review version

International Journal of
Information Systems and Project Management
ISSN (print):2182-7796, ISSN (online):2182-7788, ISSN (cd-rom):2182-780X
For peer review only

Determinants of Analytics-based Managerial Decision-making

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Abstract:
This study investigates how managerial decision-making is influenced by Big Data analytics, analysts' interaction skills and quantitative skills of senior and middle managers. The results of a cross-sectional survey of senior IT managers reveal that Big Data analytics (BDA) creates an incentive for managers to base more of their decisions on analytic insights. However, we also find that interaction skills of analysts and – even more so – managers' quantitative skills are stronger drivers of analytics-based decision-making. Finally, our analysis reveals that, contrary to mainstream perceptions, managers in smaller organizations are more capable in terms of quantitative skills, and they are significantly more likely to base their decisions on analytics than managers in large organizations. Considering the important role of managers' quantitative skills in leveraging analytic decision support, our findings suggest that smaller firms may owe some of their analytic advantages to the fact that they have managers who are closer to their analysts – and analytics more generally.

Keywords:
Big Data analytics; decision-making; quantitative skills; interaction skills; firm size

1. Introduction

During the past few years, the terms *Big Data* (BD) and *Big Data Analytics* (BDA) have become increasingly important for both academics and business professionals in IT-related fields and other disciplines [1]. Furthermore, executives increasingly acknowledge the potential benefits associated with BD [2] and global private and public investment in BD has reached billions of dollars per annum [3],[4]. BD has become a popular term which essentially represents the fact that data generated and available today is *big* in terms of volume, variety, and velocity [4],[5].

But being *big* does not per se make data *useful*. It is rather the insights gained from analyzing the data which provide benefits [5], which in turn requires organizations to develop or acquire new quantitative skills [6]. The claimed power of BDA does not replace the need for human insight [7]. Equipped with BDA experts, who can provide such insights from data, managers are expected to make better (informed) decisions [6],[8],[9] – provided they actually use those insights to guide their decision-making.

Some high-performing organizations use BDA as critical differentiator and driver of growth [1],[11],[12], but often executives still struggle to understand and implement BD strategies effectively [10]. Furthermore, it is unclear to what extent managers actually use any available BDA output to support their decisions. Some even argue that the biggest challenge in BDA is that managers do not comprehend how to gain benefits from analytics [11], and even managers themselves are concerned about their ability to uncover and take advantage of meaningful insights [11]. Accordingly, the first research question in this paper is: *Are managers in organizations with sophisticated BDA more likely to base their decisions on analytics (facts, evidence) than managers in organizations low on BDA?*

Being able to provide sophisticated BDA is, however, not the only skill data analysts require. They also have to be able to effectively relate to, cooperate with and communicate with internal and sometimes external parties. Such professional interaction skills are often associated with being able to effectively liaise with stakeholders and sponsors, understand the needs of internal customers, effectively collaborate and contribute to team results, successfully negotiate and resolve conflicts, and effectively communicate problems and solutions [12]. Accordingly, our second research question inquires *to what extent interaction skill levels of analysts/analytic experts influence the level of reliance on analytics in managerial decision-making.*

Considering that some managers have particular difficulties understanding analytics in the BD era [10], our third research question addresses the role of managerial capabilities in the context of BDA and decision-making. Managerial quantitative skills (MQS) refer to the collection of experience, skills, and know-how of managers with regards to quantitative methods [13]. *But do variations in managers' quantitative skills actually influence the extent to which they rely on analytics in their decision-making?*

To answer these research questions, we collected survey responses from 163 senior finance managers across a broad range of industries in Australia. The results suggest that managerial quantitative skills are the strongest driver of analytics-based decision-making, but both BDA sophistication and interaction skills of analysts also have a significant effect. Our test results also reveal an unexpected negative effect of the control variable firm size on analytics-based decision-making.

The remainder of the paper is organized as follows: Section two elaborates on the constructs of interest and makes predictions about their relationships (hypotheses); section three explains the research methods, including construct measurement, and section four presents the results. Finally, the implications and the limitations of our research are discussed in section five.

2. Theory/Hypotheses development

Big Data (BD) refers to a set of techniques and technologies that require new forms of integration in order to uncover hidden value from large datasets that are diverse, complex, and of a very large scale. Today, data are generated, changed and removed more frequently than in the past, and increasingly analogue data are converted into digital form [14]. Consequently organizations need new platforms and tools for analyzing data. "Analytics is the science of analysis" [15, p. 86]. Data analytics uses data for quantitative and/or qualitative analysis to help organizations to better understand their business and markets (knowledge discovery) and to support timely business decisions

[5],[20],[24],[16]]. Data analytics in a BD environment is different from conventional data analytics, because many of the analytic algorithms used on BD had to be adapted or newly developed in response to the high volume, variety, and velocity of data [7].

Big Data Analytics (BDA) applies scientific *methods* to solve problems previously thought impossible to solve, because either the data or the analytic *tools* did not exist [17]. BDA can help organizations to create actionable strategies by providing constructive, predictive and real-time analytics, and to gain deeper insights in how to address their business requirements and formulate their plans [18]. With new technologies and analytic approaches, BDA can provide managers with information for real-time planning and continuous forecasting [7],[18],[19]. BDA techniques are capable of analyzing larger amounts of increasingly diverse data. With algorithms advancing BDA can help improve decision efficiency and effectiveness [20]. In summary, BDA can have a significant impact on decision-making processes, provided managers perceive analytic output as useful and use it to support their decisions [28]-[30].

Research findings are still inconsistent in terms of what managers base their decisions on. Even when managers claim to use a rational approach in their decision-making process, they still also use soft problem structuring methods [21] and heuristics (including intuition) to cope with bounded rationality at some stages in this process [22]. However, when analytic results are insightful and timely, and when they contradict intuition, managers are said to set aside their intuition and rely on data [7]. We therefore predict as follows:

H1: Big Data analytics sophistication leads to more *analytics-based* decision-making.

Sophisticated analytic methods and tools are, however, not always enough to convince managers of the *usefulness* of analytics. Analysts also need to be able to properly communicate solutions or insights to their stakeholders – both verbally and visually [23]. In addition, they require relationship skills to facilitate an interaction and ongoing communication with decision makers [24] and to enable a shift from ad hoc analysis to an ongoing managerial conversation with data. As analysts make discoveries, they have to be able to communicate what they have learnt and suggest implications for new business directions [23]. In the context of business analytics, such “interaction skills are represented by the business analyst's ability to relate, cooperate, and communicate with different kinds of people including executives, sponsors, colleagues, team members, developers, vendors, learning and development professionals, end users, customers, and subject matter experts” [12, p. 207]. It is argued that analysts’ interaction skills (AIS) can improve managers’ perceptions of the usefulness of analytic output, and therefore have a significant impact on managerial decision-making processes.

H2: Better interaction skills of analysts lead to more *analytics-based* decision-making.

Quantitative skills refer to the ability of generating, transforming and interpreting numerical data by applying mathematical and/or statistical rules, thinking and reasoning [25]. Quantitative skill requirements vary depending on the roles and responsibilities of individuals, as well as the scope and sophistication of the organizational operations and data [26]. Analytic professionals are expected to have advanced quantitative skills, but whether such capabilities are required at the managerial level is questionable – even more so as newer Artificial Intelligence (AI) methods are capable of making decisions without human involvement.

On the other hand, research shows that organizations still need managers with sound quantitative skills [27]. Managers are required to identify and define business problems, ideally with having quantitative solution methods in mind. Decision makers are also required to use their judgment and focus on what they perceive to be potentially important so as to enable the selection of the right subsets of the available data [10],[28]. Managers also need quantitative skills in order to properly evaluate analytic outputs (of new analytical methods) [27] and to correctly deploy resulting actions in their organizations [27].

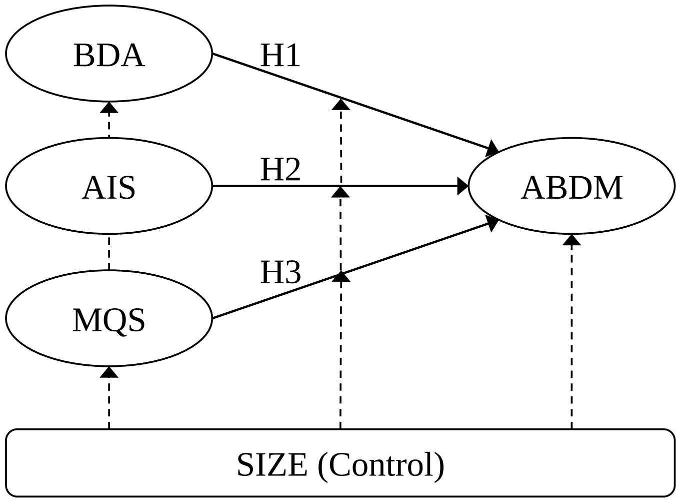

Figure 1: Research Model

When competing with analytics, quantitative skills are also required at the strategic decision-making level [29],[30], and previous studies suggest that there is indeed a positive association between managers' quantitative skills and the quality of their decisions [31],[32]. In fact, engineers often become successful CEOs, because they are detail-oriented and possess strong quantitative and problem-solving skills [33].

As far as the use of analytic 'output' in managerial decision-making is concerned, we expect that managers with stronger quantitative skills perceive such output as more useful, because they better understand the methods used to generate it. Accordingly, they will be more likely to base their decisions on analytics.

H3: Managers' quantitative skills have a positive effect on *analytics-based* decision-making.

In our research model (Figure 1), we control for firm size, because larger firms are considered to (a) have more financial resources available for investment into BDA (both analytic human capital and analytic tools); (b) be in a better market position for hiring managers with strong quantitative skills (MQS); and (c) have more formalized procedures for decision-making and therefore rely more extensively on analytical decision support [34]. As such effects may also interact with the relationships predicted in H1-H3, we also test for moderation effects of firm size.

3. Research method

To acknowledge the exploratory nature of this research, a cross-sectional survey was considered to be the most suitable research method [35]. The survey targeted CIOs and senior IT managers of Australian-based medium to large for-profit organizations. The survey procedures were guided by Dillman et al. [36]. As each variable in the hypotheses is latent, constructing proper indicators and scales was essential. This process was informed by previous academic studies, but where required, practitioner literature was also consulted. During questionnaire design, necessary procedural remedies were applied to control for and minimize the impact of common method biases [37]. The face and content validity of the prototype of the questionnaire as well as the appropriateness of Likert scale endpoints were assessed as follows [37]: Five experts in survey research were invited to evaluate the draft questionnaire, and their feedback was used to refine the design and content of the survey. The revised version of the questionnaire was then delivered to a group of industry experts and academics for final pilot testing.

3.1 Construct Measurement

In the absence of any (known) measurement scale for *analytic sophistication* in the context of BD, we had to develop our own scales. As a starting point, we operationalized BDA along three dimensions [38]: (a) analytic methods, (b) analytic tools and (c) quantitative skills of analysts. Analytic *methods* include a vast range of statistical methods, machine learning/data mining/artificial intelligence, operations research techniques (e.g. optimization models), and decision analysis [39]. Analytic *tools* refer to software applications that analytic professionals use in data analytics. They range from basic spreadsheet models to business intelligence (BI) tools, large-scale statistical packages, data mining suites, data visualization tools, high performance computing tools and combinations of the former. During pilot testing, respondents were asked to rate their analytics expert or expert team in terms of quantitative skills and in terms of frequency of use of various analytic tools and methods, as derived from industry surveys [40],[41] and professional guidelines [12] (Table 1). The analysis of the pilot test data revealed that *skills* and *methods* cross-loaded on each other and that the skill-construct did not meet the required measurement quality criteria. The latter was therefore dropped from the survey, and only the first order constructs *methods* and *tools* were used to generate *BDA sophistication* as a second order formative construct BDA (following the recommendations of Wetzels et al. [42]).

Table 1 - Descriptive statistics and validity and reliability measures (first order constructs)

	Mean (Range)	Std. Dev.	Composite Reliability	Cronbach's Alpha	AVE
Analytic Tools	1 - 7		.860***	.807***	.508***
Spreadsheets#	6.55	0.795			
BI Planning/Reporting Suites	4.88	2.056			
Data ETL/Management Solutions	4.32	2.246			
Statistical Suites – Basic Use	2.73	1.966			
Statistical Suites – Advanced Use	2.42	1.866			
Specialized Data Mining Suites	2.02	1.593			
Data Visualization Tools	3.53	2.215			
BD/High Performance Computing Tools#	2.13	1.709			
Analytic Methods	1 - 7		.911***	.855***	.774***
Statistical Methods	3.44	2.114			
Machine Learning, Data Mining, AI	2.45	1.846			
OR, Optimization Methods	2.53	1.789			
Path Modelling#	1.76	1.285			
Analytics-based Decision-Making	1 - 7		.936***	.918***	.710***
Decisions about Products/Services/Markets	4.73	1.667			
Decisions about Strategic/Key Suppliers	4.46	1.508			
Decisions about Outsourcing/BPM	4.32	1.570			
Decisions about Sales and Marketing	4.80	1.576			
Decisions about Operations	5.02	1.486			
Decisions about Procurement	4.52	1.446			
Overall, Organization Acts on Insights#	4.78	1.445			
Analyst Interaction Skills	1 - 7		.923***	.889***	.749***
Understanding the needs of (internal) customers/clients	5.22	1.237			
Collaborating & contributing to team results	5.20	1.319			
Liaising with stakeholders & sponsors	5.11	1.252			
Effectively communicating problems and solutions	4.96	1.244			
Managers' Quantitative Skills	1 - 7		.920***	.900***	.594***
Strong analytical skills (senior managers)	4.52	1.619			
Strong numerical skills (senior managers)	5.47	1.353			
Subst. experience with quantitative methods (senior mgr.)	3.66	1.599			
Competent in statistics (senior managers)	3.74	1.574			
Strong analytical skills (middle managers)	4.42	1.494			
Strong numerical skills (middle managers)	5.31	1.420			
Subst. experience with quantitative methods (middle mgr.)	3.50	1.668			
Competent in statistics (middle managers)	3.66	1.608			

1-tailed: p <.05; p <.01**; p <.001***; # Indicator omitted from final analysis*

Interaction skills refer to the ability of the analyst to relate, cooperate and communicate with internal and external parties. Successful interaction requires liaising with stakeholders and sponsors, understanding the needs of internal customers, collaborating and contributing to team results, negotiating and conflict resolution,[1] and effectively communicating problems and solutions [12]. In our study, respondents were asked to rate their analytics expert/team in those areas on a seven point Likert scale (1 = very poor and 7 = excellent).

Experience and competence in analytic methods are typically associated with the quality of decisions [31]. Quantitative skills assist managers at all levels with identifying problems, interpret scenarios and solutions and monitor/assess the impact of decisions. Considering the seniority of the survey respondents, we did however only ask for an assessment of the analytic competencies of other (non-IT) senior and middle managers. Quantitative skills encompass general

1 'Negotiating and conflict resolution' loaded poorly on the analyst interaction skills construct and was therefore eliminated.

numeracy skills (mathematics) and proficiency in statistical concepts and methods and other quantitative methods (such as Operations Research methods). Respondents were asked to rate the level of quantitative skills of their senior and middle managers in those areas on a seven point Likert scale (1 = strongly disagree and 7 = strongly agree). We also included two reverse coded questions to assess – and confirm – the quality of the responses.

When deciding about the measurement scale for *analytics-based decision-making*, the following constraints had to be considered: (a) the level of seniority of the respondents, and (b) the cross-sectional nature of the survey. To acknowledge the former, the questions were kept broad, representing the tactical and strategic levels of decision-making [43]. To comply with the latter constraint, the questions had to be applicable to all industries in the target sample. Respondents were asked to rate for each decision area to what extent their organization relies on insights derived from data analysis/analytics (Likert scale: 1 = strongly disagree and 7 = strongly agree) (Table 1).

Firm size was measured using a scale based on the number of full-time equivalent (FTE) employees distinguishing small (50-100 FTE employees), medium (101-500) and large business units (501+). Organizations with less than 50 FTE employees were excluded, because overall they were not expected to have dedicated BD-Analysts.

3.2 Survey response

The initial survey invitation was emailed to 1,595 potential respondents, but 263 invitations did not reach the addressees (bounce-backs). A total of 174 responses were received during the survey period, but 11 had to be excluded, because they did not meet the selection criteria (e.g. a minimum tenure of one year in that organization, or a minimum response time of five minutes). The final response rate of 12.24% may appear low, but is not unusual in Australian business surveys, even more so as BD is still an emerging topic for many. 84% (43%) of the responses came from organizations with more than 100 (500) FTE employees, and CIOs (52.1%) and other senior IT managers (47.9%) were almost equally represented.

3.3 Data characteristics and quality

In order to determine appropriate analysis and testing techniques (parametric vs. non-parametric) [44], test for normality were conducted for both indicator data and latent constructs. Both the *Shapiro-Wilk* test and the *Kolmogorov-Smirnov* test revealed that none of the indicators is normally distributed (p < .05). Accordingly, we used non-parametric data analysis and testing techniques (PLS-SEM and bootstrapping) [45].

In addition to the procedural remedies applied during the development of the questionnaire, post-hoc statistical remedies were used to test for potential method bias [37]. *Harman's* single factor test was run across the set of 31 measurement indicators yielding seven factors with Eigenvalues exceeding 1, therefore indicating that common method bias is not present.

Responses were also tested for non-response bias by comparing early and late responses. The results of independent samples test (*Levene*'s Test for Equality of Variances and t-Test for Equality of Means) confirm that there are no significant differences in the indicator values between the early (n = 83) and late (n = 80) response group.

After the elimination of four low-loading indicators, all remaining items have significance levels of p < .001 and load primarily on their assigned construct. The measurement model was further assessed for reliability and validity of the construct measures. Reflective measurement models are assessed for: (a) internal consistency (composite reliability), (b) indicator reliability (composite reliability), (c) convergent validity (average variance extracted and communality), and (d) discriminant validity [35],[45]-[47]. Table 1 confirms that the first three of those criteria are fully met. The *Fornell-Larcker* criterion [48] was applied to assess for discriminant validity of latent constructs, and all of them meet the criterion (Table 2).

Table 2 - Fornell-Larcker criterion for discriminant validity

	Tools	Methods	ABDM	IA Skills	MQS
Tools	**.713**				
Methods	.600	**.880**			
ABDM	.367	.387	**.842**		
Analyst Interaction Skills	.370	.256	.445	**.866**	
Managers' Quantitative Skills	.364	.484	.584	.460	**.771**

Values in the diagonal are the square-roots of the AVE of each of the constructs.

The heterotrait-monotrait (HTMT) ratio between the average of the heterotrait-heteromethod correlations and the average of the monotrait-heteromethod correlations [47] is used to further ensure discriminant validity. A HTMT value of two latent constructs of less than .85 confirms discriminant validity between the pair. Table 3 reveals that all HTMT scores are clearly below the benchmark confirming discriminant validity of our model.

Table 3 - HTMT values for discriminant validity (first order constructs)

	Tools	Methods	ABDM	IA Skills
Methods	.718			
ABDM	.408	.427		
Analyst Interaction Skills	.423	.280	.474	
Managers' Quantitative Skills	.411	.543	.630	.505

4. Results

The structural model shown in Figure 1 was used to test all hypotheses, while controlling for direct and moderating SIZE effects. The results of the PLS analysis and bootstrapping are presented in Table 1, both for direct (model 1) and moderating (model 2) effects. The bootstrapped significance levels were identical for the t-statistic, the confidence interval and bias-corrected confidence interval methods [35]. The analysis was performed with SmartPLS Version 3.00 M3. To report the measurement quality and structural model results (see Table 4) we use the guidelines provided by Chin [49] and Ringle et al. [50]. The significance of each effect was determined using bootstrapping with 2,000 samples. For the moderating effects the two-stage procedure with standardized product terms was used [35].

As predicted in hypothesis 1, BDA sophistication has a significant positive effect on ABDM (H1: β =.158, p <.05), although the effect size in terms of relative R-square contribution (f square) is rather small (.03). Hypothesis 2, which predicted a positive effect of AIS on ABDM, is also confirmed (H2: β =.202, p <.01; f = .05), but the dominating predictor of ABDM are managers' quantitative skills (MQS) (H3: β =.404, p < .001; f =.19), which account for the majority of the R-square in the model.

Contrary to the rationale for including firm size as a control, this variable has a significant *negative* direct (β = –.128, p < .05, f = .03) and total (β = –.155, p <.01) effect on ABDM. Such negative effect is also evident in the moderation models (models 2a – 2c), but the interaction terms with SIZE are not significant. As expected, larger firms are able to provide slightly more sophisticated BDA (β = .094, *n.s.*), but managers in those firms tend to have less quantitative skills (β = –.104, *n.s.*) and base their decisions to a significantly lesser extent on analytics than managers of smaller firms (β = –.128, p < .05).

Table 4. Structural model results

	Model 1	*f* square	Model 2a	Model 2b	Model 2c
BDA → ABDM (H1)	**.158***	**.03**	**.150***	**.149***	**.157***
AIS → ABDM (H2)	**.202****	**.05**	**.196****	**.196****	**.202****
MQS → ABDM (H3)	**.404*****	**.19***	**.403*****	**.395*****	**.405*****
Controls:					
SIZE → ABDM	*–.128** [#)]	*.03*	*–.132***	*–.127**	*–.128**
SIZE → BDA	*.094*	*.01*			
SIZE → MQS	*–.104*	*.01*			
*SIZE * BDA → ABDM*			*–.048*		
*SIZE * AIS → ABDM*				*–.078*	
*SIZE * MQS → ABDM*					*–.002*
R-square: ABDM	**.409*****		**.412*****	**.417*****	**.410*****

1-tailed: p < .05; p < .01**; p < .001****

[#)] *The total effect of SIZE on ABDM is –.155*, but the indirect effects of SIZE on ABDM via BDA and MQS are not significant.*

5. Conclusion, implication, and limitations

The study presented in this paper attempted to determine the impact of Big Data analytics (BDA) sophistication, analysts' interaction skills (AIS) and managers' quantitative skills (MQS) on managers' decision-making behavior, in particular the extent to which they base their decisions on analytics (rather than heuristics and intuition). The results of our analysis suggest that while each of those three factors is positively associated with analytics-based decision-making (ABDM), MQS has by far the strongest impact.

These findings have important implications for research and practice: First, the results empirically confirm the often unverified claims that BDA has an impact on managerial decision behavior insofar as more advanced analytics creates an incentive for managers to actually base their decisions on the analytic insights. Second, the results also confirm that particular soft skills expected from analysts [12] do make a difference, i.e. higher interaction skills presented by analysts do create an incentive for managers to make analytics-based decisions. Third – and most importantly – our findings suggest that quantitative skills of senior and middle managers are the main underlying driver of analytics-based decision-making [51]. The practical implications of these findings are as follows: Investing in BDA tools and data scientists/analysts creates an incentive for managers to make more informed decisions, even more so if analysts match their technical skills with interaction skills. But in order to fully leverage such analytic resources, it requires managers who possess strong quantitative skills.

One possible interpretation of these findings is that managers with poor quantitative skill do not appreciate the value of analytics as much as managers who have developed such skills. Alternatively – or in addition – quantitatively capable managers may find it easier to interpret the analysis provided by data scientists and are therefore more likely to use it. Overall, 'upskilling' of managers in terms of quantitative methods or using the latter as job selection criteria for managerial positions may have a more beneficial effect on decision-making than investing into advanced analytic tools and broadly skilled data scientists.

Our study also yielded some unexpected but interesting side-results: When including firm size as control, our test results reveal that managers in smaller organizations are significantly *more* likely to base their decisions on analytic outcomes than managers in large organizations. This finding contradicts the mainstream view held in academic literature assuming that larger organizations have more formalized procedures for decision-making and (therefore) rely more on extensively on analytical decision tools and information [34]. On the other hand, the finding is in line with some cases reported in the practitioner literature, which suggest that smaller businesses are in a good position to compete on analytics [10]. Our findings are corroborated by the fact that the smaller organizations in our sample scored higher on managerial quantitative skills. Considering that the latter play a very important role in creating BDA impact, we conclude that smaller firms may owe some of their analytic advantages to the fact that they have managers who are ‘closer to’ analytics. More research is required though to investigate the impact of firm size on managerial decision making in more detail.

Like any study, our research is not free of limitations. Despite the fact that we deployed several procedural and statistical remedies to avoid biases [37], survey-based research is never completely immune against biases. Second, the survey respondents were exclusively CIOs and other senior IT managers, which inevitably introduces an IT-centric perspective. Future research could attempt to capture a more balanced perception, especially with regards to managerial decision-making in the context of a more holistic enterprise information management perspective [52]. Finally, we do not explicitly measure decision-making quality, but rather rely on prior research [31],[48], which suggests that ABDM is associated with better decision-making.

Acknowledgments

We would like to thank the Accounting Discipline Group at the UTS Business School for the financial support for this project, but also for the valuable feedback provided in several workshop sessions. We also acknowledge the valuable feedback received at the CENTERIS 2017 conference in Barcelona, Spain, which helped shape the final version of this paper.

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