AN EMPIRICAL STUDY OF BUSINESS INTELLIGENCE IMPACT ON CORPORATE PERFORMANCE MANAGEMENT

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AN EMPIRICAL STUDY OF BUSINESS INTELLIGENCE IMPACT ON CORPORATE PERFORMANCE MANAGEMENT

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Abstract

Business intelligence technologies have received much attention recently from both academics and practitioners. However, the impact of business intelligence (BI) on corporate performance management (CPM) has not yet been investigated. To address this gap, we conducted a large-scale survey collecting data from 337 senior managers. Partial least square method was employed to analyse the survey data. Findings suggest that the more effective the BI implementation, the more effective the CPM-related planning and analytic practices. Interestingly, size and industry sector do not influence the relationships between BI effectiveness and the CPM. This research offers a number of implications for theory and practice.

Keywords: Business intelligence, Corporate performance management, Empirical Study.
1. INTRODUCTION

In today’s competitive business environments, firms need to stay ahead of their competitors by actively measuring, monitoring, and analysing their performance (Vuksic et al. 2013). One way which firms are now measuring their performance is through the use of corporate performance management (CPM) systems. CPM, which is also known by many other terms such as business performance management or enterprise performance management, can be viewed as a combination of management practices and technologies that enable business performance (Frolick & Ariyachandra 2006). Although one critical set of technologies, business intelligence (BI) has often been linked with CPM (Clark et al. 2007), yet academic studies examining how BI influences CPM remain sparse (Vuksic et al. 2013). The growing interest in BI has attracted the attention of scholars who have examined, among other topics, the impact of BI on operational processes (Elbashir et al. 2008), critical success factors for BI, (Yeoh & Koronios 2010), BI best practices (Wixom & Watson 2010), and BI maturity models (Dinter 2012; Lahrmann et al. 2011). Nevertheless, there is still limited BI-related study that explicitly explores the impact of BI on corporate performance management.

BI is seen as a broad category of applications that extract and transform data from source systems, facilitate data visualisation and allow users to select subsets of data along different dimensions (Chen et al. 2012). Our aim in this study is not to explore the full gamut of technologies that might be considered BI, but to examine the impact of commonly used BI technologies on CPM, in particular the CPM-related management practices which include planning, measurement, and analysis (Turban et al. 2011). In fact, not all BI initiatives are successful (Ko & Abdullaev 2007) and that the ways in which organisations apply the various management practices varies (Stenfors et al. 2007). Thus, this research examines the effectiveness of BI implementation relative to the effectiveness of the CPM-related management practices.

This study will make a significant contribution to both research and practice. First, this research contributes to the growing Information Systems (IS) literature which aims to examine the value of investing in information technology (IT). IS practitioners and researchers have often questioned the added value of the amount of investments spent by firms on IT, and the business value of IT has recently been a subject of intensive debate (Melville et al., 2004). In particular, Melville et al.’s (2004) IT business value model asserts that IT integrates with other complementary organisational resources to improve business processes, which in turn improves organisational performance. The authors suggest that sustained theorising on the value of IT to organisations must include a definition of the types of IT and the complementary resources involved. Studies have examined the value of various enterprise information systems such as Customer Relationship Management (CRM), Supply Chain Management (SCM), and Enterprise Resource Planning (ERP) systems (Hendriks et al. 2007). These studies have examined IT value and the organisation’s performance using firms’ stock prices. Although stock value can provide a general indicator of a firm’s performance, it does not illuminate the specific processes that might be involved such as marketing, human resource or supply chain management. Similarly, Elbashir et al. (2008) explored the impact of BI on operational processes, but did not examine the degree to which complementary resources, such as the organisation’s CPM-related management practices, influenced the impact of BI systems.

This research therefore extends previous BI value studies by examining the relative impact of BI within a framework of CPM-related management practices. Our systemic view builds on prior research within this domain but recognises the evolution of BI to include analytics (Chen et al., 2012). In addition, we do not assume that BI or the complementary CPM-related management practices are implemented with an equal degree of effectiveness; rather, we explicitly explore the relationships among the tools and practices based on their perceived relative effectiveness. In practical terms, the research identifies the roles that BI plays in supporting CPM-related management practices enabling IT practitioners to better understand the influence of BI technologies across the CPM cycle. The remainder of this article has been structured as
follows. The next section reviews the related work and develops research hypotheses for the study. The third section outlines the research method before presenting the research results. In the subsequent sections, the implications for theory and practice are discussed. Then followed by the conclusion and research contribution, and finally proposals for further research.

2. RESEARCH BACKGROUND AND HYPOTHESES

The management practices involved in CPM cycle typically includes planning, measurement, and analysis (Turban et al. 2011). Various authors acknowledge the fact that technology is needed to support CPM (Bose 2006; Elbashir et al. 2008; Wixom et al. 2008). Traditionally, BI is thought to contribute to the measurement and analysis practices by enhancing access to performance information (Müller et al. 2010; Ranjan 2008), however, since BI supports decision making and because decisions are made during each step of the CPM cycle, BI plays a role in all of the management practices involved in CPM.

It has been argued that many BI implementations fail to influence decision making in organisations (Ko & Abdullaev 2007), and that in fact, many such implementations fail altogether due to fundamental miscommunication of information needs between IT professionals and business users. Similarly, the various management practices involved in CPM are implemented differently in organisations (Stenfors et al. 2007), and in many cases, positive linkages between these practices and organisational performance has not been empirically established. For example, the literature is equivocal on the impact of strategic planning (Greenley 1994; Titus et al. 2011), performance measurement (Burkert et al. 2010), and process management (Kolbacher 2010).

These findings suggest that the degree to which organisations realise value from their BI investments is likely dependent on the effectiveness to which the CPM-related management practices supported by BI are conducted. Studies attempting to link BI directly to organisational performance tend to ignore the interdependencies of CPM management practices. While the literature does address BI maturity (Dinter 2012; Larhmann et al. 2011), a construct whose underlying assumption is associated with the degree of effectiveness and therefore value realised from BI systems, our review of the literature uncovered limited studies addressing the relative effectiveness of BI related to specific CPM management practices.

Accordingly, this research situates BI within the context of three CPM-related management practices stating that the more effective the BI implementation, the more effective the CPM-related management practices, and following the logic of the IT business value model (Melville et al., 2004), that an improvement in the management practices leads to improved process effectiveness.

Figure 1: Research framework
The research framework adopted for this study is depicted in Figure 1. The framework proposes that BI directly supports measurement, analytics and planning. Given the fact that plans define objectives and given the fact that measures are typically developed in order to track progress against these objectives, it follows that planning also influences the development of measures. Analytics involves the use of measures to make informed decisions. Therefore the framework considers that measurement effectiveness influences analytics effectiveness and the entire framework influences organisational performance by improving the execution of business processes (Atkinson et al. 1997, Elbashir et al. 2008; Mooney et al. 1996). The research framework and the associated hypotheses are discussed in the following sections.

2.1 The Role of BI

BI technologies are specifically designed to systematically report on performance (Chen & Siau 2012; Negash 2004). No one technology comprises a BI system; rather, most systems include a number of different technological components (Baars & Kemper 2008; Ramakrishnan et al. 2012). Prior literature, however, suggests that online analytic processing (OLAP) is a core technology that allows decision-makers to view data from a variety of perspectives (Baars & Kemper 2008; Wixom, et al. 2008). For example, a user might want to examine sales of a specific product then drill-down to better understand sales of this product in a specific region or over a specific time frame. This multi-dimensional exploration of performance information is complemented by tools that facilitate the distribution of online reports (some that also feature “drill to detail” capabilities), as well as scorecards or dashboards (Bose 2006). While reports can feature any view of the data needed by a manager, scorecards and dashboards provide summary information regarding company performance in a visual format that allows for variance analysis by decision-makers.

Because BI enables exploration of performance data by end users (as opposed to the situation where users request reports from the IT department), it provides faster and more accurate access to performance measures (Müller et al. 2010; Negash 2004). It can also facilitate analysis of the data and thus improve managers’ ability to extract meaning from the information provided (Negash 2004; Watson & Wixom 2007; Sahay & Ranjan 2008). It is therefore possible that BI impacts the CPM cycle in a number of ways. First, it enables rapid and accurate delivery of performance information that directly impacts planning and measurement. BI may also provide additional data-manipulation functionality and thus directly impact analytics. Given the fact that the ultimate organisational performance driver is the effectiveness of operational business processes (Elbashir et al. 2008; Mooney et al. 1996) because these processes lead directly to the accomplishment of secondary organisational objectives such as customer satisfaction or supply-chain efficiency (Atkinson et al. 1997), we position operational processes as the ultimate dependent variable.

Despite the commonly-held view that BI technologies are meant to influence decision making within organisations, the specific consideration of “analytics” within the BI context is a relatively new phenomenon. For example, Elbashir et al. (2008) found that BI influenced internal process efficiency, understanding of customers, and business supplier partnerships. Similarly, Wixom et al. (2008) and Watson (2009) highlight the impact of BI tools on improving managers’ understanding of organisational outcomes. The ways in which analytics plays in role in these processes however were not explored.

In some cases, BI tools could be directly integrated into an operational process (Elbashir et al. 2008) thus automating some parts of the process (for example, credit risk assessment). In other cases, BI is used to monitor outputs of a process or series of processes. These outputs are often linked to business objectives, which are aligned with an organisation’s strategy. Therefore, within a CPM cycle, BI tools provide accurate up-to-date information on the accomplishment of objectives allowing managers to analyse performance gaps and take corrective action. These actions might include the modification of objectives (i.e., adjusting plans based on actual performance), or they might include taking steps to improve processes to better accomplish established targets. The point is that, while in some situations, BI might be directly integrated into a process to automate certain types of decisions, in other situations, BI provides
information to enable monitoring of the outputs of a process. An analysis of the information thus provided
permits managers to take actions to modify plans, or to improve process efficiency and effectiveness.

We therefore examine the following hypotheses:

H1a – Business intelligence positively influences planning effectiveness;
H1b – Business intelligence positively influences measurement effectiveness;
H1c – Business intelligence positively influences analytics effectiveness; and
H1d – Business intelligence indirectly influences process effectiveness through analytics and
planning.

2.2 Planning

The management of organisational performance starts with an assessment of the business environment
followed by definition of the primary (i.e., strategic) and secondary (i.e., operational) objectives
(Atkinson et al. 1997). Effective planning enables alignment both vertically and horizontally throughout
the organisation (Franco-Santos & Bourne 2005) by providing overall guidance for employees who
develop and implement operational processes. While the impact of planning on operational processes has
not been the subject of much empirical research, one such study (Gates 1999) found that 52% of a sample
of 113 companies showed improved financial performance attributable to the linking of strategic
objectives to operational activities across different business units. Furthermore, the research suggests that
firms that use validated causal models linking strategic objectives to operational activities outperform
other companies (Ittner et al. 2003). Therefore, it is reasonable to propose that an effective planning
process can influence the effectiveness of operational processes by guiding the design of strategically
consistent process activities. Accordingly, we test the following hypothesis:

H2 – Effective planning positively influences process effectiveness.

In addition to influencing process effectiveness, it has been argued that planning helps to define key
performance measures (Gates 1999; Kaplan & Norton 1997). These measures serve as a monitoring tool
that allows managers to control operational process activities that ultimately lead to positive financial
results (Atkinson et al. 1997; Franco-Santos & Bourne 2005). For example, if the organisation competes
on the basis of product differentiation, the use of measures can help to ensure that employees and
managers focus their operational processes on activities that are consistent with this competitive strategy.
Accordingly, we test the following hypothesis:

H3 – Effective planning positively influences measurement effectiveness.

2.3 Analytics

Business analytics, the use of data to make informed decisions, is rapidly becoming a key competitive
weapon for many organisations (Davenport 2006). As outlined in the CPM cycle depicted in Figure 1, the
raw material for analytic processes includes performance measures defined within the CPM system. Most
often, these measures are used in “variance analysis”; managers examine actual results in comparison
with expected results and make changes to organisational activities in order to improve performance. As
discussed earlier, BI helps in delivering measurement information to managers. Changes made to
organisational activities, however, depend on the analytic activities of these managers. In other words,
one measures are available, managers must actually use them effectively in order to gain insight into
what changes are required (Braam & Nijssen 2004). Accordingly, we suggest that analytics is most
closely related to process effectiveness and we therefore test the following hypothesis:

H4 – Analytics effectiveness positively influences process effectiveness.
3. RESEARCH METHOD

3.1 Data Collection

This study was conducted in collaboration with two industry partners, PricewaterhouseCoopers (PwC) and the Canadian Advanced Technology Association (CATA). These industry partners collectively represent more than 50 years of experience in the field of performance management and therefore they confirmed face and content validity of the survey used in collecting data. The study used an online survey method for data collection. Survey questions were developed based on the research hypotheses and on feedback from the industry partners. Survey respondents were recruited through e-mail invitations distributed to 1,300 senior managers from PwC’s and CATA’s databases. A total of 337 complete responses were received and analysed using the Partial Least Squares (PLS) method.

3.2 Measures

The variables in this research were operationalized by first defining (based on the literature and on the experience of industry partners) the methods used for planning and analytics, tools used for business intelligence and the types of measures used by organisations. Exploratory factor analysis (EFA) was then employed to reduce the number of variables, followed by confirmatory factor analysis using SmartPLS.

As noted in the hypotheses, we were interested in whether the effectiveness of each of the various practices contributed to the effectiveness of the other practices as well as their overall impact on operational process effectiveness. Therefore, the survey asked respondents to record their perceptions of the effectiveness of the various practices on a scale of 1 to 7. Tables 1 and 2 provide the results of the EFA.

<table>
<thead>
<tr>
<th>Planning</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cronbach’s alpha</td>
<td>.90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effective use of vision</td>
<td>.680</td>
<td>.147</td>
<td>.085</td>
</tr>
<tr>
<td>Effective use of budgets</td>
<td>.626</td>
<td>.171</td>
<td>.162</td>
</tr>
<tr>
<td>Effective use of business cases</td>
<td>.748</td>
<td>.262</td>
<td>.186</td>
</tr>
<tr>
<td>Effective use of business plans</td>
<td>.757</td>
<td>.265</td>
<td>.186</td>
</tr>
<tr>
<td>Effective use of SWOT analysis</td>
<td>.761</td>
<td>.248</td>
<td>.294</td>
</tr>
<tr>
<td>Effective use of strategy maps</td>
<td>.735</td>
<td>.384</td>
<td>.314</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Business Intelligence</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cronbach’s alpha</td>
<td>.91</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effectiveness: BI implementation</td>
<td>.262</td>
<td>.770</td>
<td>.326</td>
</tr>
<tr>
<td>Effectiveness: business process management tools implementation</td>
<td>.332</td>
<td>.747</td>
<td>.291</td>
</tr>
<tr>
<td>Effectiveness: database tools implementation</td>
<td>.227</td>
<td>.786</td>
<td>.216</td>
</tr>
<tr>
<td>Effectiveness: online reports implementation</td>
<td>.097</td>
<td>.774</td>
<td>.119</td>
</tr>
<tr>
<td>Effectiveness: dashboard/scorecard software implementation</td>
<td>.199</td>
<td>.709</td>
<td>.261</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Analytics</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cronbach’s alpha</td>
<td></td>
<td></td>
<td>.85</td>
</tr>
<tr>
<td>Effective use of variance analysis (plan/budget)</td>
<td>.274</td>
<td>.057</td>
<td>.508</td>
</tr>
<tr>
<td>Effective use of driver-based forecasting</td>
<td>.282</td>
<td>.323</td>
<td>.766</td>
</tr>
<tr>
<td>Effective use of alerts</td>
<td>.177</td>
<td>.142</td>
<td>.819</td>
</tr>
<tr>
<td>Effective use of rolling forecasts</td>
<td>.170</td>
<td>.307</td>
<td>.754</td>
</tr>
<tr>
<td>Effectiveness data mining</td>
<td>.242</td>
<td>.328</td>
<td>.810</td>
</tr>
</tbody>
</table>

Principal Components Analysis with Varimax rotation (Kaiser normalization)

Table 1: Exploratory factor analysis of planning, analytics and business intelligence
Interpretation of the factors set out in Table 1 confirms the specific practices that are grouped into each of the CPM stages of planning, measurement and analytics. For example, the “planning” construct includes the six practices listed under Factor 1. Similarly, Factor 2 shows groupings related to the use of various technologies. As discussed earlier, BI in this case represents OLAP capability (based on feedback from the test phase of the survey, the term OLAP was not well understood and thus BI was used instead). As can be seen, a variety of other tools such as databases, online reports, dashboards and scorecards, which are often grouped under the rubric of “BI,” are also included in this factor. The final factor we named “analytics.” Technically speaking, analytics is defined as the use of data to make informed decisions (Davenport 2006). The first four measures in this construct (variance analysis, driver-based forecasting, alerts and rolling forecasts) are all related to comparing actual performance with planned performance. The last item, data mining, is a more detailed use of data to explore hidden patterns.

As shown in Table 2, the measurement construct was reduced to the four variables noted in Factor 1 because they loaded significantly on this factor, with little to no cross loadings and a Cronbach’s alpha of 0.83. From a practical perspective, these measures also more or less mirror the four perspectives of a standard balanced scorecard (BSC) (Kaplan & Norton 2000). The logic of the BSC is that financial results are driven by the degree to which customers’ needs are satisfied (customer service), which in turn is driven by internal process effectiveness (employee performance). Employee satisfaction would be associated with the “learning and growth” perspective of the BSC. Factor 2 focuses on customer communication, but the Cronbach’s alpha was 0.67, below the accepted cut off of 0.70 and so it was not included in the study. Factor 3 had only one item with cross loadings below 0.40, and thus it was eliminated from the study.

The dependent variable was defined as “process effectiveness” as measured by items situated in different sections of the survey. The first asked respondents to identify, on a scale of 1 to 7, how successful their companies were in executing processes. The second asked them to identify (using the same scale) how effective they were at quality management. The third asked them to identify the overall effectiveness of their processes. The Cronbach’s alpha for this scale was 0.715. As can be seen in Table 3, the PLS algorithm found two measures strongly related to this factor: overall process effectiveness and quality management effectiveness. The third, the degree of success in process execution, showed a loading of 0.40, which was considered too low to be included in the analysis. Based on the two measures, the

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cronbach’s alpha</td>
<td>.813</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Financial results</td>
<td>.710</td>
<td>-.001</td>
<td>.158</td>
</tr>
<tr>
<td>Customer service</td>
<td>.738</td>
<td>.332</td>
<td>.159</td>
</tr>
<tr>
<td>Employee satisfaction</td>
<td>.763</td>
<td>.116</td>
<td>.160</td>
</tr>
<tr>
<td>Employee performance</td>
<td>.761</td>
<td>-.003</td>
<td>.324</td>
</tr>
<tr>
<td>Cronbach’s alpha</td>
<td></td>
<td>0.67</td>
<td></td>
</tr>
<tr>
<td>Advertising</td>
<td>-.008</td>
<td>.778</td>
<td>.138</td>
</tr>
<tr>
<td>Branding</td>
<td>.258</td>
<td>.834</td>
<td>.006</td>
</tr>
<tr>
<td>Cronbach’s alpha</td>
<td></td>
<td></td>
<td>NA</td>
</tr>
<tr>
<td>Corporate social responsibility</td>
<td>.163</td>
<td>.488</td>
<td>.537</td>
</tr>
<tr>
<td>Pricing</td>
<td>.608</td>
<td>.436</td>
<td>.008</td>
</tr>
<tr>
<td>Customer satisfaction</td>
<td>.784</td>
<td>.415</td>
<td>-.003</td>
</tr>
<tr>
<td>Innovation</td>
<td>.419</td>
<td>.393</td>
<td>.417</td>
</tr>
<tr>
<td>Marketing</td>
<td>.369</td>
<td>.543</td>
<td>.433</td>
</tr>
<tr>
<td>Acquisitions</td>
<td>-.002</td>
<td>.180</td>
<td>.836</td>
</tr>
<tr>
<td>Process effectiveness</td>
<td>.512</td>
<td>.006</td>
<td>.644</td>
</tr>
<tr>
<td>Cost</td>
<td>.528</td>
<td>-.007</td>
<td>.583</td>
</tr>
</tbody>
</table>

Note: Principal Components Analysis with Varimax rotation (Kaiser normalization)

Table 2: Exploratory factor analysis of measurement variables
composite reliability was calculated at 0.98, thus suggesting that these measures captured the same aspects of the construct. Accordingly, the process success measure was included to better reflect the construct (Hair et al. 2014).

<table>
<thead>
<tr>
<th>Factor loadings</th>
<th>Standard error</th>
<th>T-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alerts</td>
<td>0.7739</td>
<td>0.0616</td>
</tr>
<tr>
<td>Driver-based forecasting</td>
<td>0.8713</td>
<td>0.0387</td>
</tr>
<tr>
<td>Data mining</td>
<td>0.824</td>
<td>0.0479</td>
</tr>
<tr>
<td>Rolling forecasts</td>
<td>0.7736</td>
<td>0.0531</td>
</tr>
<tr>
<td>Variance analysis</td>
<td>0.9224</td>
<td>0.0163</td>
</tr>
</tbody>
</table>

| Analytics (AVE=0.70, composite reliability =0.92) |
| Business Intelligence (AVE=0.53, composite reliability=0.82) |
| Measurement (AVE=0.76, composite reliability=0.90) |
| Planning (AVE=0.52, composite reliability=0.81) |
| Process effectiveness (AVE=0.65, Composite Reliability=0.83) |

Table 3: Factor loadings

3.3 Validity and Reliability

Convergent validity is confirmed when measurement items load with a significant t-value on their related latent constructs (Gefen & Straub 2005). Table 3 provides the factor loadings for all constructs showing that their measures do in fact load significantly (p<=0.05).

Discriminant validity is demonstrated when the average variance extracted (AVE) related to the latent construct is at least 0.50 and when the square root of the AVE is larger than the correlation of the construct with any other construct. Tables 3 and 4 confirm that this is indeed the case. Hence, based on these assessments, it is obvious that the constructs demonstrate adequate reliability and validity.

<table>
<thead>
<tr>
<th>Analytics</th>
<th>Business Intelligence</th>
<th>Measurement</th>
<th>Planning</th>
<th>Process</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.83</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.4873</td>
<td>0.71</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.1384</td>
<td>0.2156</td>
<td>0.79</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5162</td>
<td>0.448</td>
<td>0.1776</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td>0.4763</td>
<td>0.2794</td>
<td>0.1221</td>
<td>0.3693</td>
<td>0.81</td>
</tr>
</tbody>
</table>

Note: Diagonals display the square root of the AVE.

Table 4: Latent variable correlations
Furthermore, factors should load more highly on their related constructs than on any other construct. Gefen and Straub (2005) suggest that item loadings on the related construct should be larger than the loadings on any other construct. The data analysis also indicates that this is the case for all constructs.

3.4 Control Variables

Research suggests that organisational size (Hoque & James 2000) and industry sector (Dehning & Richardson 2002; Elbashir et al. 2008) can influence the ways in which CPM is employed in organisations. Accordingly, size and industry sector are considered as control variables for this study. For organisation size, we use the number of employees as the basis for creating categories of small (less than 250 employees) and large (250 or more employees) organisations. For the sector variable, we collapsed the various industry sectors represented into service and non-service based on the argument that firms differ most markedly in their use of CPM systems along this line of delineation (Elbashir et al. 2008).

4. RESEARCH RESULT

Figure 2 provides the results of the PLS analysis. Hypothesis 1a, which posits that the more effective the BI implementation, the more effectively managers plan, is supported \( r=0.45, p<0.001 \). Similarly, hypothesis 1c, which posits that BI effectiveness positively influences analytics effectiveness, is supported \( r=0.48, p<0.001 \). Hypothesis 1d, which posits that BI effectiveness indirectly influences process effectiveness through planning and analytics, is partially supported. The data suggest that BI effectiveness indirectly influences operational processes through analytics \( r=0.27 \), but hypothesis 2 (that planning influences process effectiveness) is not supported by the data; therefore we see no indirect effect of BI through planning. Similarly, planning was not shown to be related to measurement effectiveness; therefore, hypothesis 3 is not supported. Hypothesis 4 (that analytics influences process effectiveness) is, however, supported by the data \( r=0.39, p<0.001 \).

To test the mediation effect of BI on process effectiveness through analytics, we follow the bootstrapping recommendations of Hair et al. (2014). In this approach, we first confirm that BI is related to process effectiveness in absence of the mediator. The estimation returns a weight of 0.270 and a \( t \)-value of 3.0 indicating that BI is indeed significantly related to process effectiveness in the absence of the analytics variable. Both paths BI to analytics and analytics to process should also be significant which is the case (weights and \( t \)-values of 0.48, 4.68 and 0.39, 2.97 respectively). Finally, the indirect path from BI to process effectiveness (defined by the product of 0.49 and 0.39 = 0.186) should also be significant. This calls for an estimation of the standard deviation of indirect effect estimated from all bootstrap samples (which serves as the bootstrap standard error) which in this case, was 0.49. The \( t \)-value is calculated by dividing the indirect effect by the standard error which returns a value of 3.79 indicating that the indirect effect is indeed significant. Finally, we calculate the total effect by adding direct and indirect effects \( (0.270+0.186=0.450) \) and calculate the percentage of variance accounted for by the indirect effect \( (0.186/0.450=0.41) \). Thus, 41% of the total effect of BI on process effectiveness is accounted for by analytics.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Independent variable</th>
<th>Dependent variable</th>
<th>Path coefficient</th>
<th>Supported?</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a</td>
<td>BI</td>
<td>Planning effectiveness</td>
<td>0.45***</td>
<td>Yes</td>
</tr>
<tr>
<td>H1b</td>
<td>BI</td>
<td>Measurement effectiveness</td>
<td>0.17</td>
<td>No</td>
</tr>
<tr>
<td>H1c</td>
<td>BI</td>
<td>Analytics effectiveness</td>
<td>0.48***</td>
<td>Yes</td>
</tr>
<tr>
<td>H1d</td>
<td>BI (through analytics)</td>
<td>Process effectiveness</td>
<td>0.0.270</td>
<td>Partially</td>
</tr>
<tr>
<td>H2</td>
<td>Effective planning</td>
<td>Process effectiveness</td>
<td>0.168</td>
<td>No</td>
</tr>
<tr>
<td>H3</td>
<td>Effective planning</td>
<td>Measurement effectiveness</td>
<td>0.101</td>
<td>No</td>
</tr>
<tr>
<td>H4</td>
<td>Analytics effectiveness</td>
<td>Process effectiveness</td>
<td>0.39***</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*** Significant at \( p \leq 0.01 \)

Table 5: Results of hypothesis testing
In addition, we examined potential heterogeneity of the findings using the control variables identified earlier in this paper by comparing the outer loadings of the measurement model subsets of small/large, service/non-service organisations. A comparison of the regression weights was then performed using the PLS-MGA approach (Hair et al. 2014). No significant differences were noted between or among the segments.

5. DISCUSSION

The following hypotheses were supported by the survey data:
- BI effectiveness positively influences planning effectiveness;
- BI effectiveness positively influences analytics effectiveness;
- BI effectiveness indirectly positively influences operational process effectiveness, through analytics; and
- Analytics effectiveness positively influences operational process effectiveness.

The research finding suggests that BI delivers data which enables the planning process. For example, BI reports provide historical data that directly inform the setting of objectives for subsequent planning periods. Planning practices tend to be information rich in that managers often conduct external and internal environmental scans in order to test past activities against planned results and then use the findings to inform objective setting. Therefore, this specific practice is highly information intensive and can benefit greatly from the functionalities available in many BI products.

The data also show that BI effectiveness positively influences analytics. Clearly, BI helps to deliver data quickly and accurately to decision-makers, but now many tools also provide the means to better manipulate data to provide greater insight. For example, two of the key analytic processes involved in managing performance are variance analysis (comparing actual versus planned) and cause-effect analysis.
(understanding the influence of specific processes on organisational outcomes). Cause-effect analysis helps to define the processes that most significantly impact organisational outcomes thus allowing for process improvement. BI tools such as dashboards and scorecards allow for rapid variance analysis, while the use of statistical tools (such as data mining) permits sophisticated analysis of patterns of relationships within each data set.

The survey finding indicates that, through analytics, BI has an indirect impact on operational process effectiveness. As discussed above, the fact that data are available within the organisation does not in and of itself improve processes. It is the analysis of data that defines specific improvement opportunities. The finding that BI indirectly impacts process effectiveness is consistent with this reasoning.

On the other hand, the result suggests that neither BI nor planning effectiveness influences measurement effectiveness. In the case of measurement, one of the salient points in the literature on this topic is whether broad-based measures or measures focused on value drivers are more effective (Ittner et al. 2003). BI does not influence measurement selection, though it does influence the speed at which measures can be delivered to decision-makers. Therefore, the fact that BI was not found to be related to measurement effectiveness suggests that the types of measures used by an organisation might be more important than the ways in which they are delivered.

The finding that planning effectiveness does not influence measurement effectiveness is surprising. It has been suggested, however, that whether organisations adopt a broad or narrow set of measures depends on organisational strategy. Organisations using a prospector strategy might do better with broad-based measures (Abernethy & Guthrie 1994), in which case planning might not necessarily be directly linked to measures. Organisations following a defender strategy might, on the other hand, use more focussed measures since their environment might be less turbulent. This study did not distinguish the different strategic foci of the organisations involved. It is therefore possible that this finding reflects the fact that, since most contemporary organisations operate in relatively turbulent operating environments, many might simply capture as many measures as possible thus attenuating the link between planning and measurement.

Neither measurement nor planning effectiveness was shown to influence operational process effectiveness. It might seem reasonable that measurement does not directly influence process effectiveness because it is really the decisions made by managers that drive process changes. These decisions are based on analysing the measures to better understand what factors drive success. As will be discussed later, analytics was shown to be directly related to operational process effectiveness suggesting that, as hypothesised, the effectiveness of analysis influences process, measurement effectiveness itself does not necessarily lead to organisational improvement.

The fact that planning effectiveness was not found to influence process effectiveness could be related to the level of this study. Those responding to the survey were predominantly senior managers. The view of planning at this level in the organisation might not be directly related to process effectiveness since processes tend to be linked to secondary objectives, which are typically the responsibility of middle level managers (Atkinson et al. 1997).

6. IMPLICATION

6.1 Implication for theory

It has been suggested that to better understand IT value, researchers should focus on specific types of information systems and the practices they support (Mukhopadhyay et al. 1995). Furthermore, recent studies have shown contradictory findings in regard to the relationships between investments in information systems and the value that they offer to companies (Otim et al. 2012). This study responds to
both of these issues by first operationally defining a CPM system and then empirically investigating the role of BI within this complex CPM cycle.

The first contribution of this study is that it fills a gap in the existing literature related to the value of IT implementations and investments. Previous studies examining the value of IT have either focused on general IT (Wong & Dow 2011), or on older technologies such as ERP system (Hendriks et al. 2007). This study has focused on a recent technology – BI, which is increasingly capturing the attention of scholars and practitioners due to the availability of data driven by advancement in the “Internet of Things” and Big Data. Previous IT value studies have also examined the performance of companies using stock returns, but this approach does not offer useful guidance to companies in terms of which specific aspects of company performance are influenced by IT. By examining the relationships between BI implementation and CPM effectiveness, this study provides a new perspective on the impact of BI on organisational success.

Second, the study examines relationships among a number of management practices involved in CPM. The research indicates that the degree to which BI has been effectively implemented directly influences the effectiveness of planning, measurement and analytics and indirectly influences operational process effectiveness. The implication is that BI likely provides faster and more accurate access to information thus enabling better management practices. In addition, the added analytic functionality afforded by the tools likely provides additional insights. Although the role of analytics has been mentioned in previous research, it has not been addressed as a separate sub-process within the CPM context. Research on analytic processes themselves is scarce, and there is evidence that most organisations do not pay close attention to how decisions are made using analytics (Davenport 2006). Accordingly, another contribution of the paper is the inclusion and testing of analytics as a distinct management practice within the CPM cycle. Also, this study contributes an integrated view of CPM as a system and extends previous research examining the role of BI on operational processes to the management domain.

6.2 Implication for practice

This research offers a number of implications for practice, especially for BI stakeholders who are involved in planning, reviewing or implementing BI to support CPM. BI adoption has become widespread as organisations continue to search for ways to support business performance management. Yet, it has been reported that between 70% and 80% of BI projects fail due to inadequate communication between IT and business users about the specific uses of the tools being implemented (Goodwin 2011). The view promoted in this study – that BI should be an integral part of a management system – would enable a better understanding of the specific uses to be made of the various BI tools available.

For organisations that might want to explore BI tools to support CPM, this study raises some interesting questions. Firstly, since BI is still considered to be a collection of different technologies, organisations can select a variety of tools that are to be included in the BI package. By using the CPM cycle as a guiding principle and by recognising that BI can support all steps in this cycle, BI packages can be designed with specific organisational needs in mind. Secondly, it is important to recognise that it is the use of measures in an analytic process that impact organisational performance. Therefore, assuming that the organisation has source systems in place, analytic tools are likely priority items in the BI package.

Thirdly, our hypotheses were tested in organisations of various sizes and in different industries. Our results show that, contrary to earlier studies that indicated that larger organisations or organisations from specific industries gain more from their investments in IT, size and industry sector do not appear to impact the relationships between BI effectiveness and the CPM cycle.
7. CONCLUSION

The question of the value of IT is an important one for organisations. The research trend towards assessing the impact of specific types of IT recognises that different technologies are used for different purposes. Previous research has shown that BI can influence business processes which, in turn, influence organisational performance (Elbashir et al. 2008). This study extends this line of research by exploring the impact of BI within the CPM cycle, one of first scholarly, empirical studies to do so. The study therefore contributes to bridging the gap in the empirical literature between the IS and management-accounting disciplines. The former explores the impact of various IT systems while the latter explores the components of CPM as a management-control system enabling organisational performance. In order to better appreciate the specific management practices supported by BI, such interdisciplinary examination is necessary. As for future research, a longitudinal approach is suggested to better understand the specific mechanisms through which BI supports CPM over time.

References


