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The impact of Business Intelligence on the quality of decision making – a mediation model

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Abstract

Business Intelligence (BI) systems have been a top priority of CIOs for a decade, but little is known about how to successfully manage those systems beyond the implementation phase. This paper investigates the direct and indirect effects of BI management quality on the quality of managerial decision making using PLS analysis of survey responses of senior IT managers in Australia. The results confirm this overall relationship (total effect), but also reveal mediating effects of data/information quality and BI solution scope. The study contributes to both academia and industry by providing first time evidence of direct and indirect determinants of managerial decision support improvements related to BI solutions scope and active management of BI.

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Keywords: Business Intelligence; BI management; information quality; BI benefits; quality of decision making

1. Introduction

Business Intelligence (BI) has been a top priority of IT executives for several years and the market for related software products continues to grow rapidly, despite the challenging macro-economic conditions.[42] More recently emerging BI-related trends such as Business Analytics (BA) and management of 'Big Data' have contributed to the sustained growth of the BI software market.

Despite early calls for research in BI,[29] the wider academic research community has only gradually embraced the topic, and until today research on BI is still fragmented and sparse. Contemporary BI systems differ from earlier forms of Decision Support System (DSS)[25,27] in several ways: First, they typically involve systematic integration,

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aggregation and management of structured and unstructured data in – increasingly 'real-time' – data warehouses,[1,28] which enable new forms of fact-based DSS.[37] Second, BI solutions today deal with very large and increasing amounts of data ('Big Data') and can rely on exponentially increasing processing capacities (incl. in-memory technologies), which have created new opportunities for knowledge discovery (e.g. data mining). Third, BI solutions benefit from new ways of data interrogation and information delivery (automatic distribution to or self-service from pervasive computing devices).

Considering all these advances, it is often claimed that this new generation of DSS overcome the limitations of previous forms of management support systems.[20,22,50] But with an abundance of data available to today's organizations, do BI solutions really overcome the fundamental problem of "drowning in data whilst thirsting for information"?[21] Do they really enable better managerial decision making? And if so, what are the antecedents of such a BI success?

Interestingly, those questions are still open. Research on the *outcomes* of BI is sparse and has so far addressed costs and benefits associated with BI[22] and the effects of BI on performance[15,16,48] and on competitive advantage.[17,34] There have been a few attempts to research the impact of BI on managerial/organizational decision support,[11,33,36,48] but there is still a large gap to be filled,[25] in particular with regards to the mechanisms which lead to BI success. Accordingly, the *research question* addressed in this paper is as follows: *Does BI improve the quality of managerial decision making, and if so, how?*

2. Concepts and Theory Development

2.1. Business Intelligence

We synthesize previous definitions of[18,45] and understand BI as an analytical, technology supported process which gathers and transforms fragmented data of enterprises and markets into information or knowledge about objectives, opportunities and positions of an organisation. BI *software* denotes software products primarily designed to support this analytical process (e.g. data warehouse software, data mining software, digital dashboards software), BI *tools* (= applications) are BI software products deployed (installed, configured and usable) in an organisation, and a BI *solution* is a collective of BI tools and related technologies, applications and processes used in support of the objectives of BI.[48] These definitions are of key importance for our approach to research BI. Firstly, they emphasise that BI is not just about software and systems, but about *the whole process of managing* data to eventually support *managerial decision making*. Secondly, we make a clear distinction between *software* (which is typically available on the market as 'standard product'), *tools* or *applications* (which are software products installed, configured and usable for a particular purpose such as 'business planning'), and a *BI solution* (which is the collective of applications including the underlying IT infrastructure - servers, operating systems, integration platforms, networks, etc.). Considering the large diversity of application areas of BI and corresponding software products, it follows from the above that BI solutions can vary significantly in terms of functionality, sophistication, and complexity. We use *BI scope* as a construct for capturing these aspects, and predict a positive impact of scope on the quality of managerial decision making.

2.2. Quality of BI Management

Early studies on critical success factors of data warehouse projects[49] have already emphasised the importance of proper management of BI and holistic concepts of BI maturity[43] also include BI management as a critical dimension. From a theoretical perspective, BI management capabilities can be interpreted as a reflection of *resources*[3,12,47] and learning processes required to combine BI software and organizational strategy into BI solutions, and to ensure the on-going achievement of the objectives associated with the BI process. BI software products, on the other hand, are *assets* which are readily available in factor markets.[44] Similarly, BI software implementation services can be purchased and the on-going maintenance of BI solutions can also be outsourced. But successful management of BI also requires a close alignment of IT and business throughout the whole BI solution life cycle,[46] in particular matching decisions and requiring information,[11] asking the right questions, gaining and maintaining top-management support and championship,[5] and end-user 'buy-in', etc. Providing and maintaining a BI solution in support of "effective problem and opportunity identification, critical decision-making, and strategy formulation, implementation, and evaluation"[27] cannot be fully outsourced, but rather requires internal resources beyond the IT-department. Only if IT resources and business requirements are aligned through proper management of BI, organisations can realize the potential benefits of BI applications. Accordingly, we predict as follows: ***BI management quality is positively related to the quality of managerial decision making (H1)***.

2.3. Data/Information Quality and Quality of Managerial Decision Making

Data and information quality research has a long history in the IS discipline, with DeLone and McLean's[13,14] success model of information systems receiving most attentions and attracting many followers in the past two decades.[35] Most IS researchers, including DeLone and McLean, use the terms "data and information" as de facto synonyma,[30] whereas information theory, management science and decision science draw a very clear line between data and information. In the latter bodies of literature, data is typically referred to as facts which are collected and stored, but only develop a meaning if processed and conveyed/communicated in a way which adds to the knowledge of the receiver, i.e. information is context-specific. In contrast to data, information can relate to the future and can therefore be decision-relevant. Information reduces uncertainty for the decision maker by assisting in the identification of the alternatives available, and/or by predicting the consequences of selecting an alternative. Accordingly, we predict as follows: ***Information quality is positively related to the quality of managerial decision making (H2).***

Data quality, on the other hand, refers to the quality of representation of relevant facts. The distinction between data (quality) and information (quality) is particularly evident in the BI context. The main objective of BI is to provide high quality *information* for managerial *decision making*. This is attempted using essentially a two-stage approach: (a) identification, collection, storage and maintenance of data (e.g. in large data warehouses or data marts), and (b) retrieving, processing and conveying (communicating/presenting) data in a way which is useful for the receiver/decision maker, e.g. using OLAP technology, report frontends, dashboards or data mining tools.[23] The hierarchical relationship of data and information implies that data quality is a pre-requisite or antecedent – but not a guarantee – of information quality. One would expect that high quality data stored effectively results in better information, or in other words: ***Data quality is positively related to information quality (H3).***

It follows from H2 and H3 that data quality should indirectly 'translate' into better decision making, i.e.: ***Information quality mediates the relationship between data quality and the quality of managerial decision making (H3a)***.

BI management is responsible for the planning, implementation, and operation of both the 'data stage' and the 'information stage' of BI. Planning ideally starts with requirements analysis, i.e. anticipating future decisions ('asking the right questions'), which are then translated into information needs,[11] which then determine the data requirements. The implementation process follows an opposite direction, but both processes require cross-functional management to ensure tight collaboration between users of the information (decision makers) and IT, and adherence to data and information standards, etc. Accordingly, we predict as follows: ***BI management quality is positively related to data quality (H4)***, and: ***BI management quality is positively related to information quality (H5)***. It follows from H3, H4 and H5 that the direct effect between BI management and the quality of managerial decision making predicted in H1 can be explained by the indirect paths from BI management to decision making via data and information quality; in other words: ***The effect predicted in H1 is mediated by data quality and information quality (H1b).***

2.4. The Mediating Role of BI Solution Scope

The range of software products offered in support of BI is broad and varied in terms of purpose or role within a BI solution, detailed functionality, functional scope and level of sophistication. We therefore expect great variations in the applications deployed within each stage in organizations, e.g. some organisations may focus their BI efforts on the data stage and use simple generic reporting tools such as spread sheets to support the information stage, whereas others would have built sophisticated planning and analysis infrastructures.[34] We refer to this diversity as *variations in scope of generic BI functionality*.

All these examples of BI software can be deployed across various business functions. Enterprise data warehouses, for example, and predictive analytic tools can potentially support any business function of an organisation. Other software may have a stronger subject-oriented focus in terms of being purpose-built for particular business functions (e.g. market analysis and sales forecasting, budgeting, corporate performance management, or HR analytics). Accordingly, we also expect large variations in terms of *scope of BI business functionality* supported with BI tools. Considering the relationship predicted in H2 and the main objective of BI (i.e. managerial decision support), we expect BI solutions with greater scope (in terms of generic BI functionality and business functionality) to have stronger impacts on the quality of decision making. If follows that: ***BI solution scope is positively related to the quality of managerial decision making (H6).***

Better management of BI is expected to have two effects on BI solutions scope. Firstly, a direct effect insofar as it will result in higher project success rates and a more holistic approach towards generic BI functionality; secondly, successful BI management will increase the trust in BI resulting in higher diffusion of BI applications across various business functions. We therefore conclude: ***BI management quality is positively related to BI scope (H7)***.

It follows from hypotheses 6 and 7 that BI management is predicted to also have an indirect effect on decision making via BI scope: ***The effect of BI management quality on the quality of managerial decision making is mediated by the scope of the BI solution (H1b).***

Fig. 1 provides a graphical summary of our hypotheses (path-model). The paths shown as solid lines represent the hypotheses about direct relationships, whereas paths shown as dotted lines are indirect paths representing hypothesized mediation effects.

3. Research Design and Method

3.1. 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. 44 senior IT managers responded to the survey (10.21% of effective sample size of 431), but 11 had to be removed from the sample due to failure to meet the minimum size criteria (AU$50 million revenue of 50 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.

3.2. Measurement Model: Constructs and Evaluation

The questionnaire items can be accessed online.[51] The adequacy of our reflective measurement models is examined via: (1) individual item reliability, (2) convergent validity, and (3) discriminant validity.[7,24] Firstly, 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 in the appendix, all construct-specific loadings > .60 and each indicator's load is highest for the relevant latent variable construct.[7,24] Table 4 in the appendix reports the measurement indicators' means, standard deviations, and loadings, along with construct reliability and validity indicators. All indicator loadings are highly significant ($p < .001$). Likewise, all *composite reliability* measures exceed the recommended threshold of .70[7,19] and all Cronbach α values are > .70,[7,31] indicating strong reliability of the measurement model. Strong *convergent validity* is indicated by the average variances extracted (AVE) values, which all clearly exceed the recommended threshold of 50%.[19] As for the assessing of *discriminant validity*, the cross-loadings and the AVE-PHI matrix confirm high measurement model quality[7] (see Table 3).

4. Partial Least Square (PLS) Modelling

Structural equation models (SEM) are strongly suited for testing both theories and measurement models.[2] The partial least squares (PLS) procedure was used, because it is the most appropriate procedure for the non-normal datasets and small sample sizes in the current research.[7] PLS uses very general soft distributional assumptions and non-parametric prediction-orientated model evaluation measures.[7]

4.1. Results

The results of PLS-analysis for the direct and indirect paths are summarized in Table 5. Non-parametric bootstrapping (BT) with 500 sub-samples for multiple mediator models[6,8,38,41] was used to determine significance levels using two alternative methods: (a) the bootstrapped percentile method for a 95% confidence interval,[6,41] and (b) the t-statistic based on *beta* and its bootstrapped standard error (β/SE_{BT}) and the corresponding *p*-values.

H1 predicted a significant effect of BI management quality on the quality of managerial decision making. Zero-order correlations (r) between the constructs suggest such an effect at the bivariate level, but in the structural model, the direct effect is actually negative (β = -.28, p > .10, f^2 = .05). This unusual constellation is indicative of a negative suppression effect[10,32,40] (β = -.28, ns, f^2 = .05). Suppressor variables contribute to the quality of a model by partial ling out invalid variance of the other predictors that are correlated with and revealing the true relationships between the dependent and independent variables.[32,40] By increasing the weights of the paths of the other predictors of decision making, the suppression effect also increases the *indirect* effects of BI management on decision making which are – in combination – significant (β = .64, p < .05). The indirect effect is strong enough to compensate the negative beta of BI management resulting in a significant total (β = .36, p < .05) thereby confirming H1. While BI management does not directly translate into better managerial decision making, it does so through a set of indirect effects, in particular the two-way mediator path via data quality *and* information quality (β = .19, p < .05), as predicted by H3a.

With a moderate-to-strong effect size[9] of 0.27, information quality is the strongest individual predictor of quality of decision making (β = .54, p < .01, f^2 = .27), confirming H2. The test results also confirm the hypothised relationship (H3) between data quality and information quality (β = .48, p < .05, f^2 = .16), and the prediction that this effect translates indirectly into decision making (β = .26, p < .05). BI management quality is a particularly strong predictor of data quality (β = .75, p < .001), accounting for 56% of the variance of the latter construct (H4). The direct effect of BI management on information quality is not significant (β = .20, p > .10, f^2 = .03), but the indirect effect via data quality is (β = .36, p < .05), accumulating a strong total effect (β = .56, p < .001). H5 is therefore confirmed. The impact of BI scope on decision making (H6) is not as strong as predicted (β = .23, p < .10, f^2 = .08), but BI management quality has a significant effect on BI scope (β = .44, p < .001), confirming H6.

5. Discussion

The purpose of this research was to provide new insights into how aspects of BI directly or indirectly influence the quality of managerial decision making. The results of PLS and mediation analysis confirm that BI management quality has positive direct and/or indirect effects on data quality, information quality, and the scope of BI solutions. We also find that these effects – in combination – translate into a positive indirect effect on the quality of managerial decision making. In particular, the results reveal a significant path from BI management quality to decision making quality via (a) data quality and (b) information quality, which substantiates the calls for proper BI management (including data quality management initiatives) expressed in the practitioner literature.[49] The findings also support the critical success factor (CSF) literature by providing evidence of the importance of proper BI project management. But we also found that high quality BI management translates into more comprehensive BI solutions and stronger diffusion of BI applications across business functions. While we did not investigate the resources that drive BI management quality directly, we were able to conclude that organisations which have resources to enable superior BI management will – ceteris paribus – also realize more benefits of BI solutions.

Important implications for practice include that proper management of BI is important for data quality and/or information quality, for the diffusion of BI and eventually the benefits of BI. Furthermore, managing data to ensure correctness, consistency, completeness, transparency and therefore trust in data is an important pre-requisite to achieve high levels of information quality, but to excel on the latter, proper tools are required to easily access only relevant and current information. Rolling out large scale BI solutions may result in benefits; but it is not primarily quantity that matters, it is (data and esp. information) quality.

Overall, the study contributes to both academia and industry by providing first time evidence of direct and indirect determinants of organisational benefits from BI solutions, by conceptualising data and information quality as separate constructs, and systematically analysing the mechanisms which 'translate' (mediate) the impact of BI management on the quality of managerial decision making.

We also claim a significant contribution to advancement of research methodology, in particular path modelling and mediation analysis. We clearly demonstrate that a rejection of a hypothesis based on a not significant mediated path in e.g. a PLS path model is incorrect in cases where this path is fully mediated or even suppressed.[26] In such cases, a significant total effect justifies the acceptance of the hypothesis, despite a not significant direct path.

Like all researches in social science, the study presented in this paper has several noteworthy limitations, in particular the small sample size. PLS is quite tolerant towards small sample sizes, but even for PLS the sample size is 'borderline'. Furthermore, there are no established measures for the BI constructs (BI management quality and BI scope), which required us to develop our own measurement instrument. However, the measurement quality indicators provide strong support for high reliability and validity.

Appendix

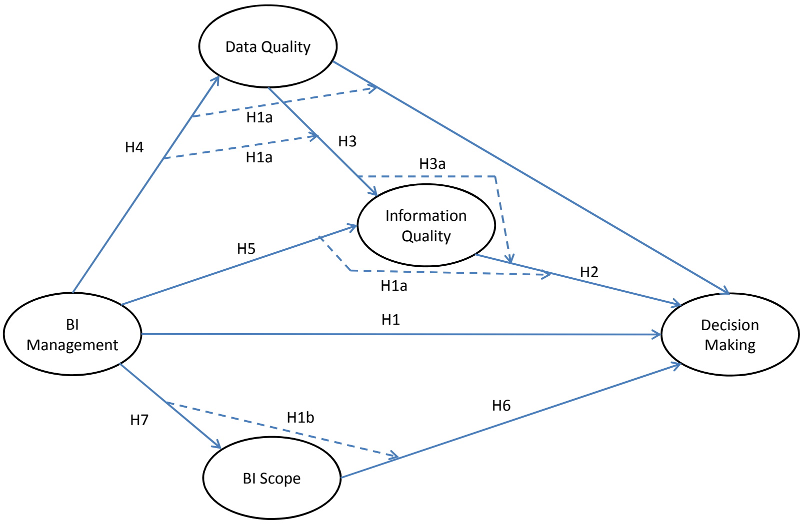

Fig. 1**:** Research Model

Table 1: Effect Sizes (f^2) and R-square Changes in PLS Model

Variables: Dependent / Independent		Information Quality	Decision Making
BI Management	ΔR^2	.02	.03
	f^2	.03	*.05*
Data Quality	ΔR^2	.10	.04
	f^2	***.16***	*.07*
Information Quality	ΔR^2		.15
	f^2		***.27***
BI Scope	ΔR^2		.04
	f^2		*.08*
$\Sigma\ \Delta R^2$		.12	.26
R^2 PLS model		.42	.45
R^2 shared		.30	.19

Effect sizes: > .05 italic; > .10 italic/bold

Table 2: Determination of Suppression Effects

	Whole Sample (r and β)		
Path:	Zero order (r)	Zero order (r)	Zero order (r)
BI Mgt → Decision Making	.36	n/a	-.28
BI Scope → Decision Making	.27	.14	→ .23
Data Quality → Decision Making	.49	.16	→ .32
Info. Quality → Decision Making	.63	.49	→ .54

The suppression effects in the PLS model were determined evaluating the structural model without the potential suppressor path BI Management → Decision Making (model') and then comparing the zero-order construct correlations, the betas of model' and the betas of the PLS model[32] Beta increases between model' and the PLS model indicate a suppression effect, and variables with a positive zero order correlation but a negative beta in the PLS model are negative suppressors.[10,32,40]

Table 3: Correlation Matrix, Discriminant Validity Assessment & PLS Cross-loadings

Panel A: Correlation Matrix and Discriminant Validity Assessment	**1**	**2**	**3**	**4**	**5**
1. BI Management	.85				
2. BI Scope	.47**	.89			
3. Data Quality	.67***	.17	.85		
4. Information Quality	.42*	.12	.62***	.75	
5. Decision Making	.33*	.29	.52**	.65***	.80
Panel B: Cross-loadings	**1**	**2**	**3**	**4**	**5**
BI resources	.84	.44	.54	.53	.38
BI development standardization	.85	.29	.71	.51	.30
BI projects on time/in budget	.87	.40	.67	.39	.24
Generic BI functionality scope	.48	.97	.25	.29	.31
BI business functionality scope	.21	.80	-.01	-.11	.08
Data correctness	.57	.18	.73	.34	.44
Data consistency	.54	-.04	.87	.59	.41
Data volume adequacy	.71	.26	.89	.54	.36
Data transparency	.62	.16	.90	.65	.43
Data trusted	.75	.26	.87	.55	.48
Completeness	.38	.08	.59	.80	.47
Volume (no overload)	.46	.02	.46	.76	.58
Relevance	.26	.03	.36	.64	.26
Currency	.59	.42	.55	.89	.56
Accessibility	.34	.10	.37	.64	.41
Timeliness/speed of decision making	.25	.08	.35	.54	.86
Decision effectiveness	.37	.42	.48	.53	.87
Making rational/informed decisions	.15	.18	.32	.53	.77
Accuracy/correctness of decision making	.46	.12	.45	.35	.66

Discriminant validity: Bold numbers on the diagonal show the square root of the average variance extracted (AVE) of each construct; all values are greater than those in the corresponding rows and columns [19] Off-diagonal values are nonparametric latent variable correlations (Spearman's r; two-tailed).
*Significance levels are *** $p < .001$, ** $p < .01$, * $p < .05$ (two-tailed).*

Table 4: Measurement Model: Indicator Reliability, Construct Reliability and Construct Validity

Composite Reliability (ρ)[a]	**Cronbach's α[a]**	**AVE[b]**
.89	.81	.73
.88	.77	.79
.93	.91	.73
.86	.80	.56
.87	.81	.64
Mean	**Std. Dev.**	**Loadings**
3.00	1.00	.83***
3.27	1.10	.85***
2.94	1.30	.87***
4.91	2.71	.97***
3.82	1.91	.79***
3.42	.83	.73***
3.48	.91	.87***
3.42	.94	.89***
3.39	.97	.90***
3.36	.93	.87***
3.03	.92	.80***
3.15	.94	.76***
3.42	.87	.64***
3.58	.90	.89***
3.30	.88	.64***
3.67	.78	.86***
3.70	.68	.87***
3.52	.67	.76***
3.53	.67	.68***

a) Internal consistency: All composite reliability (Dillon-Goldstein's ρ) indices are ≥ .60 [2] and all Cronbach's alpha indices are ≥ .70. [31]
b) Convergent validity: All average variance extracted (AVE) indices are ≥ .50. [19]

Table 5: Evaluation of Structural Model and Mediation Analysis

Hypo.	**Path/Effect**	**β**	**low[a)] 5%**	**high[a)] 5%**	**P[b)]**
	BI Mgt → Decision Making				
H1	- direct effect	-.28	-.78	.24	.20
H1a	- indirect effect via Data Quality	.24	-.11	.70	.17
H1a	**- indirect effect via Data Quality & Info Quality**	***.19****	***.01***	***.39***	***.05***
H1a	- indirect effect via Info. Quality	.11	-.10	.33	.21
H1b	- indirect effect via BI Scope	.10	-.00	.25	.12
H1a/b	**- total indirect**	***.64****	***.22***	***1.09***	***.02***
H1	**- total effect**	***.36****	***.08***	***.61***	***.02***
	Info. Quality → Decision Making				
H2	**- direct = total effect**	***.54*****	***.14***	***.81***	***.01***
	Data Quality → Info. Quality				
H3	**- direct = total effect**	***.48****	***.09***	***.82***	***.02***
	Data Quality → Decision Mak.				
	- direct effect	.32	-.15	.88	.16
H3a	**- indirect effect via Info. Quality**	***.26****	***.01***	***.51***	***.05***
	- total effect	*.58**	*.09*	*1.03*	*.03*

Hypo.	**Path/Effect**	**β & R²**	**low[a)] 5%**	**high[a)] 5%**	**P[b)]**
	BI Mgt → Data Quality				
H4	**- direct = total effect**	***.75******	***.62***	***.85***	***.00***
	BI Mgt → Info. Quality				
H5	- direct effect	.20	-.17	.55	.19
	- indirect effect via Data Quality	*.36**	*.07*	*.63*	*.02*
H5	**- total effect**	***.56******	***.22***	***.78***	***.00***
	BI Scope → Decision Mak.				
H6	- direct = total effect	*.23#*	*-.00*	*.48*	*.08*
	BI Mgt → BI Scope				
H7	**- direct = total effect**	***.44******	***.23***	***.62***	***.00***
R²	**BI Scope**	**.19**			
	Data Quality	**.56**			
	Information Quality	**.42**			
	Decision Making	**.45**			

*Significance levels are *** $p < .001$, ** $p < .01$, * $p < .05$ (one-tailed) and # $p < .10$;*
a) Lower and upper bootstrap percentile value of β; b) based on bootstrap t-statistic

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