HOW DOES BUSINESS ANALYTICS CONTRIBUTE TO BUSINESS VALUE?

Completed Research Paper

Peter B. Seddon
Department of Computing and Information Systems
The University of Melbourne, Australia
p.seddon@unimelb.edu.au

Dora Constantinidis
Department of Computing and Information Systems
The University of Melbourne, Australia
dorac@unimelb.edu.au

Harjot Dod
Department of Computing and Information Systems
The University of Melbourne, Australia
h.dod@student.unimelb.edu.au

Abstract

This paper presents a model, synthesized from the literature, of factors that explain how business analytics contributes to business value. It also reports results from a preliminary test of that model. The model consists of two parts: a process and a variance model. The process model depicts the analyze-insight-decision-action process through which use of an organization’s business-analytic capabilities create business value. The variance model proposes that the five factors in Davenport et al.’s (2010) DELTA model of BA success factors, six from Watson and Wixom (2007), and three from Seddon et al.’s (2010) model of organizational benefits from enterprise systems, assist a firm to gain business value from business analytics. A preliminary test of the model was conducted using data from 100 customer-success stories from vendors such as IBM, SAP, and Teradata. Our conclusion is that the model is likely to be a useful basis for future research.

Keywords: business analytics, business value, business intelligence, organizational benefits from business analytics, business-analytics success model, information orientation, pervasive BI
Introduction

Although there are many definitions of both “business analytics” and “business intelligence”, in this paper we define business analytics (BA) as the use of data to make sounder, more evidence-based business decisions, and business intelligence (BI) as the tools such as statistical and quantitative techniques, explanatory and predictive models, data warehouses, on-line analytical processing (OLAP), visualization, and data mining that enable BA (Negash 2004, Howson 2011). In the past decade, there has been massive interest worldwide in BA and therefore BI. As evidence, BI topped the list of “Technical priorities for CIOs” in Gartner’s annual global surveys of CIOs in the three of the five years, 2007-2011 (Hagerty et al. 2012, p.47). Further, the spate of multi-billion dollar takeovers of BI firms in the past five years, e.g., by Oracle (of Hyperion), IBM (of Cognos and SPSS), and SAP (of Business Objects), as well as SAP’s current touting of its high-performance analytical appliance (HANA) technology (SAP 2011) suggests that these vendors believe that BA is likely to make a major contribution to firm performance in the coming decade.

To help BA achieve its full potential, managers and researchers need to have a clear understanding of how an organization’s BA capabilities actually influence organizational performance. However, the various models that have been published to date, e.g., Wixom and Watson (2001), Davenport and Harris (2007), Watson and Wixom (2007), Clark et al. (2007), Sharma et al. (2010), Davenport et al. (2010), Isik (2010), Sabherwal and Becerra-Fernandez (2011), Elbashir et al. (2011), and Shanks and Bekmamedova (2012), are characterized more by their diversity than any emerging consensus. Therefore, the research question addressed in this paper is:

How does business analytics contribute to business value?

To answer this question, we synthesized an integrated model from the literature, then conducted a preliminary test of the explanatory power of the new model by examining the extent to which it corresponded to success stories about BA use that various BI vendors had published on their websites. The development of our model is discussed in the first part of this paper, and test results in the second.

Theory

The Business-Analytics Success Model (BASM) that we synthesized from the literature is shown in Figure 1. It consists of two mutually compatible views of how use of business analytics creates business value: a process model in Panel A, and a variance model in Panel B. Constructs for these two views are defined in Tables 1 and 2, respectively.

The Process Model in the BASM (Panel A in Figure 1)

The process model in the BASM (Panel A in Figure 1) presents a process-oriented explanation of how organizations use business analytics to create business value. It is intended to be consistent with the resource-based view of the firm (Barney 1991, 2011), the dynamic-capabilities view of the firm (Teece et al. 1997), Beer’s (1972, 1984) Viable System Model (VSM), and the IS literature on business analytics and business intelligence, particularly the work of Davenport and Harris (2007). It views organizations as being like living things, operating in a constantly changing competitive environment, that use their capabilities to produce outputs of value to key stakeholders, e.g., customers, shareholders, and employees.

The focal organization in the BASM may be an organization or any of its subunits, e.g., its divisions or departments. Within its environment, the focal organization uses its many capabilities to design, produce, and supply goods and/or services to its customers. This enables it to survive and in some cases, thrive. However, as pointed out by Beer (1972), managing the use of an organization’s capabilities requires huge amounts of information from both within and outside the organization. The BASM assumes that capabilities for analyzing this information are embedded throughout the focal organization.

1 Webster and Watson (2002) explain the difference between process and variance models and theories as follows:

“Variance theories incorporate independent variables that cause variation in dependent variables. In contrast, process theories use events and states to help explain dynamic phenomena.” (p.xix)
Panel A: Process Model (executed over and over again in different parts of the organization)

- Use Analytic Capabilities → Insight(s) → Decision(s) → Competitive Actions (that use the organization’s existing capabilities)
- Competitive Actions (that change the organization’s capabilities)
- Organizational Benefits from Analytics Use, from the perspective of Senior Management

Analytical Capabilities
- Enabling Technology
  - High-quality data
  - Integrated Business-Intelligence Platform
- Analytical People
  - Analytical executives
  - Analytical professionals
  - Analytical employees

Path 1: results in changes in, e.g., learning
Path 2: results in changes in
Path 3: results in changes in, e.g., learning

Panel B: Variance model

Long-term organizational benefits model
- Functional fit (FF)
- Overcoming organizational inertia (OOI)
- Delivering a working system (DWS)

Organizational Benefits from System Use, from the perspective of Senior Management, for this project.
- Continuous improvement
- Benefits from the previous system(s)

Short-term model: Factors driving benefits from each project
- On-going Business-Analytics Improvement Projects
- Project “n”
  - Benefits from the implementation
  - Benefits from the previous system(s)

Analytic Leadership
- Extent to which evidence-based decision making is embedded in the “DNA” of the organization
- Well-chosen targets
- Pursuit of the next well-chosen targets guides decisions about which BA-improvement projects are to be undertaken in future.

Organizational Benefits from Analytics Use, from the perspective of Senior Management

On-going Business-Analytics Improvement Projects
- Functional fit of BA tools
- Readily available high-quality data
- Analytical people
- Overcoming organizational inertia (OOI)

(post go-live)

Figure 1: Proposed Business-Analytics Success Model (BASM)

The left-hand side of Panel A relates to the use of business-analytic capabilities to produce information and insight. The right-hand side of Panel A relates to the use of the organization’s entire set of capabilities to produce business value. The single-line arrows in Panel A mean “leads to” and/or “causes”. The two block arrows labeled “enable” are intended to remind the reader that an organization must control resources and capabilities in order to use them. “Resources are “stocks of available factors that are owned or controlled by the firm,” whereas capabilities “refer to a firm’s capacity to deploy Resources, usually in combination, using organizational processes, to effect a desired end” (Amit & Schoemaker 1993, p.35).
It is those capabilities, owned or controlled by the organization, that are depicted on the lower left and lower right of Panel A of Figure 1.

**Table 1. Definition of concepts in the BASM Process Model (Figure 1, Panel A)**

<table>
<thead>
<tr>
<th>Concept*</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Use Analytic Capabilities</td>
<td>Use of business-analytic capabilities by any person or organizational unit to analyze routine and/or non-routine, internal and/or external data to support more evidence-based decision making. Howson (2011) classifies BA usage types as: query, report, analyze, visualize, and alert, and points out that people in different roles use BA in different ways.</td>
</tr>
<tr>
<td>2. Insight(s)</td>
<td>The gaining of a deep or deeper understanding of something, arising from use of business-analytic (BA) capabilities. In the simplest of cases, insight may flow simply as a result of reading a new report.</td>
</tr>
<tr>
<td>3. Decision(s)</td>
<td>Decisions flowing from insights flowing from use of BA capabilities.</td>
</tr>
<tr>
<td>4. Competitive actions that use the organization’s existing capabilities</td>
<td>Actions taken by the organization with a view to creating business value that use its existing organizational capabilities (defined in row 10). Shanks and Bekmamedova (2012) call this concept Operational use of BA capabilities.</td>
</tr>
<tr>
<td>5. Competitive actions to change the organization’s capabilities</td>
<td>Actions taken by the organization with a view to creating business value that lead to changes in its organizational capabilities (defined in row 10). The capability to perform such actions, which includes the IT department’s capability to run IT-based projects successfully, is a dynamic capability (Teece et al. 1997; Helfat et al. 2007).</td>
</tr>
<tr>
<td>6. Organizational Benefits from Analytics Use</td>
<td>see Table 2, row 20, for the definition of this concept</td>
</tr>
<tr>
<td>7. Enabling Technology</td>
<td>The hardware, software, data, processes (e.g., extract, transform and load processes), and governance capabilities that make up the organization’s business-intelligence platform(s). (Davenport and Harris, 2007, Ch.8)</td>
</tr>
<tr>
<td>8. Analytical People</td>
<td>see Table 2, row 18, for the definition of this concept</td>
</tr>
<tr>
<td>9. Analytical Capabilities</td>
<td>The organization’s combination of people, technology, and data-analysis processes that enable it to make more evidence-based decisions. These are a very small subset of the organization’s overall capabilities (row 10). In the empirical analysis reported later, this construct was operationalized as the union of scores for concepts in rows 7 and 8.</td>
</tr>
<tr>
<td>10. Organizational Capabilities</td>
<td>The full set of capabilities, i.e., people, technology, and processes, owned or controlled by the organization that enable it to provide goods and services (i.e., value) to its customers and other stakeholders. Some of these capabilities will be the valuable, rare, inimitable, and non-substitutable capabilities that the resource-based view of the firm (Barney 1991, Barney et al. 2011) argues are the primary source of a firm’s competitive advantage.</td>
</tr>
</tbody>
</table>

* Numbered rows correspond to row numbers in Table 3

Within the process model in Panel A, three paths have been highlighted (numbered 1 to 3). Each of these paths is now discussed in turn. First, reading horizontally from left to right across the top of Panel A, Path 1 says that in a viable organization, Use of the organization’s current Analytic Capabilities by people in many different parts of the organization produces Insights that lead to Decisions that lead (via the arrow labeled “Path 1”) to Competitive Actions that lead to outcomes, termed Organizational Benefits (e.g., profit) that senior managers in the organization would regard as beneficial. This is a resource-based view of the organization (Barney 1991). Such routine use of BA capabilities is what Shanks and Bekmamedova (2012) call Operational BA use. Path 1 usage is also consistent with Howson’s (2011)
report, based on a survey of 460 BI users, that the “most successful” (i.e., most used) BI modules were, in descending order: Business or Ad Hoc Query 62%, Fixed reports 54%, Dashboards 54%, and OLAP 36% Howson (2011, p.12). These BI tools are the sources of insight in the process model in Panel A.

Second, reading horizontally again from left to right, Path 2 says that sometimes Use of an organization’s current analytical capabilities by people in different parts of the organization produces Insights that lead to Decisions that lead (via the arrows labeled “Path 2”) to Competitive actions that change organizational capabilities. Assuming these changed capabilities enable the organization to compete more effectively in future, this is a dynamic-capabilities view of how use of business analytics creates business value (Teece 2009). This use of BA capabilities to trigger changes in organizational capabilities is what Sharma et al. (2010) call Dynamic BA capabilities.

Third, Path 3 on the left of Panel A is intended to recognize that Use of analytic capabilities may sometimes lead directly to changes in those analytic capabilities. Examples of such changes might include improved data quality as the result of data-cleansing efforts, or more capable analytical people, as a result of learning how to use analytic tools. Path 3 is not discussed any further in this paper.

A good example to illustrate the meaning of Paths 1 and 2 in the process model in Panel A comes from Davenport and Harris (2007). According to those authors, some years ago the UK supermarket chain, Tesco, set up a Clubcard loyalty program that motivates customers to present their card with most purchases. Tesco now uses its analytic capabilities to analyze checkout data to provide insights into the purchasing preferences of its customers. Based on those insights, Tesco makes automated offers in its direct-marketing program. This program has apparently been so effective that at the time the book was written Tesco had a coupon redemption rate ten times the industry average:

“Tesco says that it issues 7 million targeted variations of product coupons a year, driving the coupon redemption rate, customer loyalty, and ultimately financial performance to market-leading heights.”

(Davenport and Harris 2007, pp.90-91)

The setting up of the loyalty program and the building of the systems and processes to analyze data correspond to Competitive actions that change the organization’s capabilities. It is not clear from Davenport and Harris (2007) whether the decision to build these capabilities at Tesco was based on use of business analytics, but if it had been, it would have been an example of execution of Path 2, i.e., of use of analytics that resulted in a change in organizational capabilities. Once the new BA capabilities were built, Tesco’s regular use of these capabilities to make offers in its direct-marketing program corresponds to Path 1 in Panel A in Figure 1, i.e., to Shanks and Bekmamedova’s (2012) Operational BA use.

Extending the Tesco example further, non-routine analysis of the same checkout data might lead Tesco to see patterns of purchases in inner city stores that lead it to create new organizational capabilities, e.g., to open a new chain of convenience stores that sells only a narrow range of products. Such actions would be another example of execution of Path 2 in Panel A of Figure 1. Subsequent operations of these stores (not necessarily involving use of BA) would be the source of business value for Tesco flowing from the BA-driven decision to change organizational capability.

Completing this discussion of the process model in Panel A of Figure 1, the five dot points in the Business Analytical Capabilities box on the lower left of Panel A, and their grouping under the headings Enabling Technology and Analytical People, is our attempt to summarize concepts discussed in chapters 8 and 7, respectively, of Davenport and Harris (2007). In those two chapters, Davenport and Harris (2007) argue that Enabling Technology and Analytical People are key capabilities that an organization must have to be able to create business value from BA. With respect to technology, Davenport and Harris (2007) use the term “BI architecture” to describe an organization’s enabling technology and its use. In their words:

“The business intelligence architecture (a subset of the overall IT architecture) is an umbrella term for an enterprise-wide set of systems, applications, and governance processes that enable sophisticated analytics, by allowing data, content, and analyses to flow to those who need it, when they need it.”

Davenport and Harris (2007, p.155)

**The Variance Model in the BASM (Panel B in Figure 1)**

The variance model in the BASM (Panel B in Figure 1) presents a different, but complementary,
Table 2. Definition of concepts in the BASM Variance Model (Figure 1, Panel B)

<table>
<thead>
<tr>
<th>Concept*</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>11. Analytic Leadership</td>
<td>The extent to which people in any organizational unit take leadership of initiatives or projects to increase use of business analytics for organizational gain (Davenport et al. 2010, Ch.4, pp.57-72).</td>
</tr>
<tr>
<td>12. Enterprise-wide Analytics Orientation</td>
<td>The extent to which the organization has adopted an enterprise-wide orientation to the use of business analytics. Such an enterprise-wide view is normally supported by an integrated BI platform that provides “a single, holistic view of the company” (Davenport et al. 2010, p.45) rather than, for example, multiple datamarts.</td>
</tr>
<tr>
<td>13. Well-chosen targets</td>
<td>The extent to which targets for new analytics initiatives are selected carefully based on the combination of their business potential and whether the necessary resources, including data, are available. (Davenport et al. 2010, p.89).</td>
</tr>
<tr>
<td>14. Extent to which evidence-based decision making is embedded in the “DNA” of the organization</td>
<td>The extent to which a culture of evidence-based decision making is embedded in the core values and processes of the organization (Davenport and Harris 2007, Ch.2; Davenport et al. 2010, Ch.1, 7, and 8). Kettinger et al. (2011) describe this concept as the firm’s Information Orientation. Howson (2008) and IDC (Vesset and McDonough 2009) call it “pervasive BI”. Brynjolfsson calls it a “higher information metabolism” (Hopkins 2010).</td>
</tr>
<tr>
<td>15. On-going Business-Analytics improvement projects</td>
<td>A measure of the number and extent of investment in BA-improvement projects. Such projects include both the implementation of new software (that delivers new analytics functionality) and initiatives that apply existing functionality to new areas of decision making. These projects are represented by the series of BA-Improvement Projects depicted on the right of Panel B in Figure 1.</td>
</tr>
<tr>
<td>16. Functional fit of BA tools (FF)</td>
<td>The extent to which the functionality provided by the BI platform matches the functionality that the organization needs to access and analyze data effectively and efficiently. Saying that BA toolset has good functional fit is equivalent to saying that the BA toolset helps people in the organization gain useful insights from the organization’s data. This includes providing fast access to information when sought. Although FF is a meaningful concept for the organization overall, in the BASM it is conceptualized as being delivered and measured project by project (Seddon et al. 2010).</td>
</tr>
<tr>
<td>17. Readily available high-quality data</td>
<td>The extent to which relevant and accurate data are readily available for analytics use, from sources both within and external to the organization. (Davenport et al. 2010, Ch.2, pp.23-43)</td>
</tr>
<tr>
<td>18. Analytical people</td>
<td>The extent to which there are people within the organizational unit with an analytic mindset who help drive business value from BA. (Davenport et al. 2010)</td>
</tr>
<tr>
<td>19. Overcoming organizational inertia (OOI)</td>
<td>The extent to which members of the organization have been motivated to learn, use, and accept the new system. During initial implementation and subsequent projects, considerable change-management effort, training, and support are needed to overcome organizational inertia. OOI is conceptualized as being measured project by project (Seddon et al. 2010).</td>
</tr>
<tr>
<td>20. Organizational Benefits from Analytics Use, from the perspective of Senior Management</td>
<td>An overall measure of senior management’s perception of the benefits from analytics use. Such benefits—which may be assessed either for the use of BA overall, or for individual BA projects—usually revolve around the use of analytics to enable greater visibility into organizational data, resulting in better, more evidence-based, decision making. In almost all cases, such benefits vary over time, e.g., as depicted in the two graphs in Figure 1. This concept, which is directly analogous to the Organizational Benefits dependent variable in Seddon et al. (2010), is a synonym for Business Value from Business Analytics.</td>
</tr>
</tbody>
</table>

* Numbered rows correspond to row numbers in Table 3
explanation of how organizations use business analytics to create business value. It combines insights mainly from Davenport and Harris (2007), Davenport et al.’s (2010) DELTA model, Watson and Wixom (2007), and Seddon et al.’s (2010) OBES model. All five factors from DELTA, all six factors from Watson and Wixom (2007), and three of the six factors from OBES are included in this model. The model—which is a special case of both Seddon et al.’s (2010) OBES model and Murer et al.’s (2011) enterprise-architecture-planning approach applied to business analytics—argues that an important mechanism through which firms derive increased benefits from business analytics is through on-going BA-improvement projects. BA-improvement projects include both the implementation of new BI software (that delivers new analytics functionality) and initiatives that apply existing functionality to new areas of decision making.

The right-hand project side of the model in Panel B of Figure 1 hypothesizes, as H1-H4, that the greater the extent of functional fit (H1), ready availability of high-quality data (H2), analytical people (H3), and success in overcoming organizational inertia (H4) in a BA-improvement project, the greater the organization’s success in realizing benefits from that project. The left-hand side of the model hypothesizes that in the long term, it is analytic leadership (H5), the adoption of an enterprise-wide analytics orientation (H6), the selection of well-chosen targets (H7), the extent to which evidence-based decision making is embedded in the “DNA” of the organization (H8), and execution of multiple BA-improvement projects (possibly over many years) (H9) that drive benefits from business analytics. Each of these hypotheses is now explained and justified in turn.

**Hypothesis Development (Hypotheses 1-9)**

It is hypothesized in the BASM that variance in Organizational Benefits from Analytics Use (with benefits assessed from the perspective of senior management, as in Seddon et al. (2010)) is driven by variance in each of the nine independent variables defined in Table 2 and discussed below.

**Functional fit**

As defined in Table 2, row 16, *Functional fit* (FF) is “the extent to which the functionality provided by the BA platform matches the functionality that the organization needs to access and analyze data effectively and efficiently”. This is very similar to Clark et al.’s (2007) “Management Support Systems Functionality”. Our FF concept comes from Seddon et al. (2010), who argue that “organizations invest in ES for their functionality” (“ES” being “enterprise systems”). Similarly, we argue here that the fitness for purpose of functionality provided by BI toolset, e.g., for business and adhoc queries, fixed reports, dashboards, OLAP, and/or visual discovery (Howson 2011) and web-based delivery (Howson 2008), is an important determinant of the benefits that an organization can derive from a BA-improvement project. Such projects might involve either the implementation of new software to deliver new BI functionality to the organization, or initiatives that apply existing (and possibly unused) functionality to a new area of decision making. Further evidence of the importance of functional fit is that two of the three most significant path coefficients reported by Isik (2010) in her n=111 survey on BI Success were related to Functional fit (her H1e Flexibility and H2a User Access Quality). Since toolset functional fit helps to determine benefits that flow from each BA-improvement project, it is hypothesized that:

H1: The greater the Functional fit (FF) resulting from each BA-improvement project, the greater the Organizational Benefits from BA Use.

Note that current vendor interest in products such as SAP HANA, Oracle Exalytics, and Every Angle suggests that an important attribute of functional fit is *speed of access* to information. The massive reductions in the time to access information, e.g., from hours to minutes, enabled by such products make it more likely that decision makers with ready access to such tools will search for information to support decision making more frequently than those without such access, and so derive more value from business analytics.

**Readily available high-quality data**

As defined in Table 2, row 17, *Readily available high-quality data* is “The extent to which relevant and
 accurate data are readily available for analytics use, from sources both within and external to the organization”. According to Davenport et al. (2010, p.23), data are “the prerequisite for everything analytical”, and “You can’t be analytical without data and you can’t be really good at analytics without really good data.” They also argue that appropriate governance arrangements need to be in place to ensure data accessibility. Watson and Wixom (2007) and Sabherwal and Becerra-Fernandez (2011) make a similar point. For example, Watson and Wixom (2007, p.98) say that a key to BI success is that “There is a strong decision support data infrastructure”. Since readily available high-quality data is likely to vary from BA-implementation project to project, it is hypothesized that:

H2: The greater the extent of readily available high-quality data available for each BA-improvement project, the greater the Organizational Benefits from BA Use.

Analytical people

As defined in Table 2, row 18, Analytical people is “The extent to which there are people within the organizational unit with an analytic mindset who help drive business value from BA.” Such people include Davenport et al.’s (2010) analytical champions, professionals, semi-professionals, and amateurs. According to Davenport and Harris (2007, p.131), “It is people who make analytics work and who are the scarce ingredient in analytic competition”, not the organization’s access to, for example, high-powered data-mining tools. Since the availability of capable analytical people is likely to vary from project to project, it is hypothesized that:

H3: The greater the quality of analytical people available on each BA-improvement project, the greater the Organizational Benefits from BA Use.

Overcoming Organizational Inertia

As defined in Table 2, row 19, Overcoming Organizational Inertia (OOI) is “The extent to which members of the organization have been motivated to learn, use, and accept the new system”. This concept comes from Seddon et al. (2010), who argue that “no matter how good the technical system, unless people in the organization are motivated to use the system, and have sufficient knowledge of how to use the system effectively (Purvis et al. 2001), the organization is unlikely to gain the benefits it might from the system”. In a similar vein we argue here that if a BA-improvement project is intended to result in a system that users in some part of the organization must be persuaded to learn and use, the organization’s success in overcoming organizational inertia will be a key determinant of benefits from that BA project. Watson and Wixom (2007, p.98) make a similar point when they say that a key to BI success is that “Users have the necessary tools, training, and support to be successful”. Further, since the organization’s success in overcoming organizational inertia is likely to vary from project to project, it is hypothesized that:

H4: The greater the success in Overcoming Organizational Inertia (OOI) in each BA-improvement project, the greater the Organizational Benefits from BA Use.

The significant path coefficient of 0.33 (n=419, p<0.001, from 347 organizational units) between operational managers’ Absorptive Capacity (a characteristic of the people using BI) and BI Assimilation (a measure of business benefits attributed to use of BI) reported by Elbashir et al. (2011) lends further support for the likely validity of H3 and H4.

Analytic Leadership

As defined in Table 2, row 11, Analytic Leadership is “The extent to which people in any organizational unit take leadership of initiatives or projects to increase use of business analytics for organizational gain”. With respect to leadership, Davenport et al. (2010, p.57) say: “If we had to choose a single factor to determine how analytical an organization will be, it would be leadership. ... Leaders have a strong influence on culture and can mobilize people, money, and time to help push for more analytical decision making.” In a similar vein, Watson and Wixom (2007, p.98) say a key success factor for BI success is that “Senior management believes in and drives use of BI.” Since analytic leadership seems so important for the realization of benefits from BA, across projects, not just for individual projects, it is hypothesized in the BASM that:
H5: The greater the extent of analytic leadership in the organization, the greater the Organizational Benefits from BA Use.

**Enterprise-wide Analytics Orientation**

As defined in Table 2, row 12, an *Enterprise-wide Analytics Orientation* is “The extent to which the organization has adopted an enterprise-wide orientation to the use of business analytics”. The definition in Table 2 further explains that “Such an enterprise-wide view is normally supported by an integrated BI platform that provides “a single, holistic view of the company” (Davenport et al. 2010, p.45) rather than, for example, multiple datamarts’. Davenport et al. (2010, Ch.3) argue forcefully that an enterprise-wide view of the role of BA is critical to BA’s success. “To develop an enterprise-wide view of analytics, a company must do more than integrate data, combine analysts, or build a corporate IT platform. It must eradicate all of the limited, piecemeal perspectives harbored by managers with their own agendas, needs and fear—and replace them with a single, holistic view of the company.” (Davenport et al. 2010, p.45). Since an enterprise-wide analytics orientation seems so important for the realization of benefits from BA, across projects, not just for individual projects, it is hypothesized that:

H6: The greater the extent to which the organization has adopted an Enterprise-wide Analytics Orientation the greater the Organizational Benefits from BA Use.

**Well-chosen targets**

As defined in Table 2, row 13, *Well-chosen targets* is “The extent to which targets for new analytics initiatives are selected carefully based on the combination of their business potential and whether the necessary resources, including data, are available” (Davenport et al. 2010, p.89). For a firm new to analytics, Davenport et al. (2010, p.73) suggest that a specific business problem might be a good target. For more analytically advanced organizations, the best targets, according to Davenport et al. (2010), will be those that help the organization enhance the distinctive capabilities that provide it with competitive advantage. Watson and Wixom (2007, p.98) similarly draw attention to the need for well-chosen targets when they say that BI is more successful if “There is alignment between the business and BI strategies”, and “There is effective BI governance”. In a similar vein, Sabherwal and Becerra-Fernandez (2011) argue that BI governance processes, e.g., articulation of BI principles, and creation of a BI Steering Committee, are important drivers of benefits from BI. Finally, from Murer et al.’s (2011) perspective, well-chosen targets should also increase future BI agility as well as producing business value today. Since choosing sound targets for future initiatives is clearly a key driver of future BI benefits, it is hypothesized that:

H7: The sounder the governance processes for selecting (well-chosen) targets for future BI initiatives, the greater the Organizational Benefits from BA Use.

**Extent to which evidence-based decision making is embedded in the “DNA” of the organization**

In the BASM, the construct *Extent to which evidence-based decision making is embedded in the “DNA” of the organization* (Table 2, row 14) is an attempt to assess the extent to which evidence-based decision making is embedded in the core values and processes of the organization. Kettinger et al. (2011) describe this concept as the firm’s *Information Orientation*. Howson (2008) and IDC (Vesset and McDonough 2009) call it *Pervasive BI*. In the first Davenport book on BA, Davenport and Harris (2007, p.23) describe firms where evidence-based decision making has become the very basis of their competitive advantage as “analytic competitors”: “We define an analytical competitor as an organization that uses analytics extensively and systematically to outthink and out execute the competition”. However, as Davenport et al. (2010, p.vii) point out in the preface to their second book, their first book was about “the earliest and most aggressive adopters of analytics”. Many other firms, they explain in their second book, just want to know how to become more analytical. The implication of these comments is that as organizations become more analytical (i.e., as evidence-based decision making becomes more and more deeply embedded in their “DNA”) they will realize increasingly more benefits from their use of BA. Similar arguments are presented in Kettinger et al. (2011), Accenture (2011), and Watson and Wixom (2007). For example, Watson and Wixom (2007, p.98) say that BI is more successful when “The use of
information and analytics is part of the organization’s culture”. In terms of barriers to the use of analytics, Accenture’s 2010 global survey of 800 “directors and senior managers” reported that “corporate culture still represents a major barrier” to the wider use of customer “analytics and fact based decision making” (Accenture 2011, slide 2). This insight is summarized in the following hypothesis:

H8: The greater the extent to which evidence-based decision making is embedded in the “DNA” of the organization, the greater the Organizational Benefits from BA Use.

**On-going BA-improvement projects**

As defined in Table 2, row 15, *On-going BA-improvement projects* is “A measure of the number and extent of investment in BA-improvement projects. Such projects include both the implementation of new BI software (that delivers new analytics functionality) and initiatives that apply existing functionality to new areas of decision making.” The claim that on-going projects is a source of business value builds on the work of Seddon et al. (2010), who argue that the primary driver of benefits from Enterprise Systems (ES) is “on-going improvement projects that deliver new functionality to users.” A similar idea is discussed by Murer et al. (2011) in the context of enterprise-architecture, e.g., see their Figure 7.1, p.204. In the Seddon et al. (2010) paper, new functionality is delivered by projects that implement new ES software. In the BASM in Figure 1, we have extended the project concept to include both (i) projects that implement new BI software and (ii) projects that using existing software in new ways or in new areas, called new initiatives. The benefits driver in both cases is the running of new projects. This insight (that BA-improvement projects are likely to be the primary driver of new analytics capabilities that, in turn, deliver new benefits) is captured in the following hypothesis:

H9: The greater the organization’s investment in on-going Business Analytics-improvement projects, the greater the Organizational Benefits from BA Use.

**In a nutshell**

The Business-Analytics Success Model (BASM) model in Figure 1 is a synthesis of many ideas from the BA literature, particularly those from Davenport and Harris (2007), Watson and Wixom (2007), Davenport et al. (2010), and Seddon et al. (2010). It is an attempt to identify the most important mechanisms through which organizations achieve business value from business analytics, and to place them as logically as possible in a well-defined model. In terms of context, the BASM views organizations and their subunits as acting like living things within a highly competitive environment (Beer 1972, 1984).

The BASM presents two different, though mutually compatible, perspectives to explain how use of business analytics contributes to business value. First, the process model in Panel A of Figure 1 shows the focal organization’s use of its BA capabilities to conduct routine and non-routine analyses of both internally and externally-sourced data to contribute to business value by revealing insights that lead to decisions to take competitive actions. Some of these actions (path 2 in Panel A) lead to changes in organizational capabilities, but as pointed out by Shanks and Bek namedova (2012), many use existing capabilities (path 1) to produce business value. The process in Panel A is executed over and over by different people in different parts of the focal organization.

Second, in addition to the preceding process view, the BASM also offers a variance-model explanation of how firms use BA to create business value. In the variance model it is argued that in the long term the key to achieving greater business value from BA is to have strong analytical leadership (H5), adopt an enterprise-wide orientation (H6), direct resources towards high-return targets (H7), and embed a positive attitude to evidence-based decision making in the “DNA” of the focal organization (H8). In addition, the BASM argues that these four drivers will induce the organization to embark on new BA-improvement projects, either to implement new BI capabilities, or to use BI in new ways (H9).

For each of these projects, success in generating business value, the BASM argues, is likely to be higher if the new capabilities are a good fit with business needs (H1), high-quality data are readily available (H2), the organization has the analytic-people capabilities to use the BI tools available (H3), and training and change management are used to support any changes in work practices required to use new systems (H4). The actual mechanism through which all these factors contribute to business value is as shown in the
process model in Panel A.

As an example of the application of this project's side of the BASM, if the project involves developing, say, a new dashboard for assessing credit risk of customers in the Finance department of a merchant bank, the model asserts that it is the specific dashboard functionality delivered (H1), the ready availability of high-quality data (H2), the analytic capabilities of the Finance department's staff (not others elsewhere in the organization) (H3), and the capacity and motivation of dashboard users to learn to use the new functionality (H4) that will drive benefits from the project. Further, the organization’s capacity to execute this dashboard-implementation project, and to absorb the changes in work practices that flow from it, is an example of a dynamic capability (Teece et al. 1997) (Path 2 in Panel A of Figure 1). Finally, once the organization has gone live with its new dashboard system, benefits from use will flow from repeated execution of the process depicted in Path 1 in Panel A of Figure 1.

Testing the model

To conduct a preliminary test of the validity of the model in Figure 1, we downloaded a series of BA customer-success stories from various vendor websites and examined those stories to see how frequently concepts and relationships identified in the BASM were discussed in those stories in a manner consistent with the BASM. We use the word “test” here in the sense used by Weick when he said:

“...empirical confrontation is not a test of whether a theory is correct; rather, it is a discovery process: to make clear what the theory means, disclose its hidden assumptions, and clarify the conditions under which it is true or false.” Weick (1984, p.117).

The reasoning behind the “test” in this paper is that in their attempts to convince potential purchasers of the value of purchasing their software, vendors are likely to discuss the things that they think are most important to the realization of benefits from their software. Therefore, a good model should highlight things that are mentioned frequently in the vendors’ customer-success stories.

The downside of using vendors’ customer-success stories is that they always paint a rose-colored picture of the use of their software. However, success stories are built on a scaffolding of facts about people and processes that can be used, with care, to gain much easier access to a wide range of BI-using organizations than is possible through, say, organizing and conducting case studies or surveys oneself. For example, Isik (2010) reported a disappointingly low less than 1% response rate to a survey mailed out to over 11,000 “corporate and IS buyers of business intelligence”. Thus in this study, as an alternative to a survey, we used vendor-published BA customer-success stories as our source of data. Seddon et al. (2010) used a similar method in their preliminary test of their OBES model, published in MIS Quarterly.

Characteristics of the sample

Our sample of customer-success stories was gathered by visiting major BI-vendor websites and looking for stories related to the use of analytics to create business value. We found that so-called “case studies” from IBM, SAP, and Teradata were the most useful because they were typically longer than those of other vendors. Stories from other vendors, e.g., Oracle, MicroStrategy, and SAS, were less comprehensive and therefore less useful for our purpose. Customer-success stories were selected when they discussed some aspect of the use of business analytics. In other words, stories focusing on just technology or implementation, but not use, were excluded. Using these criteria, we downloaded 160 customer-success stories. These stories cover use of business analytics a wide range of different sized, mainly US-based firms, from a wide range of industries and government. From these stories we used a random-number generator to select 100 stories for analysis for this paper. The resulting sample contained 39 stories from IBM, 28 from SAP (including seven 20-minute videos from SapphireNow), 19 from Teradata, plus a handful from each of Information Builders, Microsoft, and Qliktech). In total, there are over 410 pages of text, seven 20-minute videos, and 98 PowerPoint screens. A typical example of a customer-success story is a seven-page article from IBM Cognos on Sharp HealthCare, published in 2010. An extract from this story is shown in Figure 2.
Coding

For testing the BASM, two coauthors worked together to code a small number of examples from the 100 selected. Both coders then worked independently coding the remaining stories, meeting three times to discuss and reconcile codes. We used a spreadsheet with one row per success story, and 18 columns for the 18 concepts in the BASM to record results of our analysis. For each story, coding involved asking whether any of the 18 concepts in the BASM, e.g., analytic leadership, readily available high-quality data, etc. was mentioned in the success story in a way that was consistent with its use in the model. If the answer was Yes, a ‘1’ was placed in spreadsheet in the cell for that concept (column) for that success story (row). If a concept was not mentioned in the success story in a manner consistent with the model, a zero was placed in the cell. Occasionally, if the evidence was present, but weak, we scored the strength of evidence as 0.5, not 1. Apart from the spreadsheet, no other software was used for coding. The initial level of agreement between the coders was 76%. After discussing differences, agreement increased to 98%. Final decisions on the last 2% were made by the third coauthor. After coding was complete, totals for each column were used to calculate the percentage of success stories that contained mention of a construct from the BASM in a way that was consistent with the model.

Sharp HealthCare gets ahead of the curve: Performance management with IBM Cognos software

Sharp HealthCare is a not-for-profit integrated regional health care delivery system based in San Diego, California that is comprised of four acute care hospitals, three specialty hospitals, two medical groups, a health plan and a full spectrum of other facilities and services. Sharp’s 2,600 physicians and over 14,000 employees have an unwavering commitment to excellence and a passion for caring.

Challenge
Manual, error-prone processes and disparate, unreliable data drove Sharp to adopt a performance management system that could leverage their large data stores.

Why IBM?
Sharp chose IBM Cognos software for its business intelligence (BI) and analytics engine to leverage its data and enable faster decision-making while empowering departmental users through self-service capabilities.

Solution
IBM Cognos software is deployed as Sharp’s standardized, single point of entry into their central data stores. BI is delivered to users through an easy to use, web-based, zero footprint solution that provides information faster, and in a more efficient and organized manner.

Key Benefits
Departmental users have direct access to the data they need to manage operations, understand trends and stay on top of workloads, and quality initiatives are supported with consistent and accurate data that helps Sharp measure results and improve operations.

To illustrate these coding judgments, consider the Sharp Healthcare example in Figure 2. First, the story describes a two-year project led by Vonda Brown, Manager, Decision Support Systems, to replace hundreds of Excel spreadsheets and Access databases by a central data warehouse (p.2):

“The data warehouse unites charge, expense, revenue and clinical information—from clinic, medical group, hospital, lab, pharmacy, physician orders, vital signs, allergies, immunizations, operating room, encounters and referral data—into one place to make operational decisions easier and more effective.”

This was clearly an enterprise-wide software-implementation project, led by a key manager that affected the work practices of many people at Sharp Healthcare. So there was a good fit between the project-oriented view the BASM inherited from Seddon et al. (2010), and the success story as told by IBM. Second, the “Key Benefits” section of Figure 2 says that BI is now being used in this organization as an integrated reporting tool for improving organizational effectiveness, not as the primary basis for
Seddon et. al. / How does business analytics contribute to business value?

competition like the case studies in Davenport and Harris (2007). So, again, there was a good fit between the “operational use of BA” view the process model in the BASM inherited from Shanks and Bekmamedova (2012) and this success story from IBM.

Turning now to the detailed coding, we treated comments in the text of the success stories as evidence of support for different parts of the model. For example, the following quotes from Vonda Brown:

- “I am now 100 percent confident in the data that we have so that users can count on the reliability of their reports”,
- “We capture information on about 17 different quality indicators, and are developing a dashboard and custom report that will let physicians see where they stand against each of these indicators on a monthly basis”

were treated as evidence that Ready availability of high-quality data and Ongoing projects, respectively, were important concepts in the variance model in Panel B of Figure 1 (the implication being that they led to business value). The reader is encouraged to read the success story (URL above) for more details.

Results

Results from our analysis of the 100 vendors’ business-analytics success stories are summarized in Table 3. The table reports the percentage of times that the various concepts from the BASM in Figure 1 were mentioned in the 100 vendor-sourced BA success stories in a way that was consistent with the model.

With respect to the process model (rows 1-10), we expected that all the stories would report that BA Capabilities (technology and analytical people) were being used to produce insight leading to decisions and actions that—in conjunction with each organization’s many non-BA capabilities—led to Organizational benefits. The high percentages (above 80%) for seven of the nine constructs in rows 1-8 and 10 are consistent with this expectation. Given that all the success stories came from technology vendors, it is probably no surprise that 100% of stories mentioned Enabling technology (row 7)! The implications of the two low percentages (6% in row 5 and 12% in row 8) are discussed shortly.

With respect to the variance model (rows 11-19), given the strength of Davenport et al.’s (2010) arguments about the importance of the factors in their DELTA model and Seddon et al.’s (2010) claims about the importance of the factors in their OBES model, we expected strong support for all hypotheses except for H8 (row 14), where Davenport et al. (2010) had already reported that few firms that they studied were “analytic competitors”. However, the results in Table 3 show high percentages (above 75%) for only five of these nine hypotheses. There was strong support for four of Davenport et al.’s five DELTA factors, namely, Data (H3, row 17, 86%), Enterprise-wide orientation (H6, row 12, 76%), Leadership (H5, row 11, 92%), and Targets (H7, row 13, 88%), but support was weak for DELTA’s fifth factor, Analytical people (H2, row 18, 13%). There was also strong support for one of Seddon et al.’s three factors, namely Functional Fit (H1, row 16, 89%), but support was weaker for the two other factors from OBES, On-going improvement projects (H9, row 15, 44%) and Overcoming Organizational Inertia (H4, row 19, 35%).

Discussion

What are the implications for the BASM of the cells with low percentages in Table 3? One way of interpreting the percentages in Table 3 is that they are all above zero, which means that there was evidence in at least some success stories that all constructs in the BASM are valid. However, this does not explain why six of the 18 percentages in Table 3 are so much smaller than the others. Our explanations for the six low percentages, and their implications for the BASM, are as follows:

Row 5: Only 6% of organizations in our sample made changes to organizational capabilities flowing from use of BA. This is consistent with Shanks and Bekmamedova’s (2012) punctuated-equilibrium model where firms made occasional changes to capabilities then used the resulting capabilities for months before changing them again. It is also consistent with the Tesco example discussed earlier. However, the change capabilities path (path 2 in Panel A of Figure 1) WAS sometimes taken, and when it was it led to important changes, e.g., reduction in staff. Therefore, the Change capabilities path is a meaningful option, e.g., as discussed by Sharma et al. (2010), and is worth retaining in the BASM.
Table 3: Results from analysis of 100 customer-success stories

<table>
<thead>
<tr>
<th>Concept from the Business-Analytics Success Model (BASM)*</th>
<th>% of stories mentioning*</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Process Model (Panel A, Figure 1):</strong></td>
<td></td>
</tr>
<tr>
<td>1. Use of business analytic capabilities by any organizational unit to analyze routine and/or non-routine, internal and/or external data</td>
<td>98%</td>
</tr>
<tr>
<td>2. Insight(s) (arising from use of business analytic capabilities)</td>
<td>89%</td>
</tr>
<tr>
<td>3. Decision(s) (flowing from insights flowing from use of BA capabilities)</td>
<td>81%</td>
</tr>
<tr>
<td>4. BA-driven Competitive actions that use existing organizational capabilities</td>
<td>88%</td>
</tr>
<tr>
<td>5. BA-driven Competitive actions to change organizational capabilities</td>
<td>6%</td>
</tr>
<tr>
<td>6. Organizational Benefits from Analytics Use, from the perspective of Senior Management</td>
<td>98%</td>
</tr>
<tr>
<td>7. Enabling technology</td>
<td>100%</td>
</tr>
<tr>
<td>8. Analytical people</td>
<td>12%</td>
</tr>
<tr>
<td>9. Analytical capabilities (union of the sets of codes for rows 7 and 8)</td>
<td>see row 7</td>
</tr>
<tr>
<td>10. Organizational capabilities (being used in the creation of business value)</td>
<td>100%</td>
</tr>
<tr>
<td><strong>Variance Model (Panel B, Figure 1):</strong></td>
<td></td>
</tr>
<tr>
<td>11. H5: Analytic leadership (as a long-term driver of organizational benefits)</td>
<td>92%</td>
</tr>
<tr>
<td>12. H6: Enterprise-wide Analytics Orientation (as a driver of org. benefits)</td>
<td>76%</td>
</tr>
<tr>
<td>13. H7: Well-chosen targets (for new BA initiatives) (as a driver of org. benefits)</td>
<td>88%</td>
</tr>
<tr>
<td>14. H8: Extent to which evidence-based decision making is embedded in the “DNA” of the organization (as a driver of org. benefits)</td>
<td>14%</td>
</tr>
<tr>
<td>15. H9: On-going BA-improvement projects (as a driver of org. benefits)</td>
<td>44%</td>
</tr>
<tr>
<td>16. H1: Functional fit (of the BI tools to meet the needs of users for this project)</td>
<td>89%</td>
</tr>
<tr>
<td>17. H2: Readily available high-quality data (as a driver of org. benefits, for this project)</td>
<td>86%</td>
</tr>
<tr>
<td>18. H3: Analytical people (as a driver of org. benefits for this project)</td>
<td>13%</td>
</tr>
<tr>
<td>19. H4: Overcoming organizational inertia (as a driver of org. benefits for this proj.)</td>
<td>35%</td>
</tr>
<tr>
<td>20. Organizational Benefits from Analytics Use</td>
<td>see row 6</td>
</tr>
</tbody>
</table>

* Percentages are of the 100 vendors’ customer-success stories analyzed.
# Numbered rows correspond to row numbers in Tables 1 and 2.

**Rows 8 and 18**: Only 12-13% of success stories in our sample made reference to analytical people (defined in row 18 of Table 2). The success stories frequently report people gaining insight from their use of BI tools, but as with H8 (row 14, discussed next), they don’t often discuss whether those people have analytic mindsets. Clearly, specialist analysts are required to use sophisticated BI tools, e.g., data mining, so the concept of analytical people is valid, and worth retaining in the BASM. But it appears that evidence of the extent to which regular users of the wide range of analytic tools are “analytic people” is hard to glean from vendors’ success stories.

**Row 14 (H8)**: As noted above, Davenport et al. (2010) have already reported that few firms that they studied in their second study were “analytic competitors”. It is no surprise, therefore, that only 14% of firms in our sample showed evidence of an organization-wide commitment to analytics. However, the fact that some did, and that consultants talk of “pervasive BI”, shows the value of having H8 (which is inherited from both Davenport & Harris (2007) and Davenport et al. (2010)) in the BASM.
Row 15 (H9): Only 44% of success stories in our sample discussed on-going improvement projects. This percentage was smaller than expected, but 44 organizations is more than enough to show that this concept can be an important driver of organizational benefits from BA. Therefore, both this construct and H9 are worth retaining in the BASM. Importantly, the evidence that 44% of success stories discussed multiple projects also demonstrates the merit of structuring the BASM variance model in two parts: long-term and project-by-project. (This two-part structure was inherited from Seddon et al. (2010).) If few organizations ran multiple projects, there would be little reason for structuring the BASM variance model in two parts.

Row 19 (H4): Only 35% of organizations in our sample discussed efforts to overcome organizational inertia. This percentage was also smaller than expected, but 35 organizations is still more than enough to show that this concept can be an important driver of organizational benefits from BA. Therefore, both this construct and H4 are worth retaining in the BASM.

In addition to asking whether factors included in the BASM were discussed in the vendors’ business-analytics success stories, it is also important when assessing a model to ask whether there were any factors mentioned in the stories that are not captured in the BASM or concepts that were not meaningful. Here, we have four insights to share. First, a type of benefit not captured in the current BASM is that implementation of BI tools often enables users to develop their own reports, which reduces pressure on the IT department to create new reports. This user-self-service benefit to IT was frequently reported, and needs to be factored into future versions of the BASM. Second, two success stories discussed the use of BI capabilities by their organization’s customers, not their own employees. For example, the speaker from Omnicom OMD explained that OMD’s BI/Dashboard offering had been “a key differentiator in major client account wins” (LoFrumento 2011, slide 18). To support this claim, he quoted Nancy Bhagat, Intel’s VP of Sales and Marketing, who said of Intel’s new $300-million media contract: “Each of the finalists impressed us, but OMD gave us a stronger sense of possessing world-class media-industry leadership and state-of-the-art business intelligence and analytics” (McIlroy 2008). Use of BI capabilities as a product, or for product differentiation, was not considered when the BASM in Figure 1 was formulated. Third, it is clear from the success stories that different users use different BI tools in very different ways. Drilling down into these different patterns of tool use would be helpful. Fourth, the term “Competitive Actions” in the process model in the BASM was not appropriate for government organizations. In future work, it would be useful to try to extend the BASM to reflect these four insights.

Overall, despite these suggested areas for improvement, there is strong support for the existing BASM in the vendors’ customer-success stories. In other words, the current BASM appears to provide a solid basis for future model development. Further, because the sample used to test the BASM comes from a broad range of organizations, we would expect it to be applicable to a wide range of organizations in different industries and countries.

Conclusion

As mentioned in the Introduction, many models of factors that drive benefits from BI and BA have now been published. Some of these models are very complex, e.g., Clark et al.’s (2007) model summarizes an extremely comprehensive review of the management-support-systems (MSS) literature; some of them are very high-level, e.g., Elbashir et al. (2011) who used some highly complex measures of absorptive capacity to explain BI assimilation; some are very simple, e.g., Isik (2010), who found some simple empirical relationships between technical and organizational BI capabilities and BI success; and some are very implementation-project focused, e.g., Wixom and Watson (2001). However, most of these models are so different that it is hard to identify any emerging consensus.

In an attempt to see if we could identify any underlying patterns in the literature, in this paper we set out to answer the question “How does business analytics contribute to business value?” Our answer to this question is the business-analytics success model (BASM) shown in Figure 1. This model was developed by identifying from the literature a number of key factors that affect business value from business analytics, then grouping and reorganizing those factors into what seemed to us to be (a) a coherent process model (Figure 1, Panel A) and (b) a coherent variance model (Figure 1, Panel B) of key factors that affect how business value is created through use of business analytics. In choosing factors for the model, we tried to steer a middle ground between the complexity of Clark et al. (2007), the abstraction of Elbashir et al.
(2011), the simplicity of Isik (2010), and the project focus of Wixom and Watson (2001). In particular, we found the work of Davenport and Harris (2007), Davenport et al. (2010), Watson and Wixom (2007), and Seddon et al. (2010) helpful for building the BASM. Although organized differently, many of the factors in the BASM were also identified by Clark et al. (2007).

The BASM in Figure 1, together with the two tables of definitions, the description of the process model, and justifications of hypotheses in the variance model, is the primary contribution of the paper. It combines insights into the processes and factors that lead to benefits from business analytics that have been reported by various IS researchers, plus insights from the strategic-management literature (the resource-based view of the firm, dynamic capabilities, and Beer’s Viable Systems Model) and the Enterprise Systems literature. Our contribution is to have created this synthesis.

Finally, although much more rigorous testing is clearly necessary, the empirical results summarized in Table 3 provide preliminary support for the model. Support was strong for 12 of the 18 constructs in the model. Furthermore, the discussion above shows that the other six constructs also play valid and useful roles in explaining how BA contributes value to organizations. Therefore, we argue, the BASM in Figure 1 is a useful contribution to the literature on how organizations gain value from business analytics.

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**References**


