International Journal of Accounting Information Systems 21 (2016) 1–17

Contents lists available at ScienceDirect

International Journal of Accounting Information Systems

journal homepage: www.elsevier.com/locate/accinf

Business intelligence systems use in performance measurement capabilities: Implications for enhanced competitive advantage

Matt D. Peters[a,*], Bernhard Wieder[a], Steve G. Sutton[b], James Wakefield[a]

[a] Accounting Discipline Group, University of Technology Sydney, P.O. Box 123, Broadway, NSW 2007, Australia
[b] College of Business Administration, University of Central Florida, P.O. Box 161400, Orlando, FL 32816, United States

ARTICLE INFO

Article history:
Received 26 October 2015
Received in revised form 14 March 2016
Accepted 24 March 2016
Available online 4 May 2016

Keywords:
Business intelligence (BI)
Competitive advantage
Diagnostic and interactive
Management control systems
Performance measurement
Systems quality

ABSTRACT

The purpose of this study is to better understand how the quality of a Business Intelligence (BI) system improves the diagnostic and interactive dimensions of management control systems (MCS), thereby enhancing performance measurement capabilities, which in turn are positively associated with competitive advantage. Integrating theory from performance measurement, organizational learning and the knowledge-based view of the firm, a theoretical model is developed that considers three concepts of BI quality (infrastructure integration, functionality, and self-service) and the roles they play in enhancing diagnostic and interactive performance measurement capabilities. Data collected via survey from 324 CEOs and CFOs provides support for the theorized effects of BI quality on performance measurement capabilities. These capabilities in turn are positively associated with competitive advantage.

1. Introduction

Business intelligence (BI) systems provide broad measurement and analysis capability, including the foundations for implementing integrated and comprehensive management control systems (MCS) (Elbashir et al., 2011, 2013). This broad MCS-enabling capability is derived from the hundreds of pre-designed scorecards and key performance indicators available through contemporary BI software (Howard, 2003). Prior research shows that effective assimilation of BI at the business process level can lead to enhanced organizational learning and organizational performance (Elbashir et al., 2008, 2013; Lee and Widener, 2016). These benefits arise from top management's support and knowledge of BI (Lee et al., 2014) along with a knowledge culture that promotes operational managers to use the BI and to effectively interact with IT managers to develop the BI infrastructure (Elbashir et al., 2011).

The focus of the prior research has been on top management, operational management and IT management, and their effectiveness in assimilating BI into business processes. The BI systems themselves have generally been viewed as a given, with the focus being on the human capability to adapt such systems. However, there is an absence of research focusing on how this BI capability is harnessed through effective planning and reporting to support the desired interactive and diagnostic capabilities of effective MCS.

The purpose of this study is to enhance our understanding of how BI quality enhances performance measurement practices and competitive advantage. We establish BI quality as a combination of BI infrastructure, BI functionality and BI (managerial) self-service. We apply Alavi and Leidner's (2001) three dimensions of *data*, *information* and *knowledge*, to relate BI quality to

* Corresponding author.
E-mail address: Matthew.Peters@uts.edu.au (M.D. Peters).

http://dx.doi.org/10.1016/j.accinf.2016.03.001
1467-0895/

support of the planning and reporting activities that underlie performance measurement information. The effects of BI quality are examined for their ability to lead to better performance measurement capability combining diagnostic and interactive dimensions (Simons, 1995). Diagnostic and interactive performance measurement capabilities are considered necessary to effectively support the knowledge capability of a firm (Lee and Widener, 2016) and for the pursuit of competitive advantage (Simons, 1995).

We develop a theoretical model of the relationships between BI quality, performance measurement system effectiveness, and the associated enhancement to competitive advantage, based on a combination of theory on performance measurement, organizational learning, and the knowledge-based view of the firm. The theoretical model is tested through data collected via survey from 324 CEOS/CFOs (or equivalent). The results of the Structural Equation Modeling-Partial Least Squares (SEM-PLS) analysis support the theorized relationships, including the three dimensions of BI quality, BI quality's positive relationship with enhanced performance measurement capability, and resulting competitive advantage.

The results of this study contribute to the overall understanding of how use of BI systems impacts organizational performance by focusing on how BI quality affects performance measurement capability. The research demonstrates how the manner in which BI is implemented, and the resulting facilitation of planning and reporting activities, impacts performance measurement capability.

This research has implications for both practice and research. First, we develop a multi-dimensional set of constructs for assessing BI quality, through the concepts of infrastructure, functionality and self-service. Second, we explain how BI quality improves MCS effectiveness through both the diagnostic and interactive dimensions of performance measurement capability. Third, we find support for relationships whereby: BI infrastructure enhances BI functionality; functionality in turn enhances performance measurement capability (including indirectly through BI self-service); and performance measurement capability ultimately enhances competitive advantage.

The remainder of this paper is presented in four sections. The first section overviews the background of the research and establishes the theoretical basis for the hypothesized relationships in the model. The second section provides an overview of the research method, while the third presents the results of the analysis. The final section provides a summary of the results from the research along with limitations that should be considered and implications for future research.

2. Theoretical model

BI systems[1] (and strategic information systems as a whole) are considered to be most effective at the business unit level and it is through business unit-level enhancements that overall organizational performance is enhanced (Elbashir et al., 2008). This study therefore examines BI quality and performance measurement at the business unit level. Accordingly, our theorizations draw from Simons' (1995, 89) concepts of performance measurement and from Huber's (1991) theory of advanced information systems and organizational learning. Simons (1990) concepts of interactive and diagnostic uses are the dominant performance measurement framework in recent literature (Grafton et al., 2010). As will be demonstrated, Huber's (1991) organizational learning theory aptly applies to the cybernetic learning that underlies performance measurement systems and capabilities.

Following Alavi and Leidner (2001), the BI and performance measurement concepts in the theoretical model are differentiated in terms of data, information, and knowledge. BI infrastructure integration refers to data qualities. BI functionality refers to the quality of the applications that process data into information. BI self-service and performance measurement capabilities are the extent to which such information is mediated cognitively by the knowledge bases of individual managers. A knowledge base is an individual manager's repository of learning (Thomas et al., 2001; Clark et al., 2007). Organizational learning occurs when the knowledge base of more than one manager is affected by their cognitive processing of information (Huber, 1991). Further, there is evidence that diagnostic and interactive BI uses will improve managers' knowledge bases (Lee and Widener, 2016).

Ultimately, the interest is in competitive advantage, which refers to superior business unit financial performance relative to rival firms (Grafton et al., 2010). The hypothesized relationships with competitive advantage draw on knowledge-based theory (Grant, 1996), which extends resource-based theory (Barney, 1991) to include resources that are knowledge-based, such as the knowledge embedded in and carried through organizational culture, routines, policies, systems, documents, and the minds of individual employees (Alavi and Leidner, 2001). These two theories conceptualize a firm as a bundle of assets and resources that are deployed in routines/capabilities (Barney, 1991). An "asset", such as a generic IT application, could be procured from external suppliers by any firm, and so any value it can contribute in organizational capabilities can only be a source of temporary competitive advantage — because eventually all firms could procure it such that there will be a situation of competitive parity (Barney, 1991). In contrast, a "resource" such as social complexity or managerial talent can be a source of persistent competitive advantage, at least to the extent that it is heterogeneously distributed across rival firms and immobile.

It is important to recognize that BI functionality, BI infrastructure integration, and BI self-service are each conceptualized as two-dimensional emergent (i.e., second-order formative) in the theoretical model. BI planning and BI reporting are the two dimensions that together constitute a performance measurement BI system. BI planning is for producing performance plans, for example, annual budgets and monthly forecasts. BI reporting is for management reporting and analysis of performance measurement outcomes and feedback variances. Both BI dimensions typically contain profit-planning data (i.e., traditional accounting

[1] BI is a term that broadly refers to management support systems for gathering, storing, and accessing data for decision making (Clark et al., 2007; Fedorowicz and Konsynski, 1992). BI systems are distinct from executive information systems, knowledge management systems, and decision support systems (Clark et al., 2007). Herein, we use the term BI in reference only to the category that is specific to business unit performance measurement (Chaudhuri et al., 2011). Other types of BI — such as data mining and analytics, predictive analytics, and text analytic engines (Chaudhuri et al., 2011) — are outside the scope of this research project.

data) and non-financial data (e.g., key performance indicators from a balanced scorecard). For the hypotheses section we use the higher-order emergent concept of BI, which is BI planning and BI reporting combined.

It is important to recognize that the performance measurement capabilities conceptualization is also two-dimensional emergent. Following Simons (1990, 1991, 1994, 1995) and Simons et al. (2000), a performance measurement capability combines two categories of performance measurement routines: (1) diagnostic; and (2) interactive. Diagnostic performance measurement routines are those where top managers use performance measurement information to track outcomes and to manage performance by exception, and thereby to implement business strategies (Simons, 1995). Interactive performance measurement routines are those where top and lower managers together use performance measurement information to engage in dialog and debate to manage strategic uncertainties faced by the business unit, thereby formulating business strategies (Simons, 1995). The combination of diagnostic and interactive uses comprehensively captures both the feedback and feedforward processes of learning (Simons, 1995). This combination also captures the intertwined roles of performance measurement systems in both the formulation and implementation of business strategies (Ferreira and Otley, 2009; Tessier and Otley, 2012; Mintzberg, 1978; Simons, 1995).

The model is formulated based on the theoretical streams identified in the previous section (see Fig. 1). BI quality is articulated in terms of: (1) BI infrastructure integration; (2) BI functionality; and (3) BI self-service (i.e., manager's independent use). The second part of the model pertains to how BI quality at the component level is related to performance measurement capability and also to competitive advantage.

2.1. BI quality

BI infrastructure integration concerns database structures and processes. It provides accurate, reliable, and readily available multi-dimensional data for performance measurement through four data dimensions: (1) objects; (2) attributes; (3) time; and (4) plan versions (Ariav, 1992). Objects are responsibility center arrays (e.g., profit center, revenue center, and cost center) and aggregation patterns (e.g., manager, regional, and national). Attributes are the calculative elements (e.g., monetary amounts, stock keeping units, sales volumes, and employee payroll details). Time dimensions are the calculation periods such as day, month, quarter, and year. Plan versions are model instances (e.g., actual results, budget, prior forecast, and most recent draft forecast). BI infrastructure integration depends on connectivity with underlying primary data sources and compatibility in the structure and semantics of those underlying data sources (Keen, 1991; Mithas et al., 2011). Where BI infrastructure integration is "low", data reside across an array of dispersed and fragmented spread sheets, which are manually integrated both together and with other data sources. Where BI infrastructure integration is "high", there is a "common" database configuration.

BI functionality refers to the usability of an application for modeling and interacting with multi-dimensional data hierarchies (Ariav, 1992; Clark et al., 2007; Peng et al., 2007). Multi-dimensional data hierarchies require that data objects and attributes be linked together in an integrated calculative scheme. With greater BI functionality, it is easier to navigate across various levels of aggregation or disaggregation within a multi-dimensional data hierarchy model. 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 (Ariav, 1992). Where BI functionality is "low", user modeling and data interaction occurs in spreadsheets. Spreadsheets offer only limited interactive interfacing with object and attribute multi-dimensionality and it is relatively difficult for users to switch between and view a multiplicity of time dimensions and plan versions. In contrast, where BI functionality is "high", advanced design properties enable greater ease, extent, and speed of structured data processing for a multiplicity of multi-dimensional data hierarchical models (Ariav, 1992). In summary, BI functionality is usability for multi-dimensional data modeling and analysis, whilst BI integrated infrastructure is the extent of reliable and accurate multi-dimensional data availability for such modeling and interaction. Thus, the usability of a BI interface is limited by the multi-dimensional data available to use it. This leads to the first hypothesis:

H1. BI infrastructure integration enhances BI functionality.

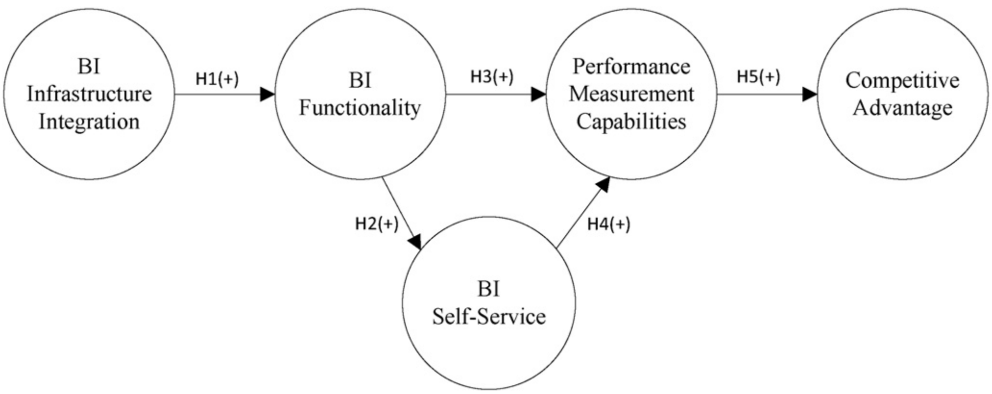

Fig. 1. Theoretical model.

A substantial body of research has investigated antecedents and consequences of information systems usage (DeLone and McLean, 2003; Clark et al., 2007). Here the focus is a concept developed within this study called BI (managerial) self-service, defined as the frequency of individual use of a BI application by business managers. Frequency of use is one of the most common measures of information systems usage (Doll and Torkzadeh, 1988; Burton-Jones and Straub, 2006; Hou, 2012). A low level of BI self-service occurs when only management accountants use that BI application. A high level of BI self-service occurs when business managers frequently use that application themselves, during annual budget setting, monthly forecasting, and periodic (e.g., daily) reporting routines. Without BI self-service, business managers rely solely on static presentations of performance measurement information that are coordinated by management accountants, whereas with BI self-service managers also rely on their own interactions with the BI system.

Drawing from prior literature, several reasons are established as to why BI functionality likely increases BI self-service. In essence, BI functionality refers to the ease, extent, and speed of structured multi-dimensional data processing (Ariav, 1992). These design features very likely enhance user satisfaction (Doll and Torkzadeh, 1988), which prior research recognizes as a critical determinant of successful ongoing use of a BI system (DeLone and McLean, 2003; Hou, 2012). By facilitating a higher quality of interaction between the user and the system, the usability qualities of BI functionality make it easier to elicit desired information, thereby increasing the likelihood of a business manager electing to use the system (Clark et al., 2007; Dilla et al., 2010; Yigitbasioglu and Velcu, 2012). In summary, BI functionality provides superior interface usability for accessing user-defined information representations. These features likely cause more business managers to use the BI application than just to rely on static reports and presentations provided by management accounting staff. This leads to the second hypothesis:

H2. BI functionality enhances BI self-service.

2.2. BI quality and performance support

Performance measurement capabilities are the collections of routines in which managers use performance measurement information to maintain or alter a business unit in line with objectives (Nelson and Winter, 1982; Simons, 1995). As discussed previously, the emergent conceptualization of performance measurement capabilities employed herein combines both the diagnostic and interactive categories of routines (Simons, 1990, 1991, 1994, 1995). Whilst the two categories differ in terms of styles of personal involvement by top management (Simons, 1991; Ferreira and Otley, 2009; Tessier and Otley, 2012), they are both underpinned by cybernetic feedback loop processes. We use the idea of cybernetic feedback loop processes to relate BI to the singular construct of performance measurement capabilities.

Cybernetic feedback loops (whether used diagnostically or interactively) comprise feedforward and feedback learning processes (Otley and Berry, 1980; Green and Welsh, 1988; Emmanuel et al., 1990). BI planning systems are needed for the feedforward stage of cybernetic control, whilst BI reporting systems are needed for the feedback stage, in which actual results are compared with feedforward data to calculate feedback variances. Managers engage in feedforward learning to develop their knowledge bases of anticipated future organizational states, whilst feedback learning develops knowledge bases for actual performance variances (Emmanuel et al., 1990; Thomas et al., 2001). Feedforward and feedback learning usually occur through an annual budgeting cycle, along with monthly forecasting and results-reporting cycles (Libby and Lindsay, 2010).

To link BI functionality to enhanced learning within cybernetic performance feedback loops, we draw from Huber's (1991) theory of advanced information systems and organizational learning. According to (Huber, 1991, 89), an "entity learns if, through its processing of information, the range of its potential behaviours is changed" and "an organization only learns if any of its units acquires knowledge that it recognizes as potentially useful to the organization" (Huber, 1991, 89). Advanced information systems can enhance organizational learning in three ways: (1) by broadening information distribution within an organization; (2) by facilitating the elaboration of more varied interpretations; and (3) by enabling more entities to develop uniform comprehensions of the various interpretations (Huber, 1991).

These three criteria from Huber (1991) lay the foundation for understanding the impact of BI functionality. First, BI functionality can broaden the distribution of information within an organization because it provides a more granular rendering of the organization along with greater ease in modeling or interacting with that rendering. These properties lead to a greater quantity of performance measurement information available for distribution within an organization. Second, BI functionality can facilitate the elaboration of more varied interpretations of plans and feedback because greater data multi-dimensionality makes more specific the underlying activities of the managers in question. This greater specificity provides more planning or feedback data points for individual managers to form interpretations that are based on their own localized perspective. Third, BI functionality can enable more entities to develop uniform comprehensions of the various interpretations because of the hierarchical structuring of the data. The syntax of the integrative calculative scheme that structures a hierarchical data model facilitates uniform interpretations of plans, results, and feedback. Thus, in summary, BI functionality likely enhances both feedforward and feedback organizational learning. Given that these learning processes underlie the effective functioning of performance measurement capabilities (Otley and Berry, 1980; Green and Welsh, 1988; Emmanuel et al., 1990), the third hypothesis is stated as:

H3. BI functionality enhances performance measurement capabilities.

BI self-service is similarly related to the enhancement of performance measurement capabilities. Again, Huber's (1991) three criteria for deriving organizational learning from advanced information systems are of interest. First, BI self-service will broaden information distribution within an organization because, by interacting with a BI application, a business manager will access more information than would otherwise be possible from static reports. Indeed, numerous studies find evidence that information systems use by managers enhances their learning (e.g., Leidner and Elam, 1995; Vandenbosch and Higgins, 1995; Maiga et al., 2013; Lee and Widener, 2016). Second, BI self-service will enable elaboration of more varied interpretations of organizational activity, because a business manager can use his/her unique knowledge base to develop unique interpretations of the information in the BI application (Thomas et al., 2001; Clark et al., 2007). Indeed, Shollo and Galliers (2015) provide evidence that BI systems enable users to conduct data analyses in ways that enable interpretations that would otherwise have been unknowable. Third, BI self-service can enable more entities within the organization to develop uniform comprehensions of those various interpretations, because a manager's enhanced interpretations can be shared with other managers in performance measurement capabilities. This is supported by prior research that finds BI can be effective in management control practices by facilitating knowledge sharing between top management and operational managers (Elbashir et al., 2011, 2013). As such, the fourth hypothesis is stated as:

H4. BI self-service enhances performance measurement capabilities.

2.3. Links to competitive advantage

Performance measurement capabilities are valuable if they enhance competitive advantage. The knowledge-based perspective (Barney, 1991; Grant, 1996; Teece et al., 1997) adapted here posits that learning routines that systematically develop and deploy the knowledge bases of managers are important drivers of competitive advantage. In knowledge-based routines, managers create and transfer knowledge to each other by learning (Kogut and Zander, 1992; Nonaka, 1994), and when that learning improves the effectiveness and efficiency of the business, it creates value for achieving competitive advantage (Barney, 1991; Grant, 1996; Teece et al., 1997). In performance measurement capabilities, these learning and knowledge creation dynamics are structured by the cybernetic mechanism. Information processing by individual managers in performance measurement routines creates and transfers knowledge between managers at all levels of the hierarchy. This knowledge concerns the actual states of existing organizational capabilities as well as possible future organizational capabilities. According to the knowledge-based perspective, where such routines require knowledge-based resources that are immobile and heterogeneously distributed amongst rival firms, value creation can be a source of relatively persistent competitive advantage (Barney, 1991; Grant, 1996).[2] Accordingly, the fifth hypothesis is stated as:

H5. Performance measurement capabilities are positively associated with competitive advantage.

Knowledge-based resources embedded in BI quality concepts also form key foundations for associated gains in competitive advantage from performance measurement capabilities. These resources flow through the mediation chains implied in the theoretical model (Fig. 1). Prior literature highlights several key knowledge-based resources that are likely embedded in each of the three BI quality concepts.

First, BI infrastructure integration requires team-embodied skills to understand, plan, and manage the complex IT change, for both adoption and maintenance (Ray et al., 2005). For adoption of BI infrastructure, Lee et al. (2014) provide evidence of positive effects from knowledge creation and sharing processes involving CIOs and top management teams. For maintenance, effective BI infrastructures must interact reflexively with changes in business processes (vom Brocke et al., 2014), requiring that IT managers work collaboratively with functional managers to coordinate complex IT activities and to understand, anticipate, and plan future business needs (Mata et al., 1995; Wade and Hulland, 2004).

Second, because BI functionality can be procured from and implemented by a variety of vendors and consultants, in itself it can only be a source of competitive advantage to earlier adopters (Barney, 1991). Much of the knowledge-based resources needed to adopt BI functionality are knowledge of “best-practice”, which will not be a long-lasting source of heterogeneity or immobility for conferring competitive advantage because it will become commonplace over time (Wade and Hulland, 2004). Nonetheless, in the context of our theoretical model, BI functionality is immobile and heterogeneous to the extent that it relies on the knowledge-based resources needed to adopt and maintain BI infrastructure integration.

Third, BI self-service can leverage managerial talent resources such as professionalism and business-specific experience (Barney, 1991). BI self-service can also leverage organizational cultures that are high in trustworthiness and low in opportunism (Mata et al., 1995; Simons, 1995) and that value analytical decision-making (Popovič et al., 2012). Further, knowledge-based resources from BI infrastructure integration should also flow through BI functionality and into BI self-service, providing BI quality with heterogeneity and further immobility.

In summary, because the three BI quality concepts contain knowledge-based resources, there will be persistence in the effects that BI quality has via the mediation chains in the theoretical model. Prior empirical studies provide some notional support for such indirect relationships with performance. Elbashir et al. (2011) link BI infrastructure sophistication to BI assimilation (which could occur through performance measurement capabilities and BI self-service) and Elbashir et al. (2013) link BI assimilation to organizational performance. Lee and Widener (2016) confirm mediation effects from organizational learning capacities on the link between BI reporting capabilities and business process performance. Elbashir et al. (2008) link BI systems to organizational performance via business process performance. Managerial IT usage (such as in BI self-service) has also been found to be

[2] Some examples of knowledge-based resources used in performance measurement capabilities are social complexity and managerial talent (Barney, 1991; Simons, 1994; Grant, 1996; Henri, 2006; Chapman and Kihn, 2009).

indirectly beneficial for organizational performance by enhancing organizational information assimilation (Vandenbosch, 1999) and associated organizational learning and enabling routines (Maiga et al., 2013; Chapman and Kihn, 2009). In aggregate, this leads to the sixth and final hypothesis:

H6. BI quality has a positive indirect association with competitive advantage.

3. Research method

This study is based on a questionnaire that was administered to senior managers of Australian-based business units. The questionnaire relied partly on established constructs and measurement instruments, and partly on new measurement scales that were necessarily developed for the three new BI constructs. The survey design and administration were therefore conducted in two stages: (1) a BI construct scale development (pre-testing and pilot-testing) survey stage; and (2) a hypotheses-testing survey stage. For both stages we applied an established methodology to develop the meanings and epistemic relationships (Bisbe et al., 2007), conventional design and administration procedures (Netemeyer et al., 2003, 100; Dillman, 2007), and procedures to ensure face and content validities (Tourangeau et al., 2000).

3.1. Pre-testing and pilot-testing survey stage

To develop an initial scale for the three new BI constructs, the practitioner literature was reviewed — including vendor promotional materials and status reports (Foster et al., 2005; Dodson et al., 2008). Industry experts were also consulted. We then pre-tested the scale with five academics and nine practitioners to ensure content and face validity, as well as the appropriateness of Likert-scale endpoints (Netemeyer et al., 2003, 100). Subsequently, a pilot-testing survey with a wide range of BI planning- and reporting-related measurement items was administered to 1200 finance managers. For the pilot-testing survey we received 142 usable responses (12.0% response rate). After performing reliability and validity analyses on this pilot-test dataset, we identified the reflective measurement scales eventually used in the main survey for the BI infrastructure integration, BI functionality, and BI self-service constructs. The questionnaire items are shown in Appendix B.

3.2. Construct measurement

All survey items were analyzed by SEM-PLS in a reflective mode. Competitive advantage and firm size (control variable) are the only latent variables measured as a unidimensional constructs. All other hypothesized latent variables are two-dimensional emergent constructs.[3]

3.2.1. BI infrastructure integration

In general, highly integrated IT infrastructures are characterized by high connectivity (reach) and compatibility (range) (Keen, 1991; Mithas et al., 2011), achieved in a single platform and single database infrastructure (Chapman and Kihn, 2009). Infrastructure integration is possible from a variety of architectural configurations. One example involves a wide-scope enterprise resource planning system (e.g., a full SAP ERP system implementation), which integrates platforms, software, and data. Another example, more focused on data integration, occurs if data from various primary sources (e.g., payroll system, customer relationship management system, accounts payable system, cost accounting systems, and a general ledger system) are routinely extracted, transformed and loaded into a central data warehouse (Rai et al., 2006). As the latter example is the most common data integration tool for BI, we measured BI infrastructure integration through four related dimensions: (1) overall systems integration (Chapman and Kihn, 2009); (2) data access; (3) data capture/exchange (Rai et al., 2006); and (4) data storage (Chapman and Kihn, 2009) (see questionnaire items in Appendix B). The latent variable scores for overall BI infrastructure integration were generated in a separate hierarchical PLS model as per Wetzels et al. (2009). This method accommodates the two emergent dimensions of BI planning infrastructure integration and BI reporting infrastructure integration.

BI planning infrastructure integration refers to the extent of connectivity of planning applications with the required data source(s) for input and output. The extent of connectivity refers to the velocity and multi-dimensional scope of the available and generated data. Higher BI planning infrastructure integration enables faster population of an individual user's planning application with more multi-dimensional data, including collaborative planning data.

BI reporting infrastructure integration refers to the extent of connectivity of reporting applications with integrated data sources, primarily for information output. The extent of connectivity refers to the velocity and multi-dimensional scope of the available data. Higher reporting infrastructure integration enables faster population of an individual user's reporting application with more multi-dimensional data.

Four questions for each of the two dimensions (see Appendix B) were developed in the pre-testing and pilot-testing stages. Scores were coded from 1 to 5, with 5 representing high infrastructure integration. Latent variable scores for each of the two dimensions were generated in a separate hierarchical PLS model as per Wetzels et al. (2009).

[3] Essentially, in an emergent construct, the dimensions each cause a unique aspect, thereby collectively defining the construct (Jarvis et al., 2003; Bisbe et al., 2007). This means that the direction of causality is from the dimensions to the construct, such that changes in the dimensions cause changes in the construct, and that a census (not a sample) of dimensions is needed in order to capture correctly the conceptual domain of the construct (Jarvis et al., 2003; Bisbe et al., 2007).

3.2.2. BI functionality

To develop the two-dimensional BI functionality construct, we drew from the academic literature (Ariav, 1992) that conceptualizes functionality as reflecting usability and multi-dimensionality. As discussed earlier, low functionality is derived from a dynamic series of spreadsheet arrays, whilst high functionality is related to specialist applications.

BI planning functionality refers to the level of usability and multi-dimensionality of a planning user-interface application, such that higher functionality enables faster creation and revision of budgets and forecasts with greater data multi-dimensionality. BI reporting functionality refers to the level of usability and multi-dimensionality of a reporting application, such that higher functionality provides more customizable reports, more sophisticated formats, and presentation features, and more multi-dimensional data structuring.

The four questions for each of the two dimensions (see Appendix B) were arrived at based on the pilot test. Scores were coded from 1 to 5, with 5 representing high functionality. Latent variable scores for each dimension were generated in a separate hierarchical PLS model as per Wetzels et al. (2009).

3.2.3. BI self-service

Consistent with the other BI constructs, the self-service construct was operationalized as two-dimensional emergent, with each dimension measured with a pair of reflective indicators. The two dimensions are: BI planning self-service and BI reporting self-service. The indicators distinctly relate to either senior manager or middle manager use of the BI system based on Dodson et al. (2008). Scores were coded from 1 to 5, with 5 representing high levels of managerial use of BI. Once again, the latent variable scores for overall BI self-service were generated in a separate hierarchical PLS model as per Wetzels et al. (2009).

3.2.4. Performance measurement capabilities

A two-dimensional emergent construct was used to measure performance measurement capabilities, with the dimensions being: (1) interactive performance measurement capabilities; and (2) diagnostic performance measurement capabilities (Simons, 1995). Each of these two dimensions was measured with two-dimensional emergent models, with the dimensions being: (1) profit-planning information; and (2) non-financial key performance indicators (Malmi and Brown, 2008). Each of the four constructs was reflectively measured with four survey items adapted from prior literature (Abernethy and Brownell, 1999; Bisbe and Otley, 2004; Naranjo-Gil and Hartmann, 2007; Widener, 2007). The scores for interactive performance measurement capabilities and diagnostic performance measurement capabilities were 1 to 5 and 1 to 7 respectively, with higher scores indicating a higher degree of performance measurement capabilities. The third-order latent variable scores for performance measurement capabilities were generated in two separate hierarchical PLS models as per Wetzels et al. (2009).

3.2.5. Competitive advantage

Competitive advantage is defined as superior firm performance relative to competitors. This approach controls for differences in performance due to industry, environment, and strategy effects (Garg et al., 2003). Respondents were asked to rate their business unit's performance last year relative to competitors across three dimensions: (1) sales growth; (2) market share; and (3) profitability. Such subjective performance measures are common in the information systems literature (Bhatt and Grover, 2005; Ravichandran and Lertwongsatien, 2005; Oh and Pinsonneault, 2007). Subjective and objective measures of financial performance have been found to correlate highly and to provide similar results in PLS modeling (Rai et al., 2006). Scores were coded from 1 to 9, with 9 representing high performance. PLS analyses of our data indicate the three measures all loaded strongly (.90, .91, and .81) on this construct, which provided confidence about reliability and validity.

3.2.6. Control: firm size

Firm size (full-time equivalent employees) was controlled for in the model as size has been found to systematically influence organizational practices (such as performance measurement), performance, and competitive advantage (Baum and Wally, 2003; Garg et al., 2003).

3.3. Sample selection and data collection

The data for hypotheses testing were collected over a three-month period using a cross-sectional mixed-mode (internet and mail) survey (Dillman, 2007) administered to 1607 managers of business units of Australian-based companies. Assuming that investments into high-quality BI are only feasible for medium or larger organizations and acknowledging that firm size can influence performance management practices (Baum and Wally, 2003; Garg et al., 2003), we limited our sample to organizations with a minimum of 100 full-time equivalent employees. To ensure all respondents in the sample had adequate time to be familiar with the BI system and performance management practices in their organization, responses from managers with a tenure of less than one year were excluded.

The survey was conducted in four rounds, each consisting of an email invitation with a hyperlink to an online questionnaire and a follow-up hardcopy of the survey mailed out three days after the email invitation. The survey yielded 507 responses (279 online and 228 paper questionnaires), 430 (203 and 227 respectively) of which were complete. This represents an overall response rate of 31.6%, and a "complete" response rate of 26.8% of the target sample of 1607. Following the removal of 106 responses that were outside our target sample, the final sample comprised 324 responses (160 online and 164 paper questionnaires). As expected, the majority of responses were received from CFOs or other senior finance managers (61.1%), while the remaining sample comprised CEOs and general managers. Consistent with the sectoral structure of Australia's economy, the majority of responses (70.1%) were from the services sector, with the remaining 29.9% from manufacturing firms.

3.4. Analysis of data characteristics and data quality

To determine the most appropriate analysis and testing techniques (parametric vs. non-parametric), all indicators and latent variables were tested for normality (Bollen and Stine, 1990; Ringle et al., 2012). The skewness and kurtosis measures exceeded two for many of the latent variables and corresponding indicators, indicating the data is not normally distributed (as shown in Table A1 in Appendix A). Small and Srivastava's multivariate tests of skew, kurtosis, and normality were also performed (DeCarlo, 1997), which confirmed that all the sets of indicators are non-normal. Consequently non-parametric test methods were required in our study (non-parametric independent samples tests, partial least square analysis, and bootstrapping), and factor-analysis was not deemed appropriate.

Several procedural remedies were applied to mitigate the potential of method bias. The potential effects of media preferences (e.g., email filters or email avoidance) were reduced by contacting all target respondents both via email and post, and independent sample tests confirmed homogeneous distribution of indicator scores across online and paper surveys. Motivational factors, ability factors, and task factors can contribute to common method bias (Podsakoff et al., 2012). These factors were addressed by eliminating or changing ambiguous items during the pre-test phase with practitioners, by targeting only senior managers, and by ensuring the voluntary survey was anonymous. To further increase participants' motivation to respond accurately, they were invited to register for a preliminary findings report by separate mail or email. The survey invitation email/letter 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. The number of Likert-scale points varied between five, seven, and nine (Netemeyer et al., 2003) and different anchor labels were used for related constructs (Podsakoff et al., 2012) (see Appendix B).

Two statistical remedies were used to assess for common method bias: (1) Harman's single-factor test; and (2) the unmeasured latent method factor technique (Podsakoff et al., 2003, 2012). First, for the Harman's test, exploratory factor analysis of the 40 indicators ($n = 324$) resulted in nine factors with eigenvalues >1, with the strongest factor explaining 30.65% of the total variance, suggesting that common method variance due to single source bias was not present (Podsakoff and Organ, 1986). Second, for the unmeasured latent method factor technique, a covariance-based structural equation modeling package (AMOS) was used to construct a version of the hypotheses-testing model. The structural model estimates mirrored our hypotheses-testing findings per the SEM-PLS procedure. When a general latent method factor was added, measured by all indicators of the constructs, the structural model estimates were qualitatively unchanged. Thus, the two procedures provide evidence that common method bias was not present (Podsakoff et al., 2003, 2012).

Non-response bias was assessed by comparing early and late respondents (Armstrong and 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 (Moore and Tarnai, 2002) and multiple follow-ups were sent out by both email and mail. Independent sample tests (Mann–Whitney U) showed no significant differences between the distribution of all data between early and late respondents, indicating that non-response bias is not a problem in this study.

3.5. Structural equation modeling-partial least squares analysis

SEM-PLS path modeling was used in the analysis as it is best suited to the non-normal dataset and relatively small sample size in our study. SEM-PLS uses very general, soft distributional assumptions and non-parametric prediction-orientated model evaluation measures (Wold, 1982; Chin, 1998). SEM-PLS is particularly suitable for indirect effect analysis in multi-mediator models (Liang et al., 2007; Taylor et al., 2008). “SmartPLS” version 2.00 M3 (Ringle et al., 2005) and “R” (package “plspm”) were used for SEM-PLS analysis and bootstrapping, and the results are reported following recent guidelines (Chin, 2010; Ringle et al., 2012).

3.5.1. Measurement model quality

All first-order constructs were measured reflectively and accordingly were tested for convergent and discriminant validity (Chin, 1998; Hulland, 1999). Regarding convergent validity, indicator reliability was assessed by examining the significance of the construct loadings. Table A2 in Appendix A reports the measurement indicator loadings, which are all significant at $p < .001$.

Regarding construct reliability and validity, Table A2 indicates high internal consistency in terms of composite reliability (Dillon-Goldstein's $rho \geq .60$ and Cronbach's $\alpha \geq .70$) (Nunnally, 1978; Fornell and Larcker, 1981; Bagozzi and Yi, 1988; Chin, 1998). Convergent validity is confirmed as all average variances extracted (AVE) clearly exceed .50 (Fornell and Larcker, 1981).

Discriminant validity of the construct indicators was examined by analyzing the loading of each indicator on its first-order construct, relative to its loading on other constructs. Table A3 in Appendix A confirms that all first-order construct-specific loadings exceed .70 (Chin, 1998; Hulland, 1999) and that each indicator's load is highest for the relevant latent variable construct (Fornell and Larcker, 1981). Discriminant validity of the constructs is evidenced by the fact that all square roots of the AVE in the diagonal in Table A5 exceed the correlations with the other constructs (Barclay et al., 1995; Chin, 1998).

3.5.2. Hypothesis testing procedures

The SEM-PLS path model (see Fig. 2) includes all hypothesized direct effects and outer weights of the latent formative variables. The magnitude of the direct effects is represented by the path coefficients. The magnitude of the indirect effects is determined by multiplying

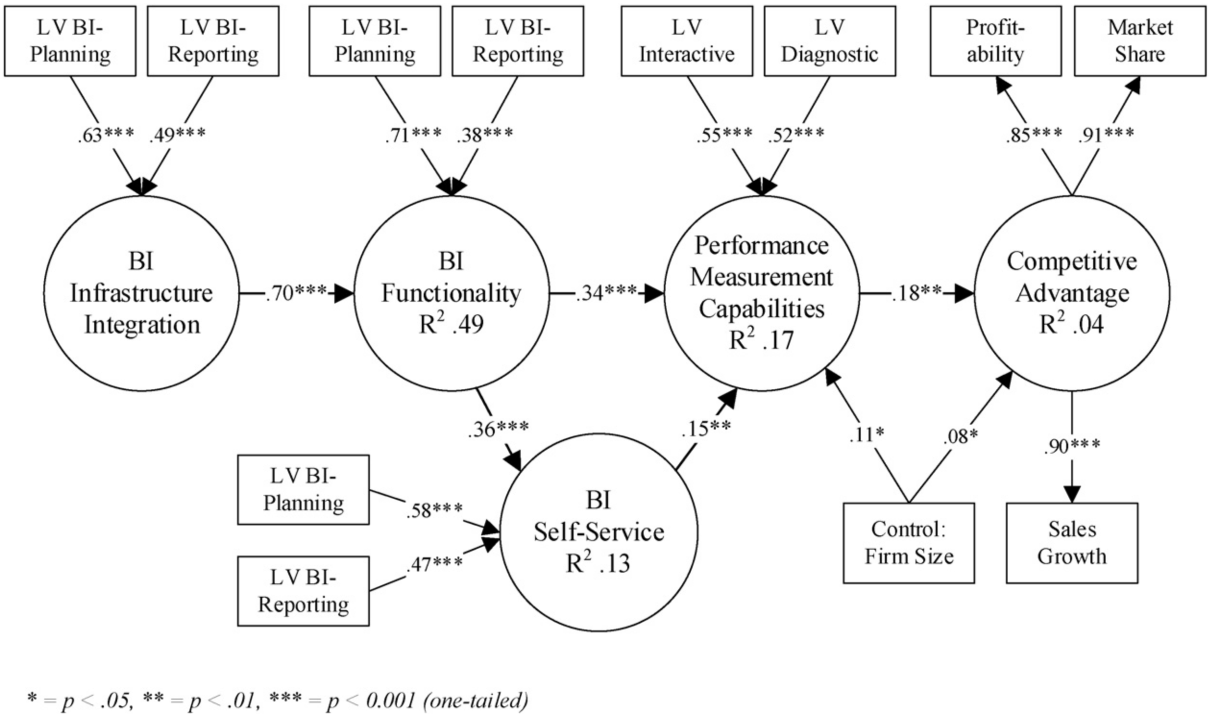

Fig. 2. Result model (n = 324).

the coefficients of the paths in the mediational chain (Baron and Kenny, 1986; Taylor et al., 2008). The significance of each effect is determined using the bias-corrected percentile bootstrap method (Preacher and Hayes, 2008; Taylor et al., 2008).[4]

4. Results

The results for the tests of H1 to H5 are all supported, as shown in Table 1 and Fig. 2. We find that BI infrastructure integration enhances BI functionality ($\beta = .70$, $p < .001$), consistent with H1. Subsequently, BI functionality enhances both BI self-service ($\beta = .36$, $p < .001$) and performance measurement capabilities ($\beta = .39$, $p < .001$), consistent with H2 and H3 respectively. Performance measurement capabilities are enhanced by both BI functionality and BI self-service ($\beta = .15$, $p < .01$), consistent with H4. The resulting performance measurement capabilities are positively associated with competitive advantage ($\beta = .18$, $p < .01$), consistent with H5.

H6 predicted that BI quality (represented by each of the three BI quality concepts) would be indirectly associated with competitive advantage. The theoretical model (Fig. 1) implies a total of five such mediation chains (i.e., indirect effects), which are all supported — as reported in Table 2. We find that BI infrastructure integration is indirectly positively associated with competitive advantage through both mediation chains: (1) via BI functionality and performance measurement capabilities ($\beta = .04$, $p < .01$); and (2) via BI functionality, BI self-service, and performance measurement capabilities ($\beta = .01$, $p < .01$). We find that BI functionality is indirectly positively associated with competitive advantage also through both mediation chains: (1) via performance measurement capabilities ($\beta = .06$, $p < .01$); and (2) via BI self-service and performance measurement capabilities ($\beta = .01$, $p < .01$). Finally, BI self-service is indirectly positively associated with competitive advantage via performance measurement capabilities ($\beta = .03$, $p < .01$). In aggregate, BI quality as defined by the three BI quality concepts is indirectly positively associated with competitive advantage, supporting H6.

The proportions of variance explained are: BI functionality $R^2 = 0.49$; BI self-service $R^2 = 0.13$; performance measurement capabilities $R^2 = 0.17$; and competitive advantage $R^2 = 0.04$. As expected, our control variable, firm size, is also a significant positive predictor of performance measurement capabilities ($\beta = .11$, $p < .05$) and competitive advantage ($\beta = .08$, $p < .05$). In summary, all of the results support our theoretical model and associated hypotheses.

[4] Bootstrap methods generally outperform other methods of significance testing in mediation models (MacKinnon et al., 2004) and — particularly with small samples — the bootstrap percentile method captures the asymmetry in the sampling distribution missed by the product-of-coefficients test using the standard error (Shrout and Bolger, 2002; Cheung and Lau, 2008). The advantages of bootstrap percentile methods have also been confirmed for three-path mediation models, and adjusting the confidence interval limits is required in case the bootstrap distribution fails to center (i.e., is biased) at the sample estimate of the mediated effect (Taylor et al., 2008).

Table 1
PLS-SEM — direct effects.

(N = 324)	
H1: **BI Infrastructure Integration → BI Functionality**	**.70*****
H2: **BI Functionality → BI Self-service**	**.36*****
H3: **BI Functionality → Performance Measurement Capabilities**	**.39*****
H4: **BI Self-service → Performance Measurement Capabilities**	**.15****
H5: **Performance Measurement Capabilities → Competitive Advantage**	**.18****
Size (Control) → Performance Measurement Capabilities	.11*
Size (Control) → Competitive Advantage	.10*

Significance levels are: ***$p < .001$, **$p < .01$, *$p < .05$ (*one-tailed*).

5. Summary and conclusions

The purpose of this study was to enhance our understanding of how BI quality may improve performance measurement capability and competitive advantage. BI quality was examined through the three key concepts of (1) infrastructure integration; (2) functionality; and (3) self-service (i.e., managers' independent use of the BI system). By studying the role of BI quality in supporting both diagnostic and interactive dimensions of performance measurement capability, we extend BI research concerning organizational learning and knowledge creation processes. We define three dimensions of BI quality, and also show how it can be effectively leveraged to support the performance measurement system component of a contemporary MCS. This relationship is important to understanding how BI supports the creation of competitive advantage.

To test the theoretical model we collected survey responses from 324 CEOs/CFOs (or equivalent) from Australian organizations with greater than 100 employees. The analysis of the research model using the survey measures indicates that the model is robust and that all of the theorized relationships amongst the constructs are significant and relevant. The model captures both the direct effects of BI quality on performance measurement quality and the indirect effects flowing through performance measurement capability that BI quality has on competitive advantage.

Our research makes three contributions to the BI literature related to MCS. First, we develop and validate a set of constructs that effectively capture BI quality. The BI quality relationships are significant and the individual constructs exhibit strong validity and reliability. Second, we take a deeper look at how BI relates to effective MCS by examining key dimensions of performance measurement capability — the support of both interactive and diagnostic performance measures. Third, our results indicate that investment in BI infrastructure integration and functionality is associated with increased competitive advantage, and that these effects occur through performance measurement capabilities.

As with any research, there are limitations that should be considered when weighing the research results. First, the measures captured by our survey provide a snapshot at a point in time. Without temporal measurement of changes in the theoretical constructs it is difficult to establish causality, as the components of the model may be fluid over time. However, a strong theoretical foundation behind the hypothesized relationships provides a level of confidence in the directionality of the effects identified. Second, because new issues and perspectives were being explored, new measures needed to be developed for the current study. However, this was countered by having the measures reviewed by expert panels and through pre-testing for assessing validity and reliability. In addition, we obtained strong results for both initial validation and for reliability testing with the final research sample. The benefit of such a rigorous approach to construct development is that the new construct measures should be useful to researchers in future studies. Third, the indirect effects involving BI self-service are very small and explain little of the overall effect of BI functionality on performance measurement capabilities. Lastly, the size of the effect from performance measurement capabilities to competitive advantage is small, and our model only explains a small percentage of the variance of competitive advantage. Future research could seek stronger relationships between BI, performance measurement capabilities and competitive advantage by studying classic MCS moderating variables, such as environmental uncertainty, business strategy and technology (Chenhall, 2003).

This research provides insights into one more piece of the puzzle underlying the nexus between BI systems, MCS, and organizational performance. As such, we better understand how BI quality leads to improvements in critical diagnostic and interactive aspects of MCS capability, and how improvements positively relate to competitive advantage. This research makes a contribution

Table 2
PLS-SEM — indirect effects (H6).

(N = 324)	
BI Infrastructure Integration → Competitive Advantage	
via BI Functionality → Performance Measurement Capabilities	.04**
via BI Functionality → BI Self-service → Performance Measurement Capabilities	.01**
BI Functionality → Competitive Advantage	
via Performance Measurement Capabilities	.06**
via BI Self-service → Performance Measurement Capabilities	.01**
BI Self-Service → Competitive Advantage	
via Performance Measurement Capabilities	.03**

Significance levels are: ***$p < .001$, **$p < .01$, *$p < .05$ (*one-tailed*).

to the unfolding body of research on BI systems and MCS. It provides evidence that BI is positively associated with organizational performance by enhanced organizational learning and business process performance improvement (Elbashir et al., 2008, 2013; Lee and Widener, 2016). The results of this research help aid our understanding of the specific mechanisms and processes by which BI can facilitate improvements in diagnostic and interactive aspects of MCS, and how this improved performance measurement facilitates organizational performance improvements.

Acknowledgments

We are grateful for the constructive input provided by the Associate Editor and for funding from the Accounting Discipline Group at the University of Technology Sydney.

Appendix A. Analysis

Table A1
Descriptive statistics.

Constructs and indicators (N = 324) (Likert scale end-points in brackets)	Mean	Standard deviation	Skew/ SE_{skew}[b]	Kurtosis/ SE_{kurt}[c]
BI Infrastructure integration (1–5)	**3.36**	**0.81**	**−1.90**	**−1.37**
BI Reporting infrastructure integration[a] (1–5)	**3.57**	**0.87**	**−4.05**	**−0.94**
Integrated architecture (1–5)	3.53	1.06	−4.55	−1.10
Shared platform/database (1–5)	3.59	0.95	−4.60	−0.14
Integration with transactional systems (1–5)	3.57	0.96	−4.38	−0.49
Data centralization (1–5)	3.58	0.97	−3.84	−1.11
BI Planning infrastructure integration[a] (1–5)	**3.13**	**0.94**	**−1.43**	**−2.07**
Integrated architecture (1–5)	2.90	1.20	−0.90	−4.07
Shared platform/database (1–5)	3.21	1.09	−2.06	−2.56
Integration with transactional systems (1–5)	3.19	1.05	−2.80	−1.57
Data centralization (1–5)	3.19	1.08	−1.70	−2.82
BI Functionality (1–5)	**2.92**	**0.86**	**0.03**	**−1.14**
BI Reporting functionality (1–5)	**2.95**	**0.90**	**−0.59**	**−1.06**
Format/Presentation feat. (1–5)	3.03	1.05	−1.18	−2.19
Interactive reporting (1–5)	2.76	1.03	0.96	−1.89
Ease of use (1–5)	2.96	1.02	−0.01	−1.86
Response/Refresh time (1–5)	3.07	1.05	−0.77	−2.33
BI Planning functionality (1–5)	**2.88**	**0.97**	**0.32**	**−2.24**
Response/Refresh time (1–5)	2.95	1.07	−0.18	−2.61
Actuals update speed (1–5)	3.03	1.10	−0.50	−3.10
Forecast speed (1–5)	2.94	1.08	−0.12	−3.25
Planning model sophistication (1–5)	2.61	1.06	1.83	−2.04
BI Self-service (1–5)	**2.88**	1.07	0.13	−2.91
BI Reporting self-service (1–5)	**2.96**	**1.12**	**−0.39**	**−3.15**
Middle manager users (1–5)	3.03	1.16	−1.24	−3.36
Senior manager users (1–5)	2.88	1.21	0.27	−3.71
BI Planning self-service (1–5)	**2.81**	**1.13**	**0.48**	**−3.44**
Middle manager users (1–5)	2.89	1.18	0.37	−3.70
Senior manager users (1–5)	2.76	1.21	0.72	3.77
Performance measurement capabilities (1–6)	**4.03**	**0.82**	**−4.90**	**3.63**
Diagnostic perf. measurement capabilities (1–5)	**3.76**	**0.70**	**−6.05**	**5.89**
DPMC profit planning (1–5)	3.90	0.78	−7.53	6.47
Follow up on targets (1–5)	3.98	0.86	−6.96	4.64
Track progress towards goals (1–5)	4.09	0.85	−8.16	6.10
Review significant deviations (1–5)	4.06	0.90	−8.08	4.59
Evaluate and control subordinates (1–5)	3.48	0.98	−4.34	−0.14
DPMC non-financial KPIs (1–5)	3.57	0.86	−5.01	2.09
Follow up on targets (1–5)	3.62	0.93	−5.21	1.09
Track progress towards goals (1–5)	3.69	0.90	−5.80	2.29
Review significant deviations (1–5)	3.62	0.96	−3.86	−0.30
Evaluate and control subordinates (1–5)	3.37	0.96	−2.58	−0.84
Interactive perf. measurement capabilities (1–7)	**4.46**	**1.17**	**−3.04**	**0.22**
IPMC profit planning (1–7)	4.46	1.37	−3.33	−1.02
Senior management interaction (1–7)	4.50	1.84	−2.93	−3.70
Senior/middle management interaction (1–7)	4.03	1.79	−0.43	−3.66

(continued on next page)

Table A1 *(continued)*

Constructs and indicators (N = 324) (Likert scale end-points in brackets)	Mean	Standard deviation	Skew/ SE_{skew}[b]	Kurtosis/ SE_{kurt}[c]
Consideration of alternatives/scenarios (1–7)	4.63	1.66	−4.31	−1.52
Strategic business change assessment (1–7)	4.68	1.69	−4.11	−2.13
IPMC non-financial KPIs (1–7)	4.46	1.28	−3.13	−0.28
Senior management interaction (1–7)	4.90	1.44	−4.93	0.10
Senior/middle management interaction (1–7)	4.67	1.44	−3.79	−0.96
Consideration of alternatives/scenarios (1–7)	4.00	1.43	−0.15	−2.09
Strategic business change assessment (1–7)	4.30	1.49	1.91	−2.42
Competitive advantage (1–9)	**5.84**	**1.42**	**0.66**	**0.06**
Sales growth (1–9)	5.85	1.51	0.43	−0.69
Market share (1–9)	5.83	1.46	1.45	−0.56
Profitability (1–9)	5.84	1.91	−1.89	−1.62
Size (log of employees)	**2.68**	**0.48**	**1.14**	**1.51**

Acronyms: SE_{skew}…skewness standard error (SES); SE_{kurt} …kurtosis standard error (SEK).
[a] The scores for the constructs are based on the unstandardized latent variable scores.
[b] Sample skewness divided by standard error of skewness (SES), with test scores >2 or <−2 suggesting significant positive or negative skew (Cramer, 1997, 85).
[c] Sample kurtosis divided by standard error of kurtosis (SEK), with test scores >2 or <−2 suggesting significant positive or negative kurtosis (Cramer, 1997, 89).

Table A2
Indicator reliability, construct reliability, and construct validity.

1st Order constructs and indicators (N = 324)	Loadings[a]	Cronbach's α[b]	Composite Reliability (ρ)[c]	AVE[c]
BI planning infrastructure integration		.91	.87	.73
Integrated architecture	.85			
Shared platform/database	.89			
Integration with transactional systems	.86			
Data centralization	.80			
BI reporting infrastructure integration		.94	.91	.78
Integrated architecture	.89			
Shared platform/database	.91			
Integration with transactional systems	.89			
Data centralization	.85			
BI planning functionality		.95	.93	.82
Response/refresh time	.89			
Actuals update speed	.93			
Forecast create/update speed	.92			
Planning model sophistication	.88			
BI reporting functionality		.92	.89	.75
Response/refresh time	.88			
Ease of use	.88			
Interactive reporting	.85			
Format/presentation features	.86			
BI planning self-service		.95	.89	.90
Middle manager planning	.95			
Senior manager planning	.95			
BI reporting self-service		.95	.89	.90
Middle manager reporting	.95			
Senior manager reporting	.95			
Diagnostic PMC: profit planning		.93	.89	.76
Follow up on targets	.89			
Track progress towards goals	.91			
Review significant deviations	.88			
Evaluate and control subordinates	.80			
Diagnostic PMC: non-financial KPIs		.95	.93	.83
Follow up on targets	.93			
Track progress towards goals	.93			
Review significant deviations	.92			
Evaluate and control subordinates	.88			
Interactive PMC: profit planning		.87	.79	.62
Senior management interaction	.77			
Senior/middle management interaction	.80			

Table A2 *(continued)*

1st Order constructs and indicators (N = 324)	Loadings[a]	Cronbach's α[b]	Composite Reliability (ρ)[c]	AVE[c]
Consideration of alternatives/scenarios	.83			
Strategic business change assessment	.74			
Interactive PMC: non-financial KPIs		.93	.91	.78
Senior management interaction	.88			
Senior/middle management interaction	.90			
Consideration of alternatives/scenarios	.90			
Strategic business change assessment	.85			
Competitive advantage		.92	.87	.79
Sales growth	.90			
Market share	.90			
Profitability	.86			

[a] All loadings are significant at $p < .001$ based on $t_{(n-2)}$, two-tailed test.
[b] Internal consistency: All composite reliability (Dillon-Goldstein's ρ) indices are ≥.60 (Bagozzi and Yi, 1988) and all Cronbach's alpha indices are ≥.70 (Nunnally, 1978).
[c] Convergent validity: All average variance extracted (AVE) indices are ≥.50 (Fornell and Larcker, 1981).

Table A3
PLS cross-loadings — 1st order constructs.

Constructs/indicators (N = 324)	1a	1b	2a	2b	3a	3b	4a	4b	4c	4d	5
1a. BI planning infrastructure integration											
Integrated architecture	**.85**	.43	.51	.36	.29	.24	.19	.24	.15	.25	.07
Shared platform/database	**.89**	.50	.52	.42	.37	.31	.27	.30	.24	.31	.02
Integration with transactional systems	**.86**	.55	.61	.52	.34	.30	.30	.26	.25	.35	.04
Data centralization	**.80**	.53	.54	.41	.23	.21	.22	.18	.19	.23	.07
1b. BI reporting infrastructure integration											
Integrated architecture	.52	**.89**	.45	.49	.21	.29	.14	.14	.14	.16	.07
Shared platform/database	.54	**.91**	.45	.52	.25	.33	.21	.17	.21	.20	.05
Integration with transactional systems	.54	**.89**	.50	.61	.18	.29	.17	.13	.17	.21	.06
Data centralization	.50	**.85**	.48	.56	.13	.26	.22	.13	.20	.22	.08
2a. BI planning functionality											
Response/refresh time	.59	.47	**.89**	.57	.29	.23	.30	.29	.32	.34	.15
Actuals update speed	.58	.50	**.93**	.60	.27	.25	.32	.31	.27	.34	.19
Forecast create/update speed	.55	.48	**.92**	.64	.28	.28	.31	.25	.29	.29	.19
Planning model sophistication	.60	.45	**.88**	.62	.36	.32	.28	.26	.30	.31	.16
2b. BI reporting functionality											
Response/refresh time	.42	.50	.56	**.88**	.21	.29	.18	.18	.16	.20	.12
Ease of use	.44	.52	.56	**.88**	.29	.37	.20	.21	.22	.24	.08
Interactive reporting	.45	.54	.58	**.85**	.19	.29	.18	.14	.15	.19	.13
Format/presentation features	.44	.58	.62	**.86**	.25	.33	.15	.16	.19	.22	.09
3a. BI planning self-service											
Middle manager	.39	.24	.31	.27	**.95**	.75	.16	.23	.11	.29	.04
Senior manager	.30	.17	.32	.25	**.95**	.78	.15	.20	.14	.26	.01
3b. BI reporting self-service											
Middle manager	.32	.30	.26	.35	.76	**.95**	.13	.21	.11	.22	.01
Senior manager	.28	.32	.30	.35	.77	**.95**	.12	.19	.12	.22	.00
4a. Diagnostic PMC — profit planning											
Follow up on targets	.26	.14	.29	.16	.09	.05	**.89**	.41	.58	.50	.20
Track progress towards goals	.26	.19	.28	.18	.12	.07	**.91**	.40	.54	.46	.22
Review significant deviations	.27	.21	.29	.17	.15	.12	**.88**	.46	.53	.47	.19
Evaluate and control subordinates	.22	.18	.30	.19	.22	.21	**.80**	.49	.47	.47	.21
4b. Diagnostic PMC — non-financial KPIs											
Follow up on targets	.26	.13	.25	.17	.22	.20	.44	**.93**	.35	.73	.10
Track progress towards goals	.26	.12	.24	.16	.16	.15	.43	**.93**	.29	.68	.15
Review significant deviations	.25	.15	.29	.17	.22	.19	.48	**.92**	.34	.69	.10
Evaluate and control subordinates	.28	.19	.32	.21	.21	.22	.50	**.88**	.37	.66	.11
4c. Interactive PMC — profit planning											
Senior management interaction	.16	.14	.25	.13	.08	.05	.49	.22	**.77**	.37	.06
Senior/middle management interaction	.16	.15	.18	.14	.03	.03	.46	.24	**.80**	.39	.12
Consideration of alternatives/scenarios	.25	.20	.29	.23	.13	.15	.52	.34	**.83**	.52	.16
Strategic business change assessment	.19	.16	.29	.14	.17	.14	.44	.35	**.74**	.48	.12
4d. Interactive PMC — non-financial KPIs											
Senior management interaction	.28	.19	.30	.16	.23	.18	.47	.70	.43	**.88**	.12
Senior/middle management interaction	.26	.17	.28	.15	.20	.14	.49	.70	.48	**.90**	.16
Consideration of alternatives/scenarios	.35	.25	.37	.29	.31	.26	.49	.64	.57	**.90**	.09
Strategic business change assessment	.29	.18	.30	.27	.28	.25	.46	.63	.51	**.85**	.08
5. Competitive advantage											
Sales growth	.02	.03	.14	.09	.01	.03	.15	.07	.13	.08	**.90**
Market share	.04	.06	.15	.09	.03	.02	.23	.10	.17	.12	**.90**
Profitability	.08	.09	.21	.14	.03	−.02	.22	.15	.10	.13	**.86**

Table A4
PLS cross-loadings — main constructs.

Constructs/Indicators (N = 324)	1	2	3	4	5
1. BI infrastructure integration					
Planning — integrated architecture	**.71**	.48	.28	.26	.07
Planning — shared platform/database	**.77**	.52	.36	.35	.02
Planning — integration with transactional systems	**.79**	.62	.34	.36	.04
Planning — data centralization	**.74**	.52	.24	.24	.07
Reporting — integrated architecture	**.80**	.51	.26	.18	.07
Reporting — shared platform/database	**.82**	.53	.31	.24	.05
Reporting — integration with transactional systems	**.81**	.60	.25	.21	.06
Reporting — data centralization	**.76**	.56	.20	.23	.08
2. BI functionality					
Planning — response/refresh time	.59	**.81**	.27	.38	.15
Planning — actuals update speed	.60	**.85**	.27	.38	.19
Planning — forecast create/update speed	.58	**.86**	.29	.34	.19
Planning — planning model sophistication	.59	**.83**	.36	.35	.16
Reporting — response/refresh time	.52	**.78**	.26	.22	.12
Reporting — ease of use	.54	**.78**	.35	.26	.08
Reporting — interactive reporting	.55	**.77**	.25	.20	.13
Reporting — format/presentation features	.58	**.80**	.30	.22	.09
3. BI self-service					
Middle manager planning	.35	.32	**.90**	.25	.04
Senior manager planning	.26	.31	**.91**	.23	.01
Middle manager reporting	.35	.33	**.90**	.21	.01
Senior manager reporting	.34	.36	**.90**	.20	.00
4. Performance management capabilities					
Diagnostic — profit planning					
Follow up on targets	.22	.25	.08	**.71**	.20
Track progress towards goals	.25	.26	.10	**.69**	.22
Review significant deviations	.27	.26	.14	**.70**	.19
Evaluate and control subordinates	.22	.27	.23	**.68**	.21
Diagnostic — non-financial KPIs					
Follow up on targets	.21	.24	.23	**.78**	.10
Track progress towards goals	.21	.22	.16	**.75**	.15
Review significant deviations	.22	.26	.22	**.77**	.10
Evaluate and control subordinates	.27	.30	.23	**.76**	.11
Interactive — profit planning					
Senior management interaction	.17	.21	.06	**.52**	.06
Senior/middle management interaction	.17	.18	.03	**.53**	.12
Consideration of alternatives/scenarios	.25	.29	.15	**.64**	.16
Strategic business change assessment	.19	.24	.16	**.58**	.12
Interactive — non-financial KPIs					
Senior management interaction	.26	.26	.22	**.78**	.12
Senior/middle management interaction	.24	.24	.18	**.81**	.16
Consideration of alternatives/scenarios	.34	.36	.30	**.80**	.09
Strategic business change assessment	.26	.32	.28	**.76**	.08
5. Competitive advantage					
Sales growth	.03	.13	.02	.13	**.90**
Market share	.06	.13	.03	.19	**.90**
Profitability	.09	.19	.00	.19	**.86**

Table A5
Correlation/path coefficient matrix and discriminant validity assessment.

Constructs	1	2	3	4	5
1. BI infrastructure integration	.78				
2. BI functionality	.69***	.81			
3. BI self-service	.35***	.34***	.90		
4. Performance measurement capabilities	.33***	.36***	.25***	.71	
5. Competitive advantage	.10*	.20***	.02	.21***	.89

*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. Off-diagonal values are nonparametric latent variable correlations (Spearman's ρ; two-tailed). Significance levels are ***p < .001, **p < .01, *p < .05 (two-tailed).*

Appendix B. Questionnaire items

Construct	Questions/Indicators
BI reporting infrastructure integration	Our management reporting and analysis systems (1 to 5): • are purely spreadsheet based (1) vs. have a fully integrated IT systems architecture (5); • consist solely of isolated and individualized spreadsheets (1) vs. are integrated by a common, shared online platform and database (5); • use highly manual processes to extract data from transactional systems (1) vs. have fully automated integration with all relevant transactional systems (5); • are based on data from disparate spreadsheets (1) vs. source all data from a single data warehouse (5).
BI planning infrastructure integration	Our planning, budgeting, and forecasting systems (1 to 5): • are purely spreadsheet based (1) vs. have a fully integrated IT systems architecture (5); • consist solely of isolated and individualized spreadsheets (1) vs. are integrated by a common, shared online platform and database (5); • use highly manual processes to extract data from transactional systems (1) vs. have fully automated integration with all relevant transactional systems (5); • are based on data from disparate spreadsheets (1) vs. source all data from a single data warehouse (5).
BI reporting functionality	Our management reporting and analysis systems [strongly disagree (1); strongly agree (5)]: • have sophisticated formats and presentation features; • have highly interactive reporting features; • are very easy to use and navigate by all users; • have rapid response and refresh times.
BI planning functionality	Our planning, budgeting, and forecasting systems [strongly disagree (1); strongly agree (5)]: • have rapid response and refresh times; • are very quickly updated with actual and base-level information; • allow forecasts and budgets to be quickly created and revised; • allow sophisticated planning models to be easily implemented and changed.
BI self-service	For our management reporting and analysis systems: • dedicated analysts provide all the information to middle managers (1) to middle managers access and interact with the system(s) very frequently (5); • dedicated analysts provide all the information to senior managers (1) to senior managers access and interact with the system(s) very frequently (5).
	For our planning budgeting and forecasting systems: • dedicated analysts provide all the information to middle managers (1) *to* middle managers access and interact with the system(s) very frequently (5); • dedicated analysts provide all the information to senior managers (1) *to* senior managers access and interact with the system(s) very frequently (5).
Diagnostic performance measurement capabilities	How intensively do senior managers use profit planning activities in your business unit to [strongly disagree (1); strongly agree (5)]: o follow up on targets; o track progress towards goals; o review significant deviations; o evaluate and control subordinates. How intensively do senior managers use non-financial key performance indicators in your business unit to [strongly disagree (1); strongly agree (5)]: o follow up on targets; o track progress towards goals; o review significant deviations; o evaluate and control subordinates.
Interactive performance measurement capabilities	Please indicate the degree to which you agree or disagree with the statements regarding your business unit [strongly disagree (1); strongly agree (7)]: o Senior managers meet and discuss profit planning information very frequently (e.g., weekly) o Middle and senior managers meet and discuss profit planning information very frequently (e.g., weekly) o Profit planning meetings always include consideration of multiple alternatives and scenarios o Strategic business changes are always assessed in profit planning meetings o Senior managers constantly interact with peers to discuss non-financial KPIs o Middle managers are continually involved in discussing non-financial KPIs with senior managers o Every discussion of non-financial KPIs involves intensive review and revision of action plans o Significant business development opportunities are a key focus in all discussions of non-financial KPIs.

(continued on next page)

(continued)

Construct	Questions/Indicators
Competitive advantage	Relate the situation in your business unit last year. Relative to your competitors, how has your business unit performed for the following three areas [much worse (1); much better (9)]: • Sales growth — relative to your major competitors • Market share — relative to your major competitors • Profitability — relative to your major competitors.

References

Abernethy, M.A., Brownell, P., 1999. The role of budgets in organizations facing strategic change: an exploratory study. Acc. Organ. Soc. 24 (3), 189–204.

Alavi, M., Leidner, D.E., 2001. Review: knowledge management and knowledge management systems: conceptual foundations and research issues. MIS Q. 25 (1), 107–136.

Ariav, G., 1992. Information systems for managerial planning and control: a conceptual examination of their temporal structure. J. Manag. Inf. Syst. 9 (2), 77–98.

Armstrong, J.S., Overton, T., 1977. Estimating nonresponse bias in mail surveys. J. Mark. Res. 14 (3), 396–402.

Bagozzi, R., Yi, Y., 1988. On the evaluation of structural equation models. J. Acad. Mark. Sci. 16 (1), 74–94.

Barclay, D.R., Thompson, R., Higgins, C., 1995. The partial least squares approach to casual modeling: personal computer adoption and use as an illustration. Technol. Stud. 2, 285–324.

Barney, J.B., 1991. Firm resources and sustained competitive advantage. J. Manag. 17 (1), 99–120.

Baron, R.M., Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J. Pers. Soc. Psychol. 51 (6), 1173–1182.

Baum, J.R., Wally, S., 2003. Strategic decision speed and firm performance. Strateg. Manag. J. 24 (11), 1107–1129.

Bhatt, G.D., Grover, V., 2005. Types of information technology capabilities and their role in competitive advantage: an empirical study. J. Manag. Inf. Syst. 22 (2), 253–277.

Bisbe, J., Otley, D., 2004. The effects of the interactive use of management control systems on product innovation. Acc. Organ. Soc. 29 (8), 709–737.

Bisbe, J., Batista-Foguet, J.M., Chenhall, R., 2007. Defining management accounting constructs: a methodological note on the risks of conceptual misspecification. Acc. Organ. Soc. 32 (7), 789–820.

Bollen, K.A., Stine, R., 1990. Direct and indirect effects: classical and bootstrap estimates of variability. Sociol. Methodol. 20 (1), 115–140.

Burton-Jones, A., Straub Jr., D.W., 2006. Reconceptualizing system usage: an approach and empirical test. Inf. Syst. Res. 17 (3), 228–246.

Chapman, C., Kihn, L.A., 2009. Information system integration, enabling control and performance. Acc. Organ. Soc. 34 (2), 151–169.

Chaudhuri, S., Dayal, U., Narasayya, V., 2011. An overview of business intelligence technology. Commun. ACM 54 (8), 88–98.

Chenhall, R.H., 2003. Management control systems design within its organizational context: Findings from contingency-based research and directions for the future. Acc. Organ. Soc. 2 (2-3), 127–168.

Cheung, G.W., Lau, R.S., 2008. Testing mediation and suppression effects of latent variables. Organ. Res. Methods 11 (2), 296–325.

Chin, W.W., 1998. The partial least squares approach to structural equation modeling. In: Marcoulides, G.A. (Ed.), Modern Methods for Business Research. Lawrence Erlbaum Associates, Mahwah, NJ, pp. 195–336.

Chin, W.W., 2010. How to write up and report PLS analysis. In: Vinzi, V.E., Chin, W.W., Henseler, J., Wang, H. (Eds.), Handbook of Partial Least Squares—Concepts, Methods and Applications in Marketing and Related Fields. Springer, Berlin, Heidelberg, pp. 655–690.

Clark, T.D., Jones, M.C., Armstrong, C.P., 2007. The dynamic structure of management support systems: theory development, research focus and direction. MIS Q. 31 (3), 579–615.

Cramer, D., 1997. Basic Statistics for Social Research — Step-By-Step Calculations & Computer Techniques Using Minitab. Psychology Press, London.

DeCarlo, L.T., 1997. On the meaning and use of kurtosis. Psychol. Methods 2 (3), 292–307.

DeLone, W.H., McLean, E.R., 2003. The DeLone and McLean model of information systems success: a ten-year update. J. Manag. Inf. Syst. 19 (4), 9–30.

Dilla, W., Janvrin, D.J., Raschke, R., 2010. Interactive data visualization: new directions for accounting information systems research. J. Inf. Syst. 24 (2), 1–37.

Dillman, D.A., 2007. Mail and Internet Surveys: The Tailored Design Method. Wiley, New York.

Dodson, G., Arnott, D., Pervan, G., 2008. The use of business intelligence systems in Australia. The Australasian Conference on Information Systems Christchurch, New Zealand, ACIS 2008 Proceedings.

Doll, W.J., Torkzadeh, G., 1988. The measurement of end-user computing satisfaction. MIS Q. 12 (2), 259–274.

Elbashir, M.Z., Collier, P.A., Davern, M.J., 2008. Measuring the effects of business intelligence systems: the relationship between business process and organizational performance. Int. J. Account. Inf. Syst. 9 (3), 135–153.

Elbashir, M.Z., Collier, P.A., Sutton, S.G., 2011. The role of organizational absorptive capacity in strategic use of business intelligence to support integrated management control systems. Account. Rev. 86 (1), 155–184.

Elbashir, M.Z., Collier, P.A., Sutton, S.G., Davern, M.J., Leech, S.A., 2013. Enhancing the business value of business intelligence: the role of shared knowledge and assimilation. J. Inf. Syst. 27 (2), 87–105.

Emmanuel, C., Otley, D., Merchant, K., 1990. Accounting for Management Control. Springer, London.

Fedorowicz, J., Konsynski, B., 1992. Organization support systems: bridging business and decision processes. J. Manag. Inf. Syst. 8 (4), 5–25.

Ferreira, A., Otley, D., 2009. The design and use of performance management systems: An extended framework for analysis. Manag. Account. Res. 20 (4), 263–282.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Mark. Res. 18 (1), 39–50.

Foster, S., Hawking, P., Stein, A., 2005. Business intelligence solution evolution: adoption and use. Bus. Intell. J. 10 (4), 44–54.

Garg, V.K., Walters, B.A., Priem, R.L., 2003. Chief executive scanning emphases, environmental dynamism and manufacturing performance. Strateg. Manag. J. 24 (8), 725–744.

Grafton, J., Lillis, A.M., Widener, S.K., 2010. The role of performance measurement and evaluation in building organizational capabilities and performance. Acc. Organ. Soc. 35 (7), 689–706.

Grant, R.M., 1996. Prospering in dynamically-competitive environments: organizational capability as knowledge integration. Organ. Sci. 7 (4), 375–387.

Green, S.G., Welsh, A.M., 1988. Cybernetics and dependence: reframing the control concept. Acad. Manag. Rev. 13 (2), 287–304.

Henri, J.F., 2006. Organizational culture and performance measurement systems. Acc. Organ. Soc. 31 (1), 77–103.

Hou, C.-K., 2012. Examining the effect of user satisfaction on system usage and individual performance with business intelligence systems: an empirical study of Taiwan's electronics industry. Int. J. Inf. Manag. 32 (6), 560–573.

Howard, P., 2003. Analytics Volume 1: An Evaluation and Comparison. Bloor Research, Milton Keynes, U.K.

Huber, G.P., 1991. Organizational learning: the contributing processes and the literatures. Organ. Sci. 2 (1), 88–115.

Hulland, J., 1999. The use of partial least square (PLS) in strategic management research: a review of four recent studies. Strateg. Manag. J. 20 (2), 195–204.

Jarvis, C.B., Mackenzie, S.B., Podsakoff, P.M., 2003. A critical review of construct indicators and measurement model misspecification in marketing and consumer research. J. Consum. Res. 30 (September), 199–218.

Keen, P.G.W., 1991. Shaping the Future: Business Design Through Information Technology. Harvard Business School Press, Harvard.

Kogut, B., Zander, U., 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organ. Sci. 3 (3), 383–397.

Lee, M.T., Widener, S.K., 2016. The performance effects of using business intelligence systems for exploitation and exploration learning. J. Inf. Syst. http://dx.doi.org/10.2308/isys-51298.
Lee, J., Elbashir, M.Z., Mahama, H., Sutton, S.G., 2014. Enablers of top management team support for integrated management control systems innovations. Int. J. Account. Inf. Syst. 51 (1), 1–25.
Leidner, D.E., Elam, J.J., 1995. The impact of executive information systems on organizational design, intelligence, and decision making. Organ. Sci. 6 (6), 645–664.
Liang, H., Saraf, N., Hu, Q., Xue, Y., 2007. Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management. MIS Q. 31 (1), 59–87.
Libby, T., Lindsay, R.M., 2010. Beyond budgeting or budgeting reconsidered? A survey of North American budgeting practice. Manag. Account. Res. 21 (1), 56–75.
MacKinnon, D.P., Lockwood, C.M., Williams, J., 2004. Confidence limits for the indirect effect: distribution of the product and resampling methods. Multivar. Behav. Res. 39 (1), 99–128.
Maiga, A.S., Nilsson, A., Jacobs, F.A., 2013. Extent of managerial IT use, learning routines, and firm performance: a structural equation modeling of their relationship. Int. J. Account. Inf. Syst. 14 (4), 297–320.
Malmi, T., Brown, D.A., 2008. Management control systems as a package — opportunities, challenges and research directions. Manag. Account. Res. 19 (4), 287–300.
Mata, F.J., Fuerst, W.L., Barney, J.B., 1995. Information technology and sustained competitive advantage: a resource-based analysis. MIS Q. 19 (4), 487–505.
Mintzberg, H., 1978. Patterns in strategy formation. Manag. Sci. 24 (9), 934–948.
Mithas, S., Ramasubbu, N., Sambamurthy, V., 2011. How information management capability influences firm performance. MIS Q. 35 (1), 237–256.
Moore, D.L., Tarnai, J., 2002. Evaluating nonresponse error in mail surveys. In: Groves, R.M., Dillman, D.A., Eltinge, J.L., Little, R.J.A. (Eds.), Survey Nonresponse. Wiley, New York, pp. 197–211.
Naranjo-Gil, D., Hartmann, F., 2007. Management accounting systems, top management team heterogeneity and strategic change. Acc. Organ. Soc. 32 (7), 735–756.
Nelson, R.R., Winter, S.G., 1982. An Evolutionary Theory of Economic Change. Belknap Press, Cambridge, M.A.
Netemeyer, R.G., Bearden, W.O., Sharma, S., 2003. Scaling Procedures: Issues and Applications. Sage, Thousand Oaks.
Nonaka, I., 1994. A dynamic theory of organizational knowledge creation. Organ. Sci. 5 (1), 14–37.
Nunnally, J.C., 1978. Psychometric Theory. McGraw-Hill, New York.
Oh, W., Pinsonneault, A., 2007. On the assessment of the strategic value of information technologies: conceptual and analytical approaches. MIS Q. 31 (2), 239–265.
Otley, D.T., Berry, A.J., 1980. Control, organisation and accounting. Acc. Organ. Soc. 5 (2), 231–244.
Peng, J., Viator, R.E., Buchheit, S., 2007. An experimental study of multidimensional hierarchical accounting data: drill-down paths can influence economic decisions. J. Inf. Syst. 21 (2), 69–86.
Podsakoff, P.M., Organ, D.W., 1986. Self-reports in organizational research: problems and prospects. J. Manag. 12 (4), 531–544.
Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88 (5), 879–903.
Podsakoff, P.M., MacKenzie, S.B., Podsakoff, N.P., 2012. Sources of method bias in social science research and recommendations on how to control it. Annu. Rev. Psychol. 63, 539–569.
Popovič, A., Hackney, R., Coelho, P.S., Jaklič, J., 2012. Towards business intelligence systems success: effects of maturity and culture on analytical decision making. Decis. Support. Syst. 54 (1), 729–739.
Preacher, K.J., Hayes, A.F., 2008. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behav. Res. Methods 40 (3), 879–891.
Rai, A., Patnayakuni, R., Seth, N., 2006. Firm performance impacts of digitally enabled supply chain integration capabilities. MIS Q. 30 (2), 225–246.
Ravichandran, T., Lertwongsatien, C., 2005. Impact of information systems resources and capabilities on firm performance: a resource-based perspective. 23rd International Conference on Information Systems, Barcelona, Spain.
Ray, G., Muhanna, W.A., Barney, J.B., 2005. Information technology and the performance of the customer service process: a resource-based analysis. MIS Q. 29 (4), 625–652.
Ringle, C.M., Wende, S., Will, S., 2005. Smart PLS 2.0 (M3) Beta. Hamburg University of Technology, Hamburg.
Ringle, C.M., Sarstedt, M., Straub, D.W., 2012. Editor's comments: a critical look at the use of PLS-SEM in MIS quarterly. MIS Q. 36 (1), iii–xiv.
Shollo, A., Galliers, R.D., 2015. Towards an understanding of the role of business intelligence systems in organisational knowing. Inf. Syst. J. http://dx.doi.org/10.1111/isj.12071.
Shrout, P.E., Bolger, N., 2002. Mediation in experimental and nonexperimental studies: new procedures and recommendations. Psychol. Methods 7 (4), 422–445.
Simons, R., 1990. The role of management control systems in creating competitive advantage: new perspectives. Acc. Organ. Soc. 15 (1), 127–143.
Simons, R., 1991. Strategic orientation and top management attention to control systems. Strateg. Manag. J. 12 (1), 49–62.
Simons, R., 1994. How new top managers use control systems as levers of strategic renewal. Strateg. Manag. J. 15 (3), 169–189.
Simons, R., 1995. Levers of Control: How Managers Use Innovative Control Systems to Drive Strategic Renewal. Harvard University Press, Boston.
Simons, R., Davila, A., Kaplan, R.S., 2000. Performance Measurement and Control System for Implementing Strategy. Prentice Hall, Upper Saddle River, N.J.
Taylor, A.B., MacKinnon, D.P., Tein, J.Y., 2008. Tests of the three-path mediated effect. Organ. Res. Methods 11 (2), 241–269.
Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strateg. Manag. J. 18 (7), 509–533.
Tessier, S., Otley, D., 2012. A conceptual development of Simons' levers of control framework. Manag. Account. Res. 23 (3), 171–185.
Thomas, J.B., Sussman, S.W., Henderson, J.C., 2001. Understanding "strategic learning": Linking organizational learning, knowledge management and sense making. Organ. Sci. 12 (3), 331–345.
Tourangeau, R., Rips, L.J., Rasinski, K., 2000. The Psychology of Survey Response. Cambridge University Press, Cambridge.
Vandenbosch, B., 1999. An empirical analysis of the association between the use of executive support systems and perceived organizational competitiveness. Acc. Organ. Soc. 24 (1), 77–92.
Vandenbosch, B., Higgins, C.A., 1995. Executive support systems and learning: a model and empirical test. J. Manag. Inf. Syst. 12 (2), 99–131.
vom Brocke, J., Braccini, A.M., Sonnenberg, C., Spagnoletti, P., 2014. Living IT infrastructures — an ontology-based approach to aligning it infrastructure capacity and business needs. Int. J. Account. Inf. Syst. 15 (3), 246–274.
Wade, M., Hulland, J., 2004. The resource-based view and information systems research: review, extension and suggestions for future research. MIS Q. 28 (1), 107–142.
Wetzels, M., Odekerken-Schröder, G., van Oppen, C., 2009. Using PLS path modeling for assessing hierarchial construct models: guidelines and empirical illustration. MIS Q. 33 (1), 177–195.
Widener, S.K., 2007. An empirical analysis of the levers of control framework. Acc. Organ. Soc. 32 (7), 757–788.
Wold, H., 1982. Soft modeling: the basic design and some extensions. Systems Under Indirect Observations: Causality, Structure, Prediction. K. G. Joreskog and H. Wold, Amsterdam, North-Holland, pp. 1–54.
Yigitbasioglu, O.M., Velcu, O., 2012. A review of dashboards in performance management: implications for design and research. Int. J. Account. Inf. Syst. 13 (1), 41–59.