Performance Impacts of Business Intelligence and Analytics Systems – the Mediating Role of Management Accounting Information Quality

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Abstract

Our research investigates the impact of management accounting (MA) information quality on organisational performance by considering the role of business intelligence and analytics (BI/A) systems and environmental uncertainty. By drawing on the resource-based view, dynamic capabilities theory and information and systems quality frameworks, we develop a model which establishes the scope and frequency of MA decision support methods used in an organisation and MA information service levels as performance enhancing aspects of MA information quality.

Using survey data collected from accounting and finance executives, the results of our PLS-SEM path model confirm that both of these aspects of MA information quality are positively associated with organisational performance and that such effects are – at least partly – moderated by environmental uncertainty. We also find strong support for the predicted impact of BI/A systems quality on both MA information quality constructs. Finally, the results for our path model analysis also reveal that the effects between BI/A systems quality and MA information quality characteristics also 'translate' into a significant indirect effect of BI/A systems quality on performance.

Keywords: *Management accounting, performance management, decision support, information quality, business intelligence, analytics*

1. Introduction

In the past decades, rapid advances in information systems and technology, such as enterprise resource planning (ERP) systems, self-service BI applications, Artificial Intelligence applications for robotic process automation (Whitney & Juras 2017), etc. have increasingly automated especially the routine management accounting (MA) tasks, thereby putting pressure on the profession in terms of demonstrating *value adding contributions* beyond scorekeeping and other routine tasks. In response, professional MA bodies reinforced the strategic dimension of MA, and the importance of *business partnering*, e.g. by defining MA as "a profession that involves partnering in management decision making, devising planning and performance management systems, and providing expertise in financial reporting and control to assist management in the formulation and implementation of an organization's strategy" (IMA 2008, p. 1). Increasingly, the traditional control focus of MA gets stigmatized as 'bean-counter stereotype', while the modern business partner role is pictured as the desirable and sought after position (Horton & Wanderley 2018).

Despite the recommended focus on *strategy, relationship* and *business partnering*, research on the *actual* role of management accountants suggests that most of them are far from the idealistic *business partners* and *strategic advisers* professional bodies want them to be (Beaman & Richardson 2007; De Loo, Verstegen & Swagerman 2011; Marchant 2013). In reality management accountants' role profiles are rarely one-dimensional, as they "often operate in hybrid roles with dual or multiple functions, and their levels of business involvement may reflect multiple points on a continuum between low involvement (the prototypical bean-counter) and high involvement (the prototypical business partner)" (Horton & Wanderley 2018, p. 41). The resulting dual accountability (Goretzki, Lukka & Messner 2017) has received critical attention in recent research, and some academics are sceptical about the over-emphasizing of business partnering (Burns, Warren & Oliveira 2014).

The overall aim and motivation of our study is to contribute to and extend this debate by adding an information systems perspective. In particular, our study aims to investigate the impact of MA information quality on organisational performance by considering the role of business intelligence and analytics (BI/A) systems and environmental uncertainty, to answer the following set of research questions:

RQ1: Does the quality of information provided by management accounting (MA) impact on firm performance, and if so, does (perceived) environmental uncertainty moderate any such impact?

RQ2: Are high quality business intelligence and analytics systems associated with higher MA information quality?

Our study is embedded in the broader concept of *MA quality*, which has been conceptualised along three dimensions (Fleischman, Johnson & Walker 2017): Functional quality (based on SERVPERF as proposed by Cronin & Taylor 1992), technical quality and image quality. We focus on technical quality, as it covers the *information* quality aspects of MA, which are the focus of our research. Information quality is a very well established concept in IS research, and MA researchers have largely drawn on IS literature when adopting scales for measuring MA information quality – including Fleischman, Johnson & Walker (2017). We adopt their conceptualisation of MA information quality but split it further into two sub-dimensions: *Information scope* operationalised as the range and extent/frequency of MA methods used, and *information service level,* which covers the logistics aspects of information provision, i.e. how frequently, how quickly (incl. real-time self-service), and how detailed information is provided to managers. By drawing on the resource-based view, dynamic capabilities theory and information and systems quality frameworks, we develop a model which establishes BI/A systems quality as an antecedent or enabler of MA information scope and service levels, which in turn 'translate' into increased performance.

The results of PLS-SEM analysis of survey responses from top financial managers of medium to large size private sector firms confirm our theoretical reasoning insofar as they reveal that both aspects of MA information quality are positively associated with organisational performance and that such effects are – at least partly – moderated by environmental uncertainty. We also find very strong support for the predicted impact of BI/A systems quality on both MA information quality constructs, which confirms the benefits previously associated high quality BI systems – but now extends these findings to more advanced business analytic tools and systems. However, we also find that diffusion rates of analytic tools in MA are still very low. Finally, the results for our path model analysis also reveal that the effects between BI/A systems quality and MA information quality characteristics also 'translate' into a significant indirect effect of BI/A systems quality on performance.

The remainder of this paper is structured as follows: In the next section, we analyse and categorise MA activities related to managerial decision support based on existing literature and practical observations, we discuss the impact of high quality BI/A systems on MA activities, and develop hypotheses with regards to associations between those constructs and firm performance. That section is followed by a detailed description of the research method, followed by a results section, and finally a conclusions and limitation section.

2. Theory/Hypotheses Development

Management Accounting Activities for Decision Support

Management accounting (MA) "refers to the processes and techniques that focus on the effective and efficient use of organizational resources to support managers in their task of enhancing both customer value and shareholder value" (Langfield-Smith et al. 2015, p. 7). MA is therefore a service function, supporting ongoing operational and management control, and managerial decision making more generally by providing historical (control) information and by predicting/planning the future. More recently, there have been calls for a more proactive and strategic orientation of such advisory services, delivered in a 'business partner' relationship (Arnold 2017; Hagel 2015; Lawson 2016; Wolf et al. 2015).

MA is embedded in an organisation's information systems and the services provided are essentially data and information services (collection, processing and dissemination). Depending on the trigger of such service provision, we can distinguish two broad categories:

a) Routine information activities: Such activities are performed either at an ongoing basis or at regular intervals in support of routine decisions and ongoing control (e.g. annual budget allocations, monthly budget or performance reviews), but they also generate base level data and information for later use in ad-hoc decisions (e.g. variable product cost per unit). Routine activities include standard cost planning, budgeting, actual cost determination and closing, periodic performance and variance analysis, periodic reporting, etc.
b) Ad-hoc information activities: These activities are performed 'on demand' as requested by managers inside or outside the accounting and finance (A&F) function. Such activities include project costing/budgeting/analysis, new product costing (e.g. target costing), cost-volume-profit analysis, quantifying outsourcing or pricing decisions, cost-benefit analysis, strategic risk analysis, transfer pricing, etc.

As for the use of computerised IS, *routine activities* are typically supported by larger scale semi-standard software, which ideally integrates with other sub-systems which contain data relevant for performing the routine activities (e.g. production and sales plans, actual production activities, wage rates, etc.). Most medium to large organisations therefore use integrated enterprise systems, such as ERPs, to cover the core routine activity data and processing requirements. Beyond providing high levels of data and process integration such systems also capitalize on the fact that routine activities can often be automated. ERPs are sometimes supplemented by BI tools (incl. spreadsheets) which are typically used to support especially routine planning and reporting activities. The information processed in routine activities is primarily *descriptive* and *predictive* (Davenport 2014; Minelli, Chambers & Dhiraj 2012), and *timeliness* of information provision can be achieved by routinizing and automating procedures (e.g. month-end closing).

Ad-hoc activities are typically not directly supported by ERPs, but rather require (further) processing of base-level information derived from ERPs and/or other sources in BI/A tools. Cost-volume-profit analysis, for example, relies on critical base-level information about product revenues, variable product costs and fixed costs, but is actually performed e.g. using spreadsheet templates or other BI/A tools.

The information processed in ad-hoc activities is primarily *predictive* and *prescriptive*, and *timeliness* of information provision is often critical. However, ad-hoc activities have only a *limited potential for automation*, but may rather require case-by-case modelling or even additional data collection. It follows from that above that – in contrast to routine information activities – the *scope and speed of ad-hoc information activities* has the potential to *differentiate* (Barney 1996) organisations and therefore create *competitive advantage* as reflected by superior performance. The first of the two following sections elaborates on the *scope* dimension, the second on the *speed/timeliness* dimension.

Management Accounting Ad-hoc Decision Support Methods

Traditionally, MA was primarily concerned with routine activities for determining (standard) absorption costs and product or divisional profitability (Johnson and Kaplan 1987). The emergence of more refined, decision-oriented cost and profitability accounting systems in post Second World War Europe, such as the *Grenzplankostenrechnung* (Kilger et al. 2004) in Germany, enabled the development of a broader range of decision support methods, such as *cost-volume-profit analyis* and *contribution margin analysis*. Attempts to extend the repertoire of MA decision support tools by including operations research (OR) techniques (e.g. Ijiri 1965), were only of temporary – and primarily academic – nature, whereas the use of finance methods (e.g. in capital budgeting) became established practise.

In the 1980s, Johnson and Kaplan (1987) alerted the MA community to rethink established MA practices, calling for a more *strategic orientation* of MA, which eventually resulted in the development of activity-based management and the balanced scorecard (Marchant 2013). The emerging data warehouses and BI solutions facilitated the deployment of such strategy-oriented systems, but these applications rarely evolved beyond what Davenport (2014) refers to as *Analytics 1.0* – the era of BI-reporting. The second – and so far last – generation of BI applications for MA were advanced planning and budgeting solutions (Peters & Wieder 2013).

As for the use of advanced business analytics (BA) methods in MA, some academics argue that they have been used in the past, or their use has at least been proposed in the past (Amani & Fadlalla 2017; Sutton, Holt & Arnold 2016). Others follow the tradition of Ijiri (1965) and provide new recommendations for the innovative use of such methods in MA (Nielsen 2018; Raval & Greteman 2015; Rikhardsson & Yigitbasioglu 2018). Machine learning/data mining techniques are frequently suggested advanced BA methods, but advanced visualization techniques have also attracted significant attention. In general, many of the recommendations for use of advanced BA methods in MA refer to the use of new non-financial and/or external data sources to support traditional and new tools and methods (e.g. balanced score card (BSC), forecasting, pricing and benchmarking) (Pickard & Cokins 2015; Sutton, Holt & Arnold 2016). In doing so, management accountants are advised to move away from just verifying data, towards modelling, simulation and scenario analysis, "giving a range of answers rather than one single answer" (Russell 2014). A considerable number of publications address new opportunities in inventory management, costing and asset valuation more broadly (e.g. Amani & Fadlalla 2017; CGMA 2015a; Hülle, Kaspar & Möller 2011; Moffitt & Vasarhelyi 2013). But the vast majority of advanced BA applications potentially usable in MA are *proposed* rather than empirically *validated*. We therefore seek to *empirically confirm* that such applications are actually used in MA, and that such use contributes positively to the firm performance.

In summary, we identify three groups of ad-hoc decision support methods (potentially) used in MA: (1) Traditional methods based on cost, revenue or cash flow information; (2) strategic decision support tools typically combing financial and non-financial information; and (3) more recently emerging BA methods such as data mining or OR techniques, which provide increased predictive power or even prescriptive decision making, with the extent to which they are actually used in MA still under-researched. Table 1 summarises the characteristics of each group of ad-hoc decision support methods used in MA.

	Traditional (Ongoing)	**2000+ (Ongoing)**	**2010+ (Emerging)**
Level	Operational	Strategic	Operational/Strategic
Data	Financial (cost/revenue/ cash flow based)	Financial/non-financial	Financial/non-financial
Information Sources	ERPs, operational systems	ERPs, BI, external, etc.	Any (Big Data)
Type of support	Descriptive/Predictive/ Prescriptive	Descriptive/ Predictive	Descriptive/Predictive/ Prescriptive
Methods	CVP analysis, cost-benefit analysis, capital budgeting, etc.	ERM, BSC, Benchmarking, etc.	Descr./predictive Analytics (Data mining /AI), Optimisation, Simulation, etc.
DSS	Spreadsheets	Spreadsheets, BI tools	Spreadsheets, BA tools

Table 1: Evolution and characteristics of ad-hoc decision support methods used in MA

In order to leverage the differentiation potential of ad-hoc information activities – as suggested by the Resource-based View theory (Barney 1991) – we argue that organisations which frequently use a large range of these methods frequently, ceteris paribus will make better decisions, which in turn should manifest in superior firm performance; hence:

H1: The scope and frequency of MA decision support methods used in an organisation is positively associated with firm performance.

MA Information Service Levels

With an increasing trend away from performing primarily control tasks towards high quality information service provision in MA (Burns, Warren & Oliveira 2014), *timeliness* of information provision has become a focus of attention, negotiation and even formal internal agreements. Service level agreements (SLAs) have been very commonly used to formalise the services and service quality – including corresponding metrics – expected from internal or outsourced IT service providers, and IS research on SLAs is abundant (Paschke & Bichler 2008). In accounting, SLAs have become prominent especially with outsourcing agreements, but there is also evidence of SLAs specifying the expected service-levels from internal accounting departments, in particular shared-service centres.[1]

Irrespective of the existence of formal, semi-formal or no SLAs, the role of management accountants as managerial decision supporters suggests that such support services are subject to reasonably objective quality metrics, such as on-time information provision. As mentioned above, routine information activities and ad-hoc information activities typically differ in terms of urgency or timeliness requirements. Routine activities tend to have deadlines which are known (long) in advance and can therefore be planned or even performed (long) in advance. Provided the deadlines for information generation are met, the only requirement is to distribute the relevant information to the information users in adequate detail, format and visualisation style. Some routine tasks, however, can only be executed in a short time window (e.g. certain end-of-period closing tasks), which makes these task sensitive to delays. Ad-hoc information requirements may even be due 'immediately', and delayed information provision may result in poor decisions, missed opportunities, etc. We therefore predict:

H2: MA information service levels are positively associated with firm performance.

The Moderating Role of Environmental Uncertainty

Environmental uncertainty (EU) – perceived or factual – has been discussed as contingency factor, moderator, etc. in management (accounting) research for decades, in particular in the context of MA systems sophistication (Abdel-Kader & Luther 2008), dynamic capabilities (Eisenhardt & Martin 2000; Sirmon et al. 2011) and performance more broadly (Laitinen 2014). While the precise mechanisms of how EU influences MA systems and performance is still a matter of debate, dynamic capabilities theory consistently argues that higher levels of (perceived) EU require higher levels of (dynamic) capabilities (Schoemaker, Heaton & Teece 2018). Considering that *scope and frequency of MA decision support* and *methods MA information service levels* can be considered distinguishing capabilities (Barney 1991), we predict that:

H1a: The positive association between scope and frequency of MA decision support methods used and organisational performance is positively moderated by environmental uncertainty.

H2a: The positive association between MA information service levels and organisational performance is positively moderated by environmental uncertainty.

[1] While we found no mentioning of internal A&F SLAs in the academic literature, there is substantial evidence of such internal agreements in the public sector (as per Google Search), and we assume they are also used by private sector firms, although not published on their web-sites.

BI/A Systems Support for MA

BI systems have been used for multi-dimensional MA *reporting* for approx. two decades, and their use was soon extended into multi-dimensional *planning* (Peters et al. 2016). As such, they provided – and still provide today – support for several MA methods (e.g. BSC) and practices (e.g. budgeting, performance measurement). How well these systems are able to support these methods and practices depends on their *functionality*.

BI functionality refers to the usability of an application for modeling and interacting with multi-dimensional data hierarchies. Multi-dimensional data hierarchies require that data objects and attributes be linked together in an integrated calculative scheme (Peters et al. 2016). For BI planning systems, greater functionality also facilitates more dynamic interaction with the time dimensions and plan versions of multi-dimensional data hierarchy models by providing more unified access and manipulation of and between them. This allows forecasts and budgets to be quickly created and revised and allows even sophisticated planning models to be easily implemented and changed. If planning and reporting functionality is contained in the same BI systems, plans can be quickly updated with actual and base-level information. Spreadsheets, on the other hand, offer only limited interactive interfacing with object and attribute multi-dimensionality and it is relatively difficult for users to switch between and view multiple time dimensions and plan versions. For BI reporting systems, high functionality is reflected in highly interactive reporting features, ease of navigation and sophisticated formats and presentation features (Peters et al. 2016).

BI systems have already been used successfully in performance management (Vukšić, Bach & Popovič 2013) as they improve performance measurement capabilities (Peters et al. 2016). There is also evidence that technological capabilities such as data quality, user access and the integration of BI with other systems improve managerial decision making regardless of the decision environment (Işık, Jones & Sidorova 2013; Wieder & Ossimitz 2015).

BI systems can also improve MA information service levels in various ways: BI systems have been found to have a positive impact on annual budgeting by providing faster base line information and enabling monthly rolling budgets (De Leon, Rafferty & Herschel 2012).

BA systems differ substantially from BI systems in terms of modelling functionality, they do not contain multi-dimensional data hierarchies and therefore require partly different criteria for high functionality (Chen, Chiang & Storey 2012; Holsapple, Lee-Post & Pakath 2014). In contrast to BI systems, *functional scope* in terms of the range of statistical and other methods provided is important for BA systems, and large scope is expected to have a positive impact on the range of BA methods used in MA. Relative ease of general use (for BA experts) and of model implementation enables ad-hoc information requests to be addressed in shorter time, and so does the quality of presentation of the output of modelling.

Accordingly, we expect a positive impact of BA functionality on MA information service levels.

In summary, both BI systems and BA systems have varying levels of functionality, and we refer to BI/A systems high in functionality more broadly as high in system quality. We conclude that high quality BI/A systems provide better support for MA and assist in providing on-demand, up to date, detailed and timely information to business managers; hence we hypothesise:

H3: The quality of business intelligence/analytics systems used in accounting has a positive impact the scope of management accounting methods used.

H4: The quality of business intelligence/analytics systems used in accounting has a positive impact on management accounting information service levels.

Considering the logic of H1 and H3 and H2 and H4 – and the resulting path models (Figure 1) – we predict an overall, indirect impact of BI/A system quality on performance:

H5: BI/A system quality is positively associated with firm performance.

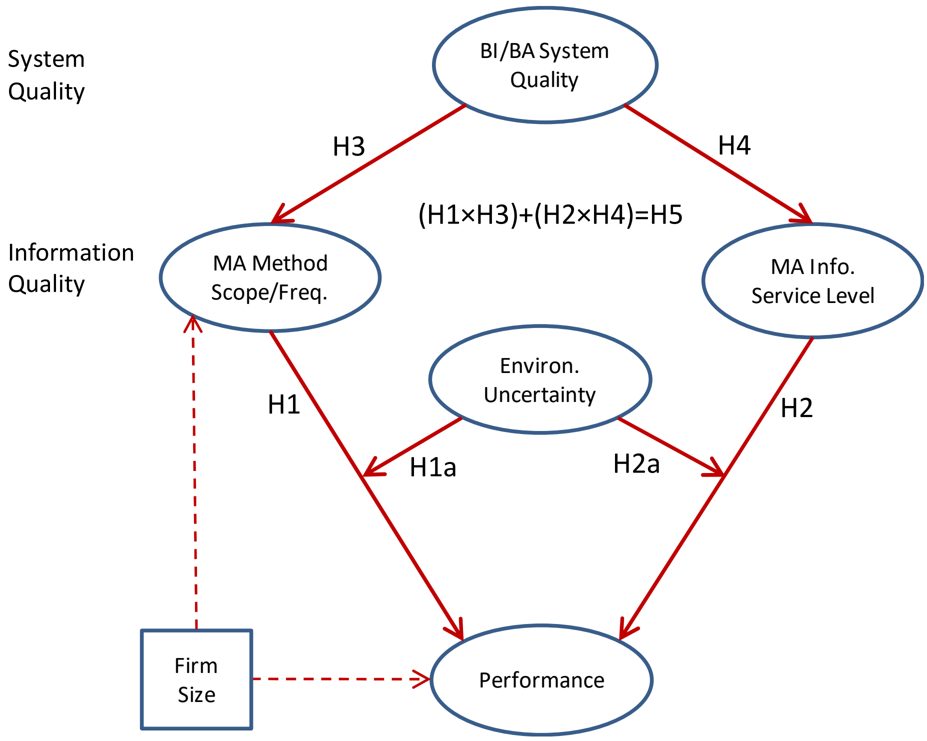

Figure 1: Research Model and Hypotheses Summary

3. Research Method

The research presented in this paper is based on a cross-sectional survey administered to top level financial managers of Australian-based, medium to large, private sector firms. The questionnaire drew partly on established (and slightly modified) constructs and measurement instruments, and partly on new measurement scales (for the newly developed dimensions of MA information quality, in particular MA method scope). The development of the new scales relied on both established scales for MA method scope and recent literature on more advanced analytics methods used in MA (Amani & Fadlalla 2017; Appelbaum et al. 2017). Conventional design and administration procedures were used, including pre-testing with four academics and two practitioners (Dillman 2007), to ensure face and content validity (Tourangeau, Rips & Rasinski 2000), as well as the appropriateness of Likert-scale endpoints (Netemeyer, Bearden & Sharma 2003, p. 100).

The survey invitation email with a link to the online questionnaire was sent to the target respondents based on an email-list purchased from a commercial provider, which comprised the names and email addresses of CFOs (or equivalent heads of A&F) from 925 Australian-based private sector firms in the following industry segments: Agriculture, mining, manufacturing, construction, retail, wholesale and distribution, transport, utilities and communications. Other industries, such as banking, insurance and business services, were excluded as they were considered too specific in terms of management accounting and information systems requirements and practices. Medium to large size (> 100 full-time equivalent employees) companies were targeted to increase the likelihood that MA had been established as a separate sub-function within A&F.

The survey was conducted in three rounds spanning over a two month period. In the first round, 75 invitation emails were blocked by a firewall and 98 'bounced back' because the target respondent had officially left the company (27) or the email address was generally reported as incorrect/unknown (71). From the remaining 752 target respondents who were technically reached, 76 started the survey (10.1% response rate) and 64 fully completed it. Three of the incomplete responses were close to completion and therefore usable, i.e. our final sample contains 67 responses. As targeted, the respondents were primarily CFOs or equivalents (e.g. 'director of finance') (68.7%), senior finance managers and financial controllers (25.4%), and less than 6% CEOs or commercial managers. In line with Australia's sectoral structure of the target sample, 16.5% were from the primary sector of the economy (agriculture and mining), 38.8% were from manufacturing firms and 44.7% from services firms. All respondents met the minimum tenure requirement of one year or more in the current organisation and a minimum of three months in the current role.

Construct measurement

To measure the *quality of business intelligence/analytic systems* (BI/A QUAL), we primarily relied on a two-dimensional scale developed, tested and deployed for BI *planning* and *reporting* systems functionality (Peters, Wieder & Sutton 2018; Peters et al. 2016), but extended it with a third dimension addressing *business analytics functionality* based on (based on Chen, Chiang & Storey 2012; Holsapple, Lee-Post & Pakath 2014). Scores were coded from 1 to 5, with 5 representing high functionality. The resulting second-order latent variable is a three-dimensional emergent construct, formatively measured by the first order, reflective constructs BI planning, BI reporting and BA (business analytics) functionality. Latent variable scores for each dimension were generated in a separate hierarchical PLS model as per Wetzels et al. (2009).

The same two-stage modelling approach was used to arrive at the second order scores for *MA decision support method scope and frequency* (MA-SERV), which has been conceptualised along three development phases: (1) *Traditional operational* MA methods, (2) *strategic* decision support methods and (3) *analytic* methods. The list for the first and second group of methods were derived from previous academic survey-based research (Abdel-Kader & Luther 2008; Gullkvist 2013; Nuhu, Baird & Appuhamilage 2017; Pavlatos & Kostakis 2015), mainstream MA textbooks (Horngren et al. 2009; Langfield-Smith et al. 2015) and practitioner literature (e.g. CIMA 2013; Clinton & White 2012). The group of analytic methods was sourced from more recent publications which identify the – actual or potential – use of advanced analytics methods in MA (Amani & Fadlalla 2017; Appelbaum et al. 2017). Respondents were asked how frequently each of the listed methods or practices (see Table 3) were used by management accountants in their organization, with possible responses ranging from 1 (never) to 5 (regularly). The mean values in Table 3 show that BA methods are used, but clearly less frequently than traditional methods and strategic methods.

For the measurement of *MA information service level* (MA SERV), respondents were provided with two questions referring to *routine* MA information (questions 1 and 4) and two asking about *ad-hoc* information delivery (questions 2 and 3). The wording of the questions was closely aligned with a scale developed and tested by Abdel-Kader & Luther (2006). Respondents were asked to rate on a scale of 1 (strongly disagree) to 5 (strongly agree) to what extend they agree with each statement. As expected, the items about routing information delivery have weaker loadings, but they are in the acceptable range, and their outer loadings and outer weights are also significant at $p < .001$.

Environmental uncertainty (ENVI-U) was measured with reference to the VUCA (volatility, uncertainty, complexity, and ambiguity) framework (Schoemaker, Heaton & Teece 2018), for which a new scale was developed and pilot tested. Respondents were asked to what extent they disagreed or agreed (1-5) that items referring to volatility, uncertainty, complexity and ambiguity had increased over the past 12 months (see Table 3). As shown in Table 7 and Table 8, the loadings of the first of the four questions were low, but discriminant validity of all four items and the construct itself was very high.

Competitive advantage is defined as superior *performance* (PERFORM) relative to competitors. This approach controls for differences in performance due to industry, environment, and strategy effects (Garg, Walters & Priem 2003; Peteraf & Barney 2003). Performance can be measured either at the business process level (operational efficiency) or the organization/firm level (overall productivity, profitability, market value) (Dehning & Richardson 2002; Melville, Kraemer & Gurbaxani 2004). Respondents were asked to rate their organisation's performance in the previous financial year relative to competitors across three firm-level and two process level dimensions: (1) sales growth; (2) return on investment (ROI), (3) net profit margin (=profitability), (4) coordination with business partners/suppliers, and (5) efficiency of internal processes (Oh & Pinsonneault 2007; Peters et al. 2016). Subjective and objective measures of financial performance have been found to correlate highly and to provide similar results in PLS modeling (Rai, Patnayakuni & Seth 2006). Scores were coded from 1 to 7, with 7 representing highest performance. PLS analyses of our data indicate the three financial measures all loaded strongly (.89, .86, and .78) on this construct, whereas the non-financial performance measures loaded slightly more weekly (.66 and .60), as expected. The latter were however strong enough by all quality criteria and significant in terms of outer loadings and outer weights ($p < .001$).

Firm size was used as a control in the model because it can systematically influence organisational practices and performance (Baum & Wally 2003; Garg, Walters & Priem 2003). Firm size is measured using the number of full-time equivalent (FTE) employees and organisations with less than 50 FTE employees were excluded.

Tests for Normality

To determine the most appropriate analysis and testing techniques (parametric vs. non-parametric), all indicators and latent variables were tested for normality (Bollen & Stine 1990; Kraska-Miller 2014; Ringle, Sarstedt & Straub 2012a). Skewness and kurtosis was analysed to confirm data distribution characteristics (West, Finch & Curran 1995). The descriptive statistics of all indicators presented in Table 3 show that 15 variables have absolute values of skewness/standard error or kurtosis/standard error > 2, which suggests that data is not normally distributed in those cases (Cramer 1997). Further testing with the *Kolmogorov-Smirnov method* reveals that none of the indicators is normally distributed ($p < .05$), whereas six of the nine latent variable scores are. Overall, the results suggest that non-parametric test methods are required in our study (non-parametric independent samples tests, partial least square analysis, and bootstrapping), and factor-analysis was not deemed appropriate (Hair et al. 2014).

Common Method Bias

To mitigate the potential of method bias, several procedural remedies were applied (Podsakoff, MacKenzie & Podsakoff 2012). To increase participant's motivations to respond accurately, they were invited to register on a separate web-site for a findings report.

Motivational factors, ability factors, and task factors were considered by targeting only top level managers. Respondents were treated as anonymous so social desirability bias is expected to be minimal. The survey invitation email and the introduction message in the online questionnaire avoided hints of our research questions and hypotheses, and the ordering of the questions was designed to mitigate the risk of respondents guessing the research relationships. Finally, different anchor labels were used for related constructs (Podsakoff, MacKenzie & Podsakoff 2012).

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 (Podsakoff et al. 2003). *Harman's single factor test* was used to determine the number of factors that are accounted for by the variance of indicator variables. The test was run across the set of 64 measurement indicators. The results show that there are 8 factors with eigenvalues greater than 1 and the first of these factors explains 35.07% of total variance (Table 4). These results indicate that common method variance due to method bias is not present. Considering frequent criticism of the Harman's factor test (Podsakoff et al. 2003), an additional, newer and PLS-SEM specific test was performed based on the procedure presented and tested by Kock (2015). To that effect, six alternative versions of the second-order structural model were created, each of them with a different single dependent variable with all other latent variables acting as independent variables. For each of those models, we performed the consistent PLS (Dijkstra & Henseler 2015), connecting all latent variables for the initial calculation and using the factor weighting scheme. The resulting inner VIF scores are reported in Table 5. As all the VIF scores are clearly < 3.3, common method bias is not a concern in our data.

Non-Response Bias

Non-response bias was assessed by comparing early and late respondents (Armstrong & Overton 1977). We used the midpoint of the data collected to classify responses as early or late, which is considered appropriate given that responses were received evenly over the survey period Tarnai (Moore & Tarnai 2002) and two follow-ups were sent out by email. Independent sample tests (Mann-Whitney U) of all the test indicators showed no significant sub-group differences, indicating that non-response bias is not a problem in this study.

Model Fit

Model fit approaches attempt to identify how well a hypothesised structural model fits the underlying data model specifications, but should be interpreted with caution (Hair et al. 2016). The standardised root mean square residual (SRMR) has been recently recognised as a meaningful statistical measure to identify a good fit (Henseler et al. 2014). Both SRMR values are borderline .10 (Table 9), indicating that two models are a reasonably good fit for the empirical data used for analysis (Henseler et al. 2014; Hu & Bentler 1998).

PLS-SEM

PLS-SEM is used, because it uses very general, soft distributional assumptions, *non-parametric* prediction-oriented model evaluation measures and allows for formative measurement models (Chin 1998; Wold 1982). PLS is appropriate in exploratory research and when latent variable scores are used in higher order modelling. It is also suitable for indirect effect and moderator-mediator analysis (Gefen & Straub 2005; Hair et al. 2014; Hair, Ringle & Sarstedt 2011). The significance of each effect is determined using bootstrapping with 3,000 samples (Chin 1998) analysing both the bootstrapped t-statistic and the (bias corrected) bootstrapped percentiles. SmartPLS Version 3.00 M3 was used, as were recent guidelines about reporting the results (Chin 2010; Ringle, Sarstedt & Straub 2012b).

Measurement Model Quality

All first-order constructs were measured reflectively and so were tested for convergent and discriminant validities (Chin 1998). For convergent validity, as shown in Table 7 in the appendix, indicator reliability was assessed by examining the significance of the construct loadings, and all but two were significant at $p < .001$ with the two exceptions significant at $p < .01$. For construct reliability and validity, Table 6 indicates high internal consistency in terms of composite reliability (composite reliability and Cronbach's $\alpha \geq .7$) (Bagozzi & Yi 1991; Chin 1998; Fornell & Larcker 1981; Nunally 1978). Convergent validity is confirmed as all average variances extracted (AVE) exceed .5 (Fornell & Larcker 1981).

Discriminant validity of the construct *indicators* was examined by assessing the loading of each indicator on its first-order construct, relative to its loading on other constructs. Table 7 confirms that that each indicator loading is highest for the relevant latent variable construct (Fornell & Larcker 1981). Discriminant validity of the *constructs* is evidenced by the fact that all square roots of the AVE in the diagonal in Table 8 exceed the correlations with the other constructs (Barclay, Higgins & Thompson 1995; Chin 1998). Further to that, all heterotrait-monotrait ratios (HTMT) are < .65, far below the required benchmark of .85 (Henseler, Ringle & Sarstedt 2015). In summary, all the standard measurement model quality requirements are met (Chin 1998).

The test results for overall model fit (Henseler et al. 2016) shown in Table 9 show that the SRMR, unweighted least squares discrepancy (d_{ULS}) and geodesic discrepancy (d_G) of the estimated model are all smaller than their 95% bootstrap quantile, indicating satisfactory overall model fit.

Results for Structural Model

Table 2 presents the results of hypotheses testing for both the main model (A) and the moderation model (B). As for H1, which predicts a positive direct association between the scope and frequency of MA decision support methods used in an organisation and performance, such an effect is confirmed (□ = .284, $p < .01$, $f^2 = .09$). Despite the clearly positive interaction effect of environmental uncertainty on the effect predicted in H1, H1a has to be rejected (□ = .145, *p* = .09, f^2 = .04)[2]. H2 predicts that MA information service levels are also positively associated with performance – a prediction which is confirmed as well □ = .072, *p* < .05, f^2 = .09). In this case, however, the predicted interaction effect of environmental uncertainty on the H2-relationship is significant (H2a: □ = .148, *p* < .05, f^2 = .05)[3], confirming that the *timeliness* of MA information provision to managers is more important in uncertain environments. Overall, the interaction effects predicted in H1a and H2a lead to a very notable increase in the R square of performance from .257 to .346 with each interaction effect contributing almost equally to the increase (as evidenced by the *f* square of each of the two interaction effects).

Table 2: Test Results for Hypotheses

		Main Model (A)			**Moderation Model (B)**		
Hypo	**Path:**	**Effect 1)**	**Coeff.**	***f* Square 2)**	**Effect 1)**	**Coeff.**	***f* Square 2)**
H1	MA-METH → PERFORM	D	.284**	.09	D	.392***	.18
H1a	MA-METH × ENVI-U → PERFORM	IA			IA	.145	.04
H2	MA-SERV → PERFORM	D	.263*	.09	D	.291*	.12
H2a	MA-SERV × ENVI-U → PERFORM	IA			IA	.148*	.05
H3	BI/A QUAL → MA-METH	D	.371***	.17*	D	.371***	.17*
H4	BI/A QUAL → MA-SERV	D	.518***	.37**	D	.518***	.37*
(H5)	BI/A QUAL → MA-METH → PERFORM	IE	.105*		IE	.145*	
(H5)	BI/A QUAL → MA-SERV → PERFORM	IE	.136*		IE	.151*	
H5	BI/A QUAL → PERFORM	T/TI	.241**		T/TI	.296***	
	ENVI-U → PERFORM	D	-.249	.08*	D	-.179	.04*
Con.	SIZE → MA METH	D	.247**	.08*	D	.247**	.08
Con.	SIZE → PERFORM	D	-.163	.03	D	-.193*	.05*
	R Squares:						
H1-2	PERFORM		.257***			.346***	
H3	MA-METH		.208**			.208**	
H4	MA-SERV		.268**			.268**	

1) D = direct effect, I = indirect effect, TI = total indirect effect, T = total effect, IA = interaction effect;
2) f square significance depends on method selected: none significant based on t-stat.; all significant based on CI method; 3 significant based on bias-corrected CI method (reported).
Significance 1-tailed: p < .05; p < .01**; p < .001****

2 Based on the bias-corrected confidence interval method.

As for the effects of *BI/A system quality* on the MA information constructs in our model, both the effect on scope and frequency of MA decision support methods used (H3: □ = .371, p < .001, f^2 = .17*) and MA information service levels (H4: □ = .518, p < .001, f^2 = .37**) is strong or very strong in terms of betas, f squares and R squares (H3-R^2: .208**; H4-R^2: .268**). The resulting two indirect effects of BI/A system quality on performance via scope and frequency of MA decision support methods used (□ = .105, p < .05) and MA information service levels (□ = .136, p < .05) are both significant and cumulate in a total indirect effect of .241 with a significance level of p < .01, confirming H5.

The control variable *firm size* has the expected positive effect on MA decision support methods used (□ = .247, p < .01, f^2 = .08*), but interestingly there is a negative – although only borderline-significant – association between firm size and performance (□ = -.163, p = .06, f^2 = .03). Environmental uncertainty – used as a control variable in Model A, and as a moderator in Model B – has the expected but only borderline-significant – negative effect on performance (□ = -.249, p = .07, f^2 = .03) in Model A.

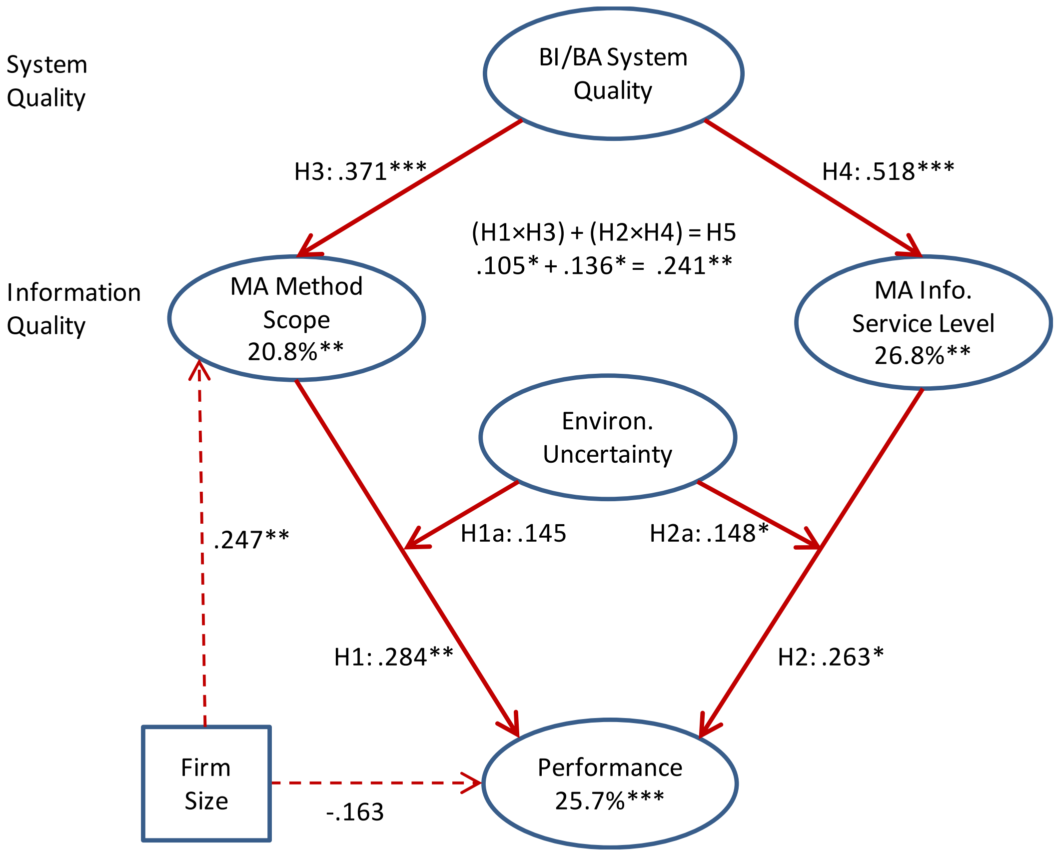

Figure 2: Research Model and Hypotheses Summary Results

4. Conclusion and Limitations

The aim of our study was to investigate the impact of MA information quality on organisational performance by considering the role of BI/A systems and environmental uncertainty. By drawing on the resource-based view, dynamic capabilities theory and information and systems quality frameworks, we developed a model which establishes *the scope and frequency of MA decision support methods* used in an organisation and *MA information service levels* as performance enhancing aspects of MA information quality.

The results of PLS-SEM analysis confirm our theoretical reasoning insofar as they reveal that both aspects of MA information quality are positively associated with organisational performance and that such effects are – at least partly – moderated by environmental uncertainty. We also find very strong support for the predicted impact of BI/A systems quality on both MA information quality constructs, which confirms the benefits previously associated high quality BI systems – but now extends these findings to more advanced business analytic tools and systems. However, we also find that diffusion rates of analytic tools in MA are still very low. Finally, the results for our path model analysis also reveal that the effects between BI/A systems quality and MA information quality characteristics also 'translate' into a significant indirect effect of BI/A systems quality on performance.

The results of our study have several noteworthy implications for academia and practice: By separating *routine* MA activities and *ad-hoc decision support activities*, we highlight and confirm that the latter are the primary performance enabler and therefore a potential source of competitive advantage. These findings also support the largely anecdotally supported claims that MA delivers value primarily by 'partnering' with business managers (CGMA 2015b). We do, however, acknowledge that routine MA activities indirectly add value insofar as they (a) provide the data and information base for ad-hoc decision support thereby increasing the timeliness and scope of such information provision, and (b) support operational and management control. Our results also suggest that firms operating in highly uncertain environments are well advised to invest in higher order MA capabilities in terms of method sophistication and information delivery ('service levels').

We also provide valuable evidence that investments into high quality BI/A systems do actually enhance MA capabilities, and as such have indirect effects on performance. In terms of measurement, we extend previously established scales for BI-quality by adding a new dimension for BA-quality, and we introduce the concept of and measurement for MA information service levels.

Like with all empirical research, we have to acknowledge several *limitations*: Due to the constraints imposed by the survey method, we were not able to collect MA quality perceptions of information consumers, i.e. business managers outside A&F. This required a limitation of MA quality to only selected aspects of MA information quality. Another limitation

– mentioned and explained earlier – is the small response rate and relatively small sample size.

Appendix

Table 3: Descriptive Statistics (Questionnaire Items/Indicators)

Indicator	Question (short version)	Scale	Mean Median	Std. Dev.	Skew / SE	Kurtosis / SE
QUAL_ PLAN1	Main planning system has rapid response and refresh times	Likert 1-5	2.69 3.00	1.29	0.68	-1.88
QUAL_ PLAN2	Main planning system is very quickly updated with actual and base-level information	Likert 1-5	2.71 2.00	1.30	0.74	-2.02
QUAL_ PLAN3	Main planning system allows forecasts and budgets to be quickly created and revised	Likert 1-5	2.66 3.00	1.24	0.79	-1.75
QUAL_ PLAN4	Main planning system allows sophisticated planning models to be easily implemented and changed	Likert 1-5	2.28 2.00	1.14	1.49	-1.32
QUAL_ REP1	Main reporting system has sophisticated formats and presentation features	Likert 1-5	2.97 3.00	1.15	-0.63	-1.29
QUAL_ REP2	Main reporting system has highly interactive reporting features	Likert 1-5	2.72 3.00	1.21	-0.11	-1.97
QUAL_ REP3	Main reporting system is very easy to use and navigate by all users	Likert 1-5	3.06 3.00	1.04	-0.71	-0.34
QUAL_ REP4	Main reporting system has rapid response and refresh times	Likert 1-5	3.00 3.00	1.15	0.00	-1.64
QUAL_ BA1	Main BA tool/system has rapid response and refresh times	Likert 1-5	2.63 3.00	1.23	0.36	-1.88
QUAL_ BA2	Main BA tool/system can provide solutions for a broad range of business problems	Likert 1-5	2.63 3.00	1.13	0.42	-1.35
QUAL_ BA3	Main BA tool/system is easy to use for people who have the necessary skills in statistics/analytics	Likert 1-5	2.65 3.00	1.10	-0.10	-1.91
QUAL_ BA4	Main BA tool/system presents output in an appealing and easy to understand way (for an expert)	Likert 1-5	2.54 3.00	1.15	0.41	-1.74
QUAL_ BA5	Main BA tool/system allows sophisticated models to be easily implemented and changed	Likert 1-5	2.45 3.00	0.98	-0.33	-1.73
MA_ INFO1	Detailed management accounting information is reported to business managers on a systematic, regular, short-term basis (weekly or monthly)	Likert 1-5	4.28 4.00	0.93	-6.03	6.43
MA_ INFO2	Detailed management accounting information is available to business managers immediately upon request	Likert 1-5	3.69 4.00	1.01	-2.69	0.30
MA_ INFO3	Detailed management accounting information can be accessed on a real-time basis (managerial self service)	Likert 1-5	2.92 3.00	1.16	0.52	-1.32
MA_ INFO4	Detailed management accounting information is reported directly to line managers	Likert 1-5	3.64 4.00	0.99	-2.67	0.39
METH_C APB	Capital budgeting (for project selection, investment planning, make-or-buy decisions, etc.) is used by management accountants for planning and decision support.	Likert 1-5	3.94 4.00	1.18	-3.63	0.57
METH_C BA	Cost-Benefit Analysis (CBA) is used by management accountants for planning and decision support.	Likert 1-5	3.74 4.00	1.11	-2.86	0.49
METH_C VP	Cost Volume Profit (Break Even Analysis) is used by management accountants for planning and decision support.	Likert 1-5	3.86 4.00	0.97	-2.53	1.03
METH_D A	Decision analysis (formal) (e.g. decision trees with risk analysis) is used by management accountants for planning and decision support.	Likert 1-5	2.56 3.00	1.36	1.12	-1.95
METH_D M_DESC	Descriptive data mining (e.g. cluster analysis) is used by management accountants for planning and decision support.	Likert 1-5	2.18 2.00	1.17	1.94	-1.28
METH_O PTIM	Optimisation techniques (e.g. linear or non-linear programming) is used by management accountants for planning and decision support.	Likert 1-5	1.99 2.00	1.09	1.79	-2.15
METH_P	Predictive analysis (e.g. regression, predictive	Likert	2.14	1.23	2.32	-1.15

Indicator	Question (short version)	Scale	Mean Median	Std. Dev.	Skew / SE	Kurtosis / SE
REDA	data mining) is used by management accountants for planning and decision support.	1-5	2.00			
METH_TSA	Time-series analysis is used by management accountants for planning and decision support.	Likert 1-5	2.42 2.00	1.43	1.35	-2.26
METHS_BENCH	Competitor analysis / Benchmarking is used by management accountants as strategic practice.	Likert 1-5	3.12 3.00	1.15	0.63	-1.33
METHS_ERM	Enterprise Risk Management is used by management accountants as strategic practice.	Likert 1-5	2.88 3.00	1.42	-0.03	-2.32
METHS_TQM	Total Quality Management, continuous improvement or Just-in-time is used by management accountants as strategic practice.	Likert 1-5	2.65 3.00	1.38	0.65	-2.18
METHS_TRANS	Transfer pricing is used by management accountants as strategic practice.	Likert 1-5	3.21 3.00	1.51	-1.07	-2.28
ENV_1	Over the past 12 months, to what extent do you agree or disagree that change happens more quickly and expansively than before	Likert 1-5	3.78 4.00	0.99	-3.40	1.23
ENV_2	Over the past 12 months, to what extent do you agree or disagree that predicting change has become more difficult and more imprecise	Likert 1-5	3.23 3.00	1.13	-0.71	-1.45
ENV_3	Over the past 12 months, to what extent do you agree or disagree that changes are more complicated and solutions to one problem often impact on other areas and issue	Likert 1-5	3.72 4.00	0.91	-2.69	0.77
ENV_4	Over the past 12 months, to what extent do you agree or disagree that the impact of the changes and the reactions to change are increasingly unclear.	Likert 1-5	3.23 3.00	1.03	-1.35	-0.64
PERF_SALES	Over the past 12 months relative to your competitor(s) or benchmark organisation(s), how has your organisation performed in sales growth?	Likert 1-7	5.05 5.00	1.42	-0.96	-1.31
PERF_ROI	Over the past 12 months relative to your competitor(s) or benchmark organisation(s), how has your organisation performed in return on Investment (ROI)?	Likert 1-7	4.83 5.00	1.4	-0.97	-0.77
PERF_MARGIN	Over the past 12 months relative to your competitor(s) or benchmark organisation(s), how has your organisation performed in net profit margin (=profitability)?	Likert 1-7	4.78 5.00	1.55	-0.98	-1.06
PERF_PARTN	Over the past 12 months relative to your competitor(s) or benchmark organisation(s), how has your organisation performed in coordination with business partners/suppliers?	Likert 1-7	4.55 4.00	1.06	1.20	-0.56
PERF_EFFIC	Over the past 12 months relative to your competitor(s) or benchmark organisation(s), how has your organisation performed in efficiency of internal processes?	Likert 1-7	4.25 4.00	1.16	-0.26	-0.30
Control						
EMPL	Full-time equivalent range of employees (median)	Range Scale 1-6	3.76 3.00	1.16	1.45	-0.69

Table 4: Harman's Single Factor Test

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	13.327	35.070	35.070
2	3.838	10.100	45.171
3	3.698	9.732	54.903
4	2.738	7.206	62.108
5	2.164	5.695	67.803
6	1.289	3.392	71.195
7	1.254	3.301	74.496
8	1.008	2.652	77.148

Table 5: VIF Values-Inner Model

VIF Values- Inner Model	BI/A QUAL	MA-SERV	MA-METH	ENVI-U	PERFORM	SIZE
BI/A System Quality		1.313	1.618	1.852	1.854	1.829
MA Information Service Level	1.286		1.814	1.804	1.633	1.777
MA Method Scope	1.409	1.613		1.602	1.456	1.450
Environmental Uncertainty	1.153	1.147	1.145		1.064	1.142
Performance	1.513	1.361	1.364	1.395		1.446
Firm Size	1.153	1.143	1.049	1.156	1.117	

Table 6: Latent Variables

Latent Variable – 2nd Order Model	Cronbach's Alpha	Composite Reliability	AVE
BI/A System Quality	.843	.905	.760
MA Information Service Level	.737	.830	.557
MA Method Scope	.750	.846	.650
Environmental Uncertainty	.812	.867	.624
Performance	.816	.874	.585

All significant at $p < .001$ (based on 3,000 sample-bootstrap)

Table 7: Discriminant Validity (Indicator Cross-Loadings)

	BI/A QUAL PLAN	BI/A QUAL BA	BI/A QUAL REP	MA-SERV	MA-METH 1	MA-METH 2	MA-METH 3	ENVI-U	PERF	SIZE
QUAL_ PLAN1	**.912**	.563	.608	.355	.113	.190	.339	-.009	.070	.034
QUAL_ PLAN 2	**.927**	.593	.522	.347	.176	.233	.359	.062	.069	-.044
QUAL_ PLAN3	**.923**	.570	.467	.315	.189	.222	.284	-.002	.112	.062
QUAL_PLAN4	**.888**	.631	.592	.333	.149	.322	.316	.017	.128	-.033
QUAL_BA1	.665	**.879**	.593	.525	.136	.301	.450	-.045	.245	.141
QUAL_BA2	.578	**.918**	.615	.584	.166	.352	.395	-.056	.379	.075
QUAL_BA3	.588	**.932**	.603	.497	.136	.278	.400	.013	.319	.008
QUAL_BA4	.563	**.925**	.660	.427	.090	.331	.294	-.015	.356	.069
QUAL_BA5	.508	**.839**	.564	.288	.177	.254	.216	.101	.243	.009
QUAL_REP1	.343	.498	**.749**	.442	.071	.251	.280	.083	.186	.108
QUAL_REP 2	.456	.556	**.821**	.400	.172	.206	.255	-.003	.170	.160
QUAL_REP 3	.390	.450	**.813**	.190	.001	.001	.070	.008	.011	.100
QUAL_REP4	.674	.627	**.811**	.345	-.026	.130	.214	.029	.154	-.114
MA_INFO1	.213	.229	.253	**.535**	.216	.022	.23	.018	.086	.188
MA_INFO2	.401	.476	.365	**.866**	.068	.238	.324	.043	.326	.108
MA_INFO3	.304	.505	.395	**.881**	-.066	.168	.227	-.093	.321	.032
MA_INFO4	.134	.212	.291	**.691**	.007	.062	.08	.028	.153	.035
METH_CAPB	.109	.063	.075	.056	**.768**	.299	.322	.046	-.088	.176
METH_CBA	.207	.129	.072	-.025	**.927**	.458	.508	.009	.054	.139
METH_CVP	.092	.189	.014	-.009	**.767**	.351	.401	.091	.076	.091
METH_DA	.172	.274	.130	.160	.486	**.755**	.607	-.185	.284	.200
METH_DM_DESC	.253	.273	.214	.260	.240	**.714**	.362	-.063	.242	-.012
METH_OPTIM	.135	.264	.108	.219	.296	**.839**	.357	-.154	.397	.234
METH_PREDA	.237	.271	.116	.061	.330	**.720**	.392	-.176	.210	.034
METH_TSA	.205	.145	.121	.058	.287	**.650**	.172	-.069	.210	.189
METHS_BENCH	.309	.297	.223	.302	.379	.386	**.664**	-.006	.132	.202
METHS_ERM	.406	.418	.276	.286	.439	.491	**.855**	-.138	.312	.329
METHS_TQM	.117	.202	.183	.093	.282	.396	**.766**	-.194	.196	.258
METHS_TRANS	.172	.197	.037	.127	.377	.269	**.615**	-.091	.231	-.014
ENV_1	.212	.220	.099	.067	.353	.016	.004	**.646^**	-.089	-.147
ENV_2	.174	.241	.171	.090	-.018	-.013	.089	**.728^**	-.115	-.055
ENV_3	-.099	-.145	-.118	-.075	.110	-.107	-.082	**.858**	-.248	-.115
ENV_4	-.010	-.045	.077	-.027	-.079	-.296	-.282	**.900**	-.292	-.112
PERF_MARGIN	.092	.355	.113	.282	.056	.314	.282	-.270	**.890**	-.007
PERF_ROI	.070	.214	.062	.217	-.005	.328	.222	-.282	**.857**	.015
PERF_SALES	.194	.381	.136	.490	-.085	.196	.148	-.092	**.780**	.062
PERF_EFFIC	.026	.095	.206	.144	.024	.383	.302	-.197	**.662**	-.051
PERF_PARTN	-.012	.242	.137	.156	.126	.190	.210	-.197	**.598**	-.128
EMPL	.005	.068	.067	.076	.162	.179	.284	-.131	-.020	**1.000**

All outer loadings significant at $p < .001$, except for those marked with ^, where $p < .01$.

Table 8: Discriminant Validity (Latent Variables)

	BI/A QUAL	MA-SERV	MA-METH	ENVI-U	PERFORM	SIZE
BI/A Sys Quality	**.872**					
MA Info Service Level	.581 .613	**.746**				
MA Method Scope	.384 .430	.264 .314	**.806**			
Environmental Uncertainty	.018^ .233	-.011^ .144	-.157^ .237	**.790**		
Performance	.245 284	.323 .381	.349 .394	-.276 .296	**.765**	
Firm Size	.055^ .058	.107^ .141	.267 .295	-.131^ .149	-.026^ .008	**1.000**

a) *Fornell-Larcker Criterion: AVE-squared in diagonal (bold) compared with latent variable correlations (first value underneath diagonal);*
b) *Heterotrait-Monotrait Ratio (HTMT) (second value underneath diagonal).*
All correlations and HTMT values significant at p < .05 or lower, except for those marked with ^ (not significant).

Table 9: Model Fit

Main Model	Estimated Model	95%	99%
SRMR	.104	.132	.135
d_{ULS}	2.267	3.661	4.705
d_G	.911	1.235	1.497

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