, BI related variables can only explain a small percentage of (firm) performance.

[12] The reporting of the PLS modeling results follows Chin’s (2010) guidelines.

Table 6: Structural Model Results

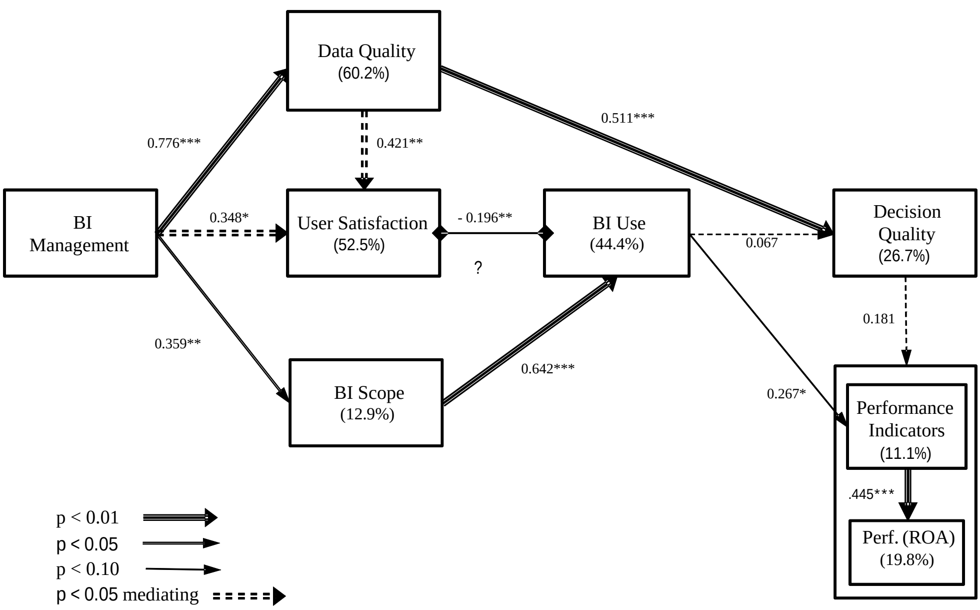
Hypothesis/Path Analysis:				Coefficient	Bootstrap t-statistic
H1:	***Data Quality***	→	***Decision Quality***	***0.511****	***3.054***
H2:	*Decision Quality*	→	*Performance (indicators)*	*0.181*	*0.753*
H3:	*BI Use*	→	*Decision Quality*	*0.067*	*0.456*
H4:	***BI Use***	→	***Performance (indicators)***	***0.267****	***1.433***
H5:	*User Satisfaction*	→	*BI Use*	*-0.196** (!)*	*1.845*
H6:	***Scope of BI***	→	***BI Use***	***0.642****	***6.431***
H7:	***BI Management***	→	***Data Quality***	***0.776****	***9.961***
H8:	***BI Management***	→	***Scope of BI***	***0.359****	***2.134***
H9a:	***BI Management***	→	***User Satisfaction***	***0.348****	***1.483***
H9b:	***BI Management***	→	***Data Quality → User Satisf.***	***0.327****	*(Table 7)*
Other paths:					
	Data Quality	→	User Satisfaction	0.421**	1.868
	Performance ind.	→	Performance (ROA)	0.445***	2.728

R-squares:

• *Scope of BI*	*12.9%*	• *Decision Quality*	*26.7%*
• *Data Quality*	*60.2%*	• *Performance (indicators)*	*11.1%*
• *User Satisfaction*	*52.5%*	• *Performance (ROA)*	*19.8%*
• *BI Use*	*44.4%*		

*** significant at p < 0.01; ** significant at p < 0.05; * significant at p < 0.10 (one-tailed)

Figure 2: Structural Model Test Results



Analysis of Mediation and Moderation

To test for mediating effects of data quality on the relationship of BI management and user satisfaction, we used the Hertel et al. (2008) multivariate adaptation of the Bollen and Stine (1990) bootstrap percentiles approach. Shrout and Bolger (2002) demonstrate and prove the superiority of Bollen and Stine's (1990) bootstrapping approach over the conventional mediation test statistics, and Hertel et al. (2008) adapted it innovatively to PLS. The essence of Bollen and Stine's bootstrapping approach is that the distribution of the *mediation scores* (a × b) (Baron and Kenny 1986) is bootstrapped and that the resulting scores are examined to determine the $(\alpha/2) \times 100\%$ and $(1 - \alpha/2) \times 100\%$ percentiles of the distribution (α = confidence interval)[13]. If both percentile scores are either below or above zero, a significant deviation from the expected distribution within the confidence interval is confirmed.

Adapted to our model, we determine the product of the bootstrapping coefficients of the paths BI Management → Data Quality and Data Quality → User Satisfaction and determine the percentiles for $\alpha = 5\%$ and $\alpha = 10\%$. The results are shown in Table 7.

Table 7: Mediation of Effect of BI Management on User Satisfaction

Effect	Estimate	Bootstrap Percentile (one-tailed)			
		95%		90%	
		Upper	Lower	Upper	Lower
Effect on User Satisfaction					
Direct via BI Management	0.348	0.707	-0.046	*0.628*	*0.010*
Indirect via Data Quality (a × b)	0.327	*-0.014*	*-0.265*	*-0.043*	*-0.248*

None of the other potential mediation paths in the model showed significant mediation.

We also tested for a potential moderating effect of BI use on decision quality, but found no such effect.

4. Discussion, Limitations and Outlook

Discussion

The *purpose of this research* was to integrate and extend the findings of previous DW/BI research by developing, testing and refining an information systems success model for the specific purpose, application, target group and technology of BI. Many of the predicted relationships in our model were confirmed. For others we could not find empirical support and contrary to established theory (DeLone and McLean, 1992; 2002;

[13] For one-tailed analysis, the formula is $(\alpha) \times 100\%$ and $(1 - \alpha) \times 100\%$.

2003), user satisfaction with BI systems was negatively associated with the scope of use of BI systems. The following sections discuss both the expected and unexpected findings.

Confirmed Predictions

Our results confirm the quality of managerial decision making is strongly influenced by the quality of data available in BI systems, and that the quality of managing BI within an organization is an important antecedent of data quality and therefore also decision making quality (total effect: 0.403). The findings substantiate the many calls for data quality management initiatives expressed in the practitioner literature (e.g. Swartz, 2007; Sandler, 2008).

We also confirmed the expected strong relationship between the scope of BI tools available and the actual use of BI, but most importantly, broader use of BI tools appears to be positively – although weekly – associated with performance. The strong total effect of BI scope on performance in the initial model (0.179) was confirmed in sensitivity analysis which revealed a significant direct relationship between BI scope and performance (0.272**). The strong relationship between the quality of BI management and BI scope reinforces the importance of properly managing BI to achieve tangible benefits.

Better BI management also leads to higher user satisfaction, both directly and mediated by data quality, but considering the controversial role of user satisfaction in the model, there is doubt about the implications of this relationship.

Unconfirmed Predictions

The expected positive relationship between managerial decision quality and performance remained unconfirmed. Possible explanations include a time lag between managerial decisions and performance, the dominance of other performance drivers not included in the model and limitations in the measurement of managerial decision quality.

Unexpected Findings

As an exogenous variable in the model, user satisfaction – and to a lesser extend BI system use – not only failed to meet the expectations ('no findings'), but had a significant negative association with BI system use and a negative association with decision quality and firm performance, and ex-post modeling also revealed a significant direct negative association with both decision quality and performance.

While we acknowledge that the object of investigation in the Delone-McLean model (1992) is the individual rather than the firm, the results are still surprising, even more so as a large range of ex-post modeling and testing confirmed the relationships revealed in our initial analysis. Limitations in the measurement model of user satisfaction may have contributed to deviations from the expected findings, but could not fully explain this 'user satisfaction paradox'.

We are not aware of any established theory capable of explaining this paradox directly. In search for our own explanation of the phenomenon, we arrived at the following potential explanation:

Frequent and advanced (business) users of IS are more likely to explore the 'boundaries' of systems, ask more challenging questions, are more likely to detect errors, and are therefore more likely to be dissatisfied with the system and challenging for the IT department than 'basic' users. BI systems are typically configured to provide relatively easy to use or fully automated standard reports, but in order to explore the real potential of these systems, ad-hoc reporting skills, advanced analytical skills and even configuration skills are required. Moving beyond the pre-configured standard functionality is likely to be associated with frustration about lack of user friendliness of the system, capabilities of the system and lack of knowledge about the system logic, functionality and the underlying models.

On the other hand, users who do not go beyond the base functionality of the system and who do not ask critical questions are more likely to be 'happy users'. But are 'happy' users 'good' users?

In the BI context, most likely they are not. More likely, they are evidence of lack of (adequate) system use or lack of BI 'mentality' of BI culture, and potentially a leading indicator of lack of performance.

Limitations and Outlook

Some of the limitations of our research have already been addressed above: The small sample size, simplified measurement of user satisfaction and managerial decision quality and reference to theory which evolved from individual user experiences with IS rather than organizational experiences.

However, many of our predictions were confirmed, and the unexpected findings provide a wide avenue for future research.

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Appendix: Measurement Details (Extract)

Scope of BI:

a) BI tools available:

'What types of BI products/tools are in use in your company? (Multiple answer option)'

OLAP Tools:
- Cognos (now IBM)
- Hyperion Solutions (now Oracle)
- Microsoft
- SAP Business Objects
- Microstrategy
- SAP BI
- Cartesis SA
- Applix
- Oracle (other than Hyperion)
- Infor
- Others (list here):

Querying and Frontend Reporting Tools
- List here:

Digital Dashboards
- List here:

Data Mining Tools
- SAS - Enterprise Miner
- SPSS - Clementine, AnswerTree, Neural Connect.
- IBM - Intelligent Miner
- Oracle - Darwin
- CSI - Advisor Toolkit
- Angoss Software - Knowledge Studio/Seeker
- Trajecta - dbProphet
- Partek
- Megaputer Intelligence - PolyAnalyst
- Silicon Graphics - MineSet
- Clopinet
- Unica
- Eudaptics Software - Viscovery
- HYPERparallel - Discovery
- Others (list here):

b) BI Functional Scope:

Which basic business functions or processes are directly supported by your BI solution? (Multiple answer option)

- Regular financial/tax reporting (external reporting)Suppliers
- Assurance and special compliance support (e.g. SOX)
- Group consolidation
- Cost analysis
- Operational planning and budgeting
- Other internal financial reporting
- Strategic planning
- Market/Sales planning/analysis
- Campaign management
- Production planning and control*)
- Supply-Chain analysis
- Supplier analysis
- HR analysis
- Other (list here)

*) excluded from analysis to avoid industry bias.

BI Use

What functional areas does the BI solution support, and how is the BI solution used in these areas?

Passive users are report receivers only.
Ad-hoc 'reporters' are producers of ad-hoc reports (rather than re-usable reports).
OLAP users are authors of re-usable reports, analysts or power users in general (but not analytic experts).
Analytic experts use 'business analytics methods', e.g. data mining techniques or artificial intelligence.

	Passive users	**Ad-hoc ‘reporters’**	**OLAP users**	**Analytics experts**
• Executives/Directors	○	○		
• Accounting/Finance	○	○	○	○
• Purchasing	○	○	○	○
• Production/SCM*)	○	○	○	○
• Marketing/Sales	○	○	○	○
• Customer Support	○	○	○	○
• Human Resource Management	○	○	○	○
• IT/ORG	○	○	○	○
• Legal Department	○	○	○	○
• R&D (incl. Product Development) *)	○	○	○	○
• Other (please specify):	○	○	○	○

*) excluded from analysis to avoid industry bias.