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Through What Mechanisms Does Business Analytics Contribute To Business Value?

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Abstract

This paper synthesizes from the literature a model of factors affecting organizational benefits from business analytics, then reports a preliminary test of that model. The model consists of two parts: a process model and a variance model. The process model depicts the analyse-insight-decision-action process through which an organization's business-analytic capabilities (high-quality data, integrated BA platform, and analytic people) create business value. The variance model proposes that the five factors in Davenport et al.'s (2010) DELTA model of BA success factors, plus three from Seddon et al.'s (2010) model of factors affecting organizational benefits from enterprise systems, assist a firm to embed evidence-based decision making in the organization, and so contribute to business value. A preliminary test of the model was conducted using data from 40 customer-success stories from IBM, SAP and Teradata websites. Our conclusion was 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

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1 INTRODUCTION

Business analytics (BA) involves the use of data to make sounder, more evidence-based business decisions. BA makes extensive use of business intelligence (BI) tools such as statistical and quantitative techniques, explanatory and predictive models, data warehouses, on-line analytical processing (OLAP), visualization, and data mining (Negash 2004). 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 years 2006-8. More recently, Gartner reported that worldwide expenditure on business intelligence grew 13.4% in 2010 (Kanaracus 2011), and respondents to Forrester's 2011 survey of 208 IT executives ranked BI as the "technology most likely to contribute to business value" over the next three years (Hopkins 2011, Figure 2, p.6). Further, the spate of multi-billion dollar takeovers of business-intelligence firms in the past five years, e.g., of Hyperion by Oracle, of Cognos and SPSS by IBM, and of Business Objects by SAP, as well as SAP's current touting of its high-performance analytical appliance (HANA) technology (SAP 2011) suggests that these vendors believe that both BA and BI are likely to make major contributions 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, to date, there have been few published reports, e.g., Davenport and Harris (2007), Watson and Wixom (2007), Sharma et al. (2010), Davenport et al. (2010), and Shanks and Bekmamedova (2012), that have explored this question in any depth. Therefore, the research question addressed in this paper is:

Through what mechanisms 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 of BA use that 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.

2 THEORY

2.1 Davenport at al.'s models of BA success (Davenport & Harris 2007, Davenport et al. 2010)

Perhaps the most comprehensive group of studies of the use of business analytics (BA) to achieve business value is that reported in the books by Davenport and Harris (2007) and Davenport et al. (2010). In their first book, Davenport and Harris used 32 in-depth case studies of business analytics use in large US corporations in a wide range of industries to understand how BA could contribute to a firm's competitive advantage. In their second book, Davenport et al. (2010) broadened the scope of their earlier work, and developed a five-factor model of factors that drive benefits from business analytics even in firms that are not using analytics as their primary source of competitive advantage. Although neither book presents a graphical depiction of its core argument, the model that seems to be implicit in these two books is shown in Figure 1[1]. The two panels in Figure 1 are alternative, mutually compatible, ways of understanding the same phenomenon. The distinction between a process and variance model is discussed in Webster and Watson (2002).

2.1.1 Process Model (Panel A in Figure 1)

In both books it is argued that use of analytical capabilities such as the enabling technology and

[1] This is our representation of the arguments in both Davenport and Harris (2007) and Davenport et al. (2010). Davenport et al. might not agree with the precise detail of this diagram. They do not talk in terms of process or variance models.

human analytical capabilities shown at the bottom of Panel A of Figure 1 (and discussed in Chapters 8 and 7, respectively, of Davenport and Harris (2007)) results in insights that lead to decisions, competitive actions, and ultimately, business value from business analytics in the process model depicted in Panel A in Figure 1. This process is executed over and over again, by different people in different parts of the organization (each possibly doing different sorts of analyses) to help create business value. As one of the many examples of the process in Panel A, Davenport and Harris (2007) describe how UK supermarket chain, Tesco, set up a Clubcard loyalty program that motivates customers to present their card with most purchases. Tesco then uses its analytic capabilities to analyse checkout data to provide insight into the purchasing preferences of its customers. Based on insights from this analysis, Tesco makes offers in its direct-marketing program. This program has been so effective that Tesco has 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)

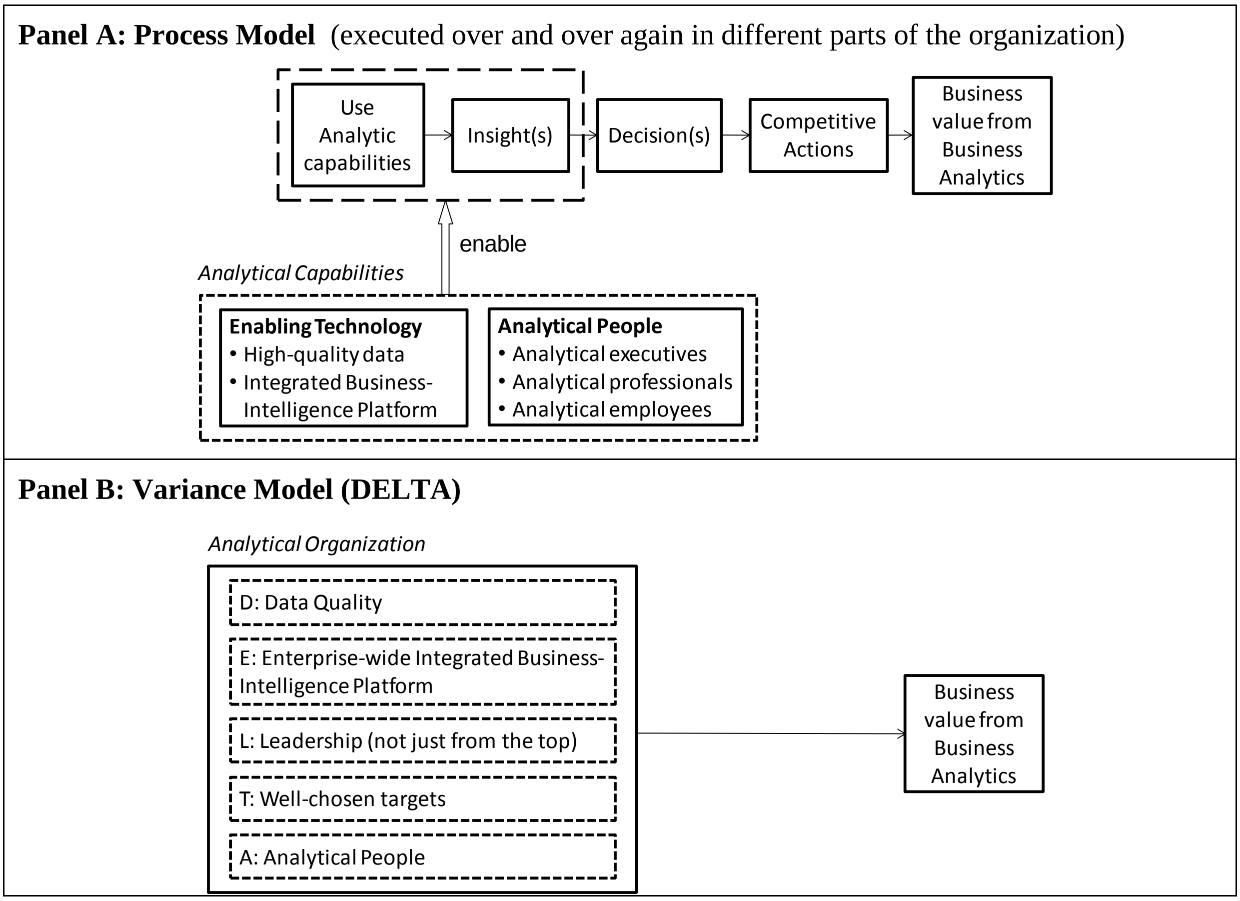

Figure 1: The Business-Analytics success models that seem to be implicit in Davenport and Harris (2007) and Davenport et al. (2010)

2.1.2 Variance Model (Panel B in Figure 1)

According to Davenport and Harris (2007), the key to achieving competitive advantage from business analytics is that firms need to build, refine, and use their analytic capabilities until they become "analytical competitors". By 2010, Davenport et al.'s (2010) key knowledge claim had become that the more that firms build, refine, and use their analytic capabilities to become stronger and stronger "analytical organizations", the more business value they will realize from business analytics. This knowledge claim is depicted in the variance model in Panel B of Figure 1. To become an analytical organization, Davenport et al. (2010) suggest that firms need to manage the five factors beginning with the letters D-E-L-T-A shown in Panel B. Each of the five factors in DELTA is discussed in a separate chapter in the opening chapters of Davenport et al. (2010), Ch. 2-6, respectively. Davenport et al. (2010) emphasize that these five factors must be developed in parallel. Indicators for measuring this development are discussed in the Appendix, pp.185-188, of their book.

The variance model in Panel B of Figure 1 is very similar to the six-factor model discussed by Watson and Wixom (2007). Watson and Wixom do not have a Well-chosen targets factor, but they do highlight the importance of BA Governance, which is likely to have a similar effect. They also include a Training and Support factor not present in Panel B of Figure 1.

2.2 A very different model of BA success factors (Shanks and Bekmamedova 2012)

A second, and very different, model for explaining how the use of business analytics may help a firm to achieve business value is that of Shanks and Bekmamedova (2012). This model, which builds on the work of Sharma et al. (2010) and Shanks et al. (2011), is shown in Figure 2. The upper half of Figure 2 proposes that Dynamic Business Analytic Capabilities sometimes lead to Managerial Actions that, in turn, lead to changes in *Operational* Business Analytic Capabilities. The lower half presents a punctuated-equilibrium view of an organization's Operational BA Capabilities as they are enhanced, first, from State 1 to State 2, second, from State 2 to State 3, and so on.

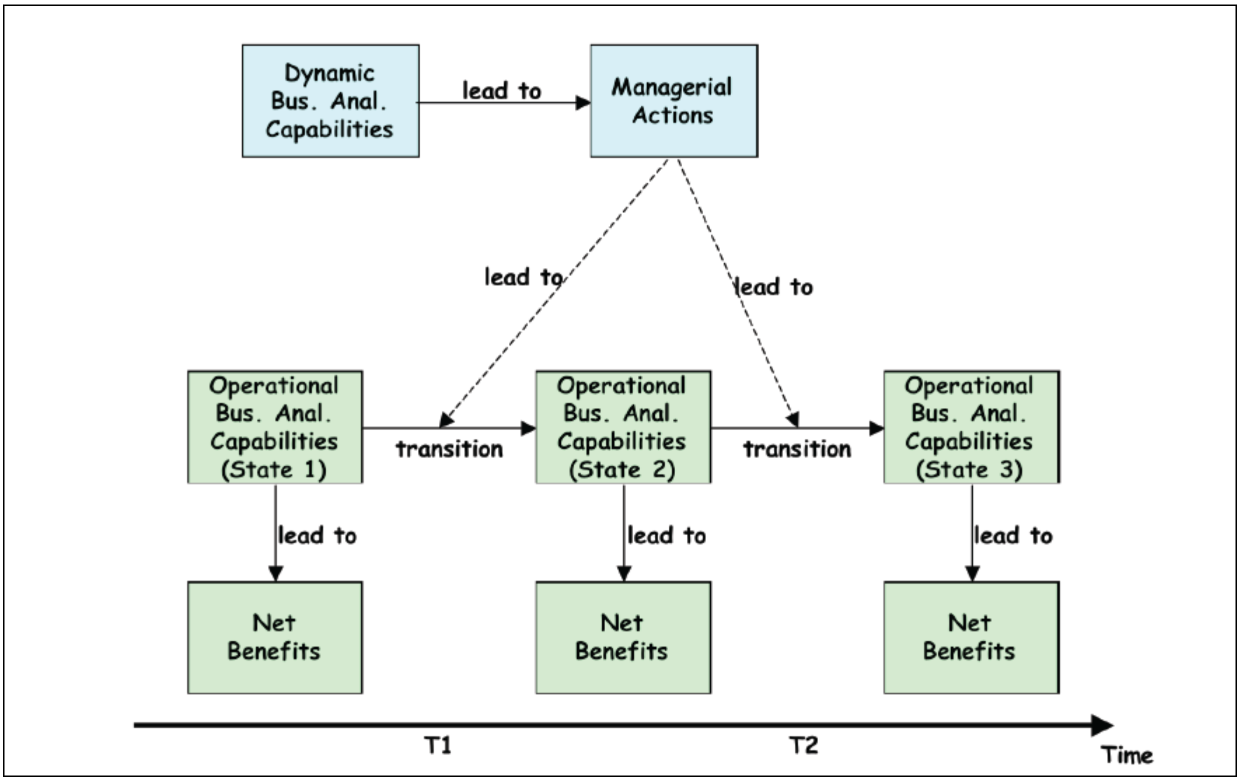

Figure 2: The Business-Analytics success model in Shanks and Bekmamedova (2012, Figure 1)

Shanks and Bekmamedova's (2012) model is valuable because it draws attention to two types of BA use, namely: (a) use leading to changes in the way an organization does things (the capacity to change being a dynamic capability (Teece et al. 1997, Helfat et al. 2007, Baretto 2010)), and (b) routine use of existing BA capabilities (Operational BA capabilities). Operational use of BA Capabilities appears to be an important source of business value from BA. For example, Tesco's use of BA capabilities for sending out millions of coupons to customers, mentioned earlier, is operational BA use.

2.3 Seddon et al.'s (2010) model of factors that drive organizational benefits from Enterprise Systems

A third model that provides yet another very different view of how firms derive value from business analytics is Seddon et al.'s (2010) organizational benefits from enterprise systems (OBES) model, shown in Figure 3. OBES argues that organizations derive benefits from enterprise-wide packaged software, including data-warehousing systems, by running successive projects that deliver new IT-based functionality to the organization. Wixom and Watson (2001) adopted a similar project-oriented view of the means through which firms derive benefits from data warehousing.

The key factors that OBES claims drive organizational benefits for individual enterprise-system projects are Functional fit and Overcoming organizational inertia, on the right-hand side of Figure 3. These factors are defined as follows (Seddon et al. 2010, p.307):

- *"Functional fit* is the extent to which the functional capabilities embedded and configured within an ES package match the functionality that the organization needs to operate effectively and efficiently."
- *"Overcoming organizational inertia* is the extent to which members of the organization have been motivated to learn, use, and accept the new system."

The key factors that drive organizational benefits from ES in the longer term are shown on the left of Figure 3. For example, H3 hypothesizes that the greater the level of integration achieved across the organization, the greater benefits the organization will achieve from ES. (H3 corresponds to the impact of variable E in Davenport et al.'s (2010) DELTA model in Figure 1, Panel B.) Over time, pursuit of the goals in the long-term model on the left of the OBES model motivates the organization to embark on various BA-improvement implementation projects, on the right. According to Seddon et al. (2010), there may be a gap of some years between the projects shown on the right.

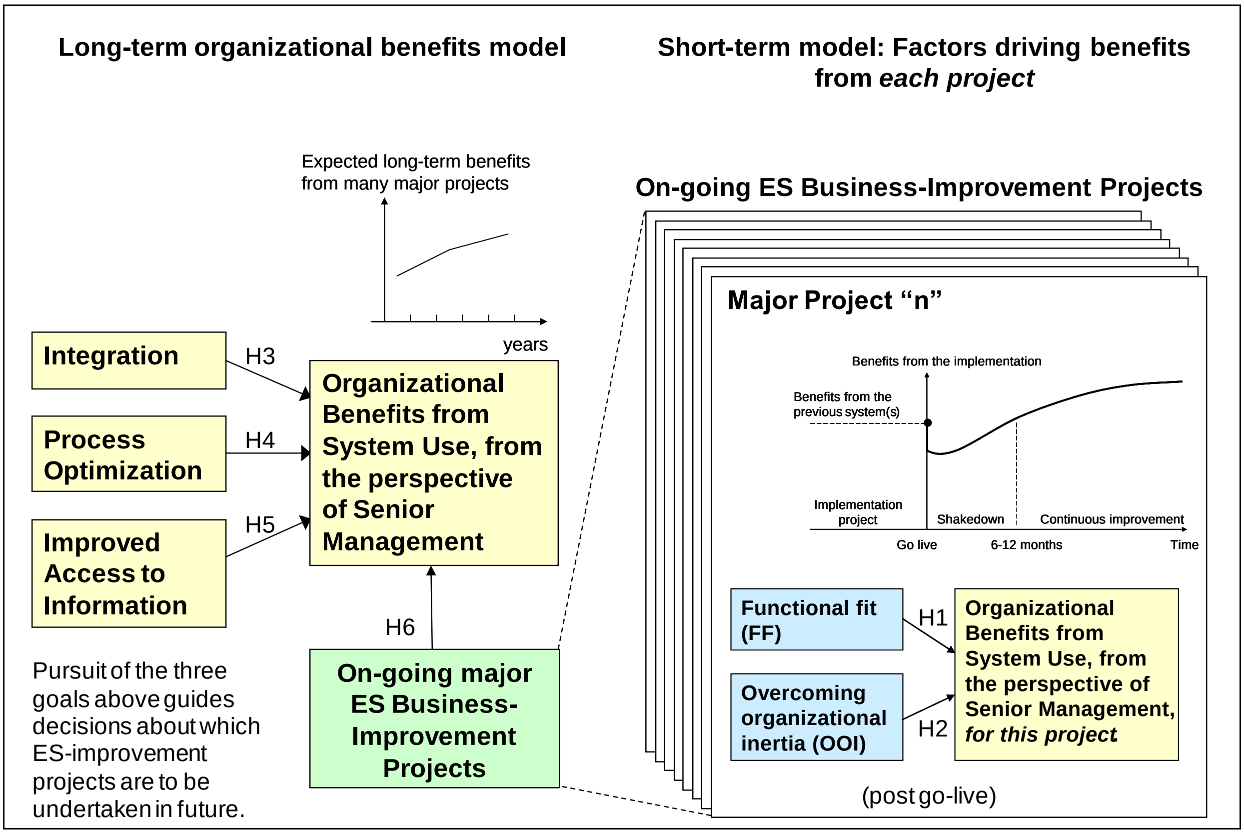

Figure 3: Seddon et al.'s (2010) OBES model of factors that drive benefits from Enterprise Systems

2.4 Synthesis

The three models above provide useful, though different, perspectives on the mechanisms through which organizations realize business value from business analytics. Our goal in writing this paper was to combine the key insights from each, as well as insights from the broader strategic-management literature (Beer 1972, 1984; Barney 1991; Helfat et al. 2007; Teece 2009), into a single integrated model. The result is the model in Figure 4, which we call our Business-Analytics Success Model (BASM). Since space is limited, terms are defined as in the earlier models, e.g., for Functional fit and Overcoming organizational inertia, and briefly again in the results table, Table 1. One important dimension of functional fit is speed of access to relevant information, e.g., via SAP's (2011) HANA.

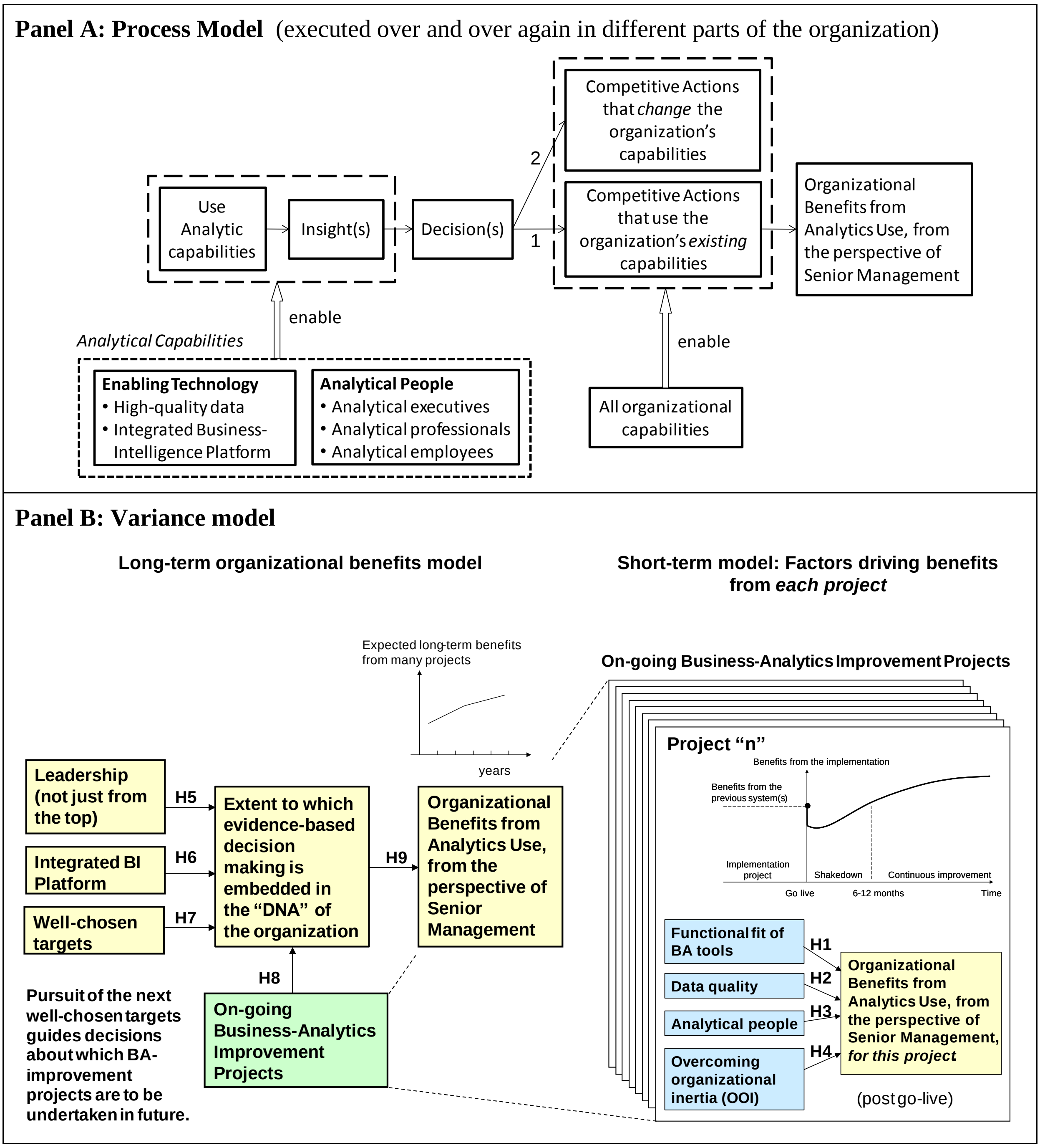

Figure 4: Proposed Business-Analytics Success Model (BASM)

In terms of context, the BASM views organizations and their subunits (e.g., its divisions or departments) as acting like living things within a highly competitive environment (Beer 1972, 1984). Within that environment, the focal organization (i.e., the organization or its subunits) uses its many capabilities to design, produce, and supply goods and services to customers, to survive and thrive. However, managing these capabilities requires lots of information, from both within and outside the organization. Capabilities for analysing this information are embedded throughout the organization. Finally, the BASM in Figure 4 is structured into two parts, a process model at the top (Panel A), and a variance model underneath (Panel B).

2.4.1 The Process Model in BASM (Panel A in Figure 4)

The process model in Panel A in Figure 4 is a slightly extended version of our earlier representation of the process model implicit in Davenport and Harris (2007) and Davenport et al. (2010) (see Figure 1). The extension is that in Panel A of Figure 4, the Competitive Actions in Figure 1 have been split into two types: (1) actions that use an organization's *existing* capabilities (including its many non-BA capabilities), and (2) those that *change* organizational capabilities (again including its many non-BA capabilities). Path 1 corresponds to Operational BA use. Path 2 comes to a "dead end" because it is assumed that changing an organization's capabilities does not, in itself, produce business value. Rather, it is subsequent use of those new capabilities that produces value. This is consistent with Shanks and Bekmamedova's (2012) model where Managerial Actions at the top of Figure 2 "lead to" the two transitions depicted in that figure, but not directly to business value. Path 2 also corresponds to Baretto's (2010, p.271) definition of dynamic capabilities as: (a) Sense opportunities and threats (equivalent to Use Analytic capabilities to produce Insight in Figure 4); (b) Make timely market-oriented decisions (equivalent to Decision(s) in Figure 4); and (c) Change the organization's resource base (equivalent to Competitive Actions that *change* the organization's capabilities in Figure 4).

To illustrate the distinction between the two pathways in Panel A of Figure 4, consider the Tesco example mentioned earlier. On path 1, routine analysis of customer purchases recorded at its checkouts allows Tesco to decide which coupons to send to which customers. Such actions induce those customers to purchase more goods from Tesco, leading in turn to greater profitability. On path 2, non-routine analysis of the same checkout data may lead to 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. Subsequent operations of these stores are the source of business value.

2.4.2 The Variance Model in BASM (Panel B in Figure 4)

The variance model (Panel B) in Figure 4 combines insights from Davenport et al.'s (2010) DELTA model (Panel B, Figure 1), Watson and Wixom (2007), and Seddon et al.'s (2010) OBES model in Figure 3. All five factors from DELTA are included in this model. All six factors from Watson and Wixom (2007) are also included in this model (Governance and Alignment are implicit in the model). The model—which is also a special case of OBES applied to business analytics—argues that an important mechanism through which firms derive increased benefits from business analytics is through well-chosen on-going BA improvement projects, i.e., projects focussed on well-chosen targets.

The right-hand project side of the model hypothesizes, as H1-H4, that the greater the extent of functional fit (H1), data quality (H2), analytic people (H3), and success in overcoming organizational inertia (H4) in a BA project, the greater the organization's success in realizing benefits from that project. H1 and H4 come from Seddon et al. (2010) in Figure 3. H2 and H3 come from Davenport et al. (2010) in Figure 1. As an example of the application of this model, 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 quality of the data used (H2), the analytic capabilities of the Finance-department staff (not others elsewhere in the organization) (H3), and their ability to learn to use the new functionality (H4) that will drive benefits from the project. 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 what Shanks and Bekmamedova (2012) call a dynamic BA capability. Once the new organization has gone live with its new dashboard system, benefits from use will flow from repeated execution of the process described in Panel A of Figure 4.

The left-hand side of the model in Panel B of Figure 4 hypothesizes, as H5-H8, that in the long term, it is leadership (H5), the building of an integrated BI platform (H6), the choice of well-chosen targets (H7), and execution of multiple projects, possibly over many years (H8), that will help the organization obtain greater benefits from business analytics. H5-H7 come from Davenport et al. (2010) in Figure 1. H8 comes from Seddon et al. (2010) in Figure 3. Finally, the left-hand side of the model in Panel B of Figure 4 hypothesizes, as H9, that the real key to success with BA is to embed evidence-based decision making into the "DNA" of the organization. H9 is our attempt to express in words the key argument in both Davenport and Harris (2007) and Davenport et al. (2010) which is that the more that evidence-based decision making is embedded in the "DNA" of the organization, the greater the business value that is likely to flow from investment in business analytics. Kettinger et al. (2011) describe this concept as the firm's Information Orientation.

2.4.3 In a nutshell

The Business-Analytics Success Model (BASM) model in Figure 4 is a synthesis of many ideas from the literature, particularly those from the three models reviewed above. 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 4 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, Figure 4) lead to changes in organizational capabilities, but as pointed out by Shanks and Bekmamedova (2012), many use existing capabilities (path 1) to produce business value.

Second, in addition to this process view, BASM also offers a variance-model perspective of how firms use BA to create business value. From a variance-model perspective, it is argued that the key to achieving greater business value from BA is to embed a positive attitude to evidence-based decision making in the DNA of the focal organization. In the long term, such positive attitudes are driven by the three factors on the left of Panel B of Figure 4 (H5-H7). In addition, the BASM also argues that projects to implement new BA capabilities are an important mechanism through which firms can improve organizational outcomes from BA (H8). With regard to projects, success in generating business value from any individual project, the BASM argues, is likely to be higher if the new capabilities are a good fit with business needs (H1), data quality is high (H2), the organization has the analytic capabilities to use the BI tools available (H3), and training and change management are used to support changes in work practices (H4). The actual mechanism through which all these factors contribute to business value is as shown in the process model in Panel A.

3 TESTING THE MODEL

To conduct a very preliminary test of the validity of the model in Figure 4, we downloaded a series of BA customer-success stories from three vendor websites (IBM, SAP, and Teradata) and examined those stories to see how frequently concepts and relationships identified in the BASM were discussed in the vendor's customer-success stories. 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 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.

Of course, vendors' customer-success stories always paint a rose-colored picture of the use of their software. However, they are built on a scaffolding of facts about people and processes that can be used, with care, to gain much easier access to a wider range of BI-using organizations than is possible through organizing and conducting case studies oneself. A similar technique was used by Seddon et al. (2010) as a preliminary test of their OBES model, published in MIS Quarterly.

3.1 Characteristics of the sample

Our sample of customer-success stories was gathered by visiting eight major BI-software-vendor websites and looking for success stories related to the use of analytics to create business value. We found that the stories from IBM, SAP, and Teradata were the most useful because they were typically of 1,500-3,000 words in length. Stories from other vendors, e.g., Oracle, were less comprehensive and therefore less useful for our purpose. For this reason, all the success stories used for testing in this paper are from IBM, SAP, and Teradata. Customer success stories from these three vendors were selected when they discussed some aspect of the use of business analytics. In other words, stories focussing on just implementation, but not use, were excluded. Using these criteria, we downloaded 116 vendor success stories: 45 from IBM, 35 from SAP, and 36 from Teradata. These stories cover use of business analytics in a wide range of industries and government using a wide range of software. From these stories we used a random-number generator to select 40 stories for analysis for this paper. A typical example of a customer-success story is an eight-page article from IBM on Sharp HealthCare, published in 2010. An extract from the Overview of the article is shown in Figure 5.

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.

Figure 5: Extract from page 1 of IBM's Sharp Healthcare case, *downloaded in late 2011 from*
http://www-01.ibm.com/software/success/cssdb.nsf/CS/SANS-893HB8?OpenDocument&Site=cognos&cty=en_us

3.2 Coding

For testing the BASM, both coders worked together to code a small number of examples from the 40 selected. Next, a random sample of six other success stories was coded independently by two coders, then compared and reconciled in a two-hour meeting. After that, coder 2 coded the remaining 30 or so stories alone. Like Seddon et al. (2010), we used a spreadsheet with one row per success story, and 15 columns for the 15 concepts in the BASM to record results of our analysis. For each story, coding involved asking whether any of the 15 concepts in the BASM, e.g., leadership, 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, the cell was left blank. Occasionally, if the evidence was present, but weak, we scored the evidence as 0.5, not 1. After coding was completed, 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.

To illustrate these coding judgments, consider the IBM Cognos Sharp Healthcare example from Figure 5. First, in terms of context, 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:

> "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." (p.2)

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 5 shows that BI is now being used in this organization as an integrated reporting tool for improving organizational effectiveness, not as the primary basis for 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 BASM inherited from Shanks and Bekmamedova (2012) and this success story from IBM.

Turning now to the detailed analysis, 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 Brown:

- "I am now 100 percent confident in the data that we have so that users can count on the reliability of their reports", and
- "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 data quality and ongoing projects, respectively, were important concepts in the variance model in Panel B of Figure 4 (the implication being that they led to business value).

4 RESULTS AND DISCUSSION

Results from our analysis of 40 vendor business-analytics success stories are presented in Table 1. The table reports the percentage of times that the various concepts from the BASM in Figure 4 were mentioned in the BA success stories. We expected that all stories would report that BA Capabilities were being used and that they provided benefits. The figures of 100% for row 1, and 96% for row 15 are consistent with this expectation. The high percentages in rows 2, 3, 4, and 6 were also much as expected. They say that (a) people were gaining insight from use of analytics (row 2), (b) insight led to decisions (row 3), (c) decisions led to competitive actions using existing capabilities (row 4), and (d) use of analytics was driven by key people (leaders) in the organization (row 6). We were surprised that the reported number of BA-driven *changes* to organizational capabilities (row 5) was so low (8%), but had not expected it to be very high. All in all, there is strong support in the vendors' customer-success stories for the process model in Figure 4. It appears to be a good description of reality.

Concept from the BASM in Figure 4	% of stories mentioning
Process model:	
1. Use of business analytic capabilities by any organizational unit to analyze routine and/or non-routine, internal and/or external data	100%
2. Insight(s) arising from use of business analytic capabilities	96%
3. Decisions flowing from insights flowing from use of BA capabilities	95%
4. BA-driven Competitive actions that use existing capabilities (operational use of BA capabilities)	95%
5. BA-driven Competitive actions to change Organizational Capabilities, i.e., that require use of the organization's dynamic capabilities	8%
(see row 15 for Organizational Benefits)	
Variance Model:	
6. Analytic leadership, i.e., people in any organizational unit who take leadership of projects to increase use of business analytics for organizational gain	91%
7. Integrated business-analytics platform as an important driver of business value from BA	99%
8. Judiciously chosen targets for analysis	65%
9. On-going major BA-improvement projects	50%
10. Extent to which evidence-based decision making is embedded in the "DNA" of the organization	15%
11. Functional fit of the BI tools to meet the needs of users (including fast access to information when sought)	68%
12. High-quality data	39%
13. Analytic people, i.e, the availability within an organizational unit of people with an analytic mindset who help drive business value from BA. This includes Davenport et al.'s (2010) analytical champions, professionals, semi-professionals, and amateurs.	19%
14. Overcoming organizational inertia, i.e., training and change management to support the introduction of the new way of working	21%
15. Organizational Benefits from Analytics Use, from the perspective of Senior Management (a synonym for Business Value from Business Analytics) in this customer-success story	96%

Table 1: Results from analysis of 40 vendor-supplied business-analytics customer success stories

Given the strength of Davenport et al.'s (2010) arguments about the importance of the factors in their DELTA model (see Figure 1) and Seddon et al.'s (2010) claims about the importance of the factors in their OBES model (see Figure 3), most of the percentages for the variance model, rows 6-15 in Table 1, were lower than expected. The exception was the use of the BI tools to create an integrated platform for analytics that provided a "single source of the truth" or a single collection of data for analysis. 39.5 (99%) of the 40 success stories we analysed (see row 7) mentioned something like this as a contributor to benefits from BA projects.

"How low could these percentages go", we asked, "before one would say that the reports in the success stories did *not* support the variance model in Figure 4?" The answer, we decided, was around 30%. For instance, a factor such as data quality is clearly important for realizing benefits from BA, yet only 39% of stories (row 12) mentioned this factor. The integrated platform that appears so important in Table 1, row 7, would be of little use if it delivered erroneous data. Further, a factor could be important, yet not discussed in the success story because it was “self evident” or because it had not been an issue. Thus we decided to treat any percentage above 30% as sufficient evidence in this preliminary test to say that there was support in the data for the model. This meant that there are three questionable factors in the variance model in Figure 4:

(a) As shown in row 10 of Table 1, despite Davenport and Harris’s (2007) and Davenport et al.’s (2010) strong arguments that some organizations rely so heavily on BA as a source of competitive advantage that they have become analytic competitors, only 15% of our customer-success stories suggested that evidence-based decision making had become embedded in the “DNA” of the organization *to any appreciable extent*. Our conclusion here is that because the variable in the model is labelled “*Extent* to which ...”, this concept is meaningful in all stories. It is just that few of the organizations in our success stories scored highly on this variable. We therefore decided that we would retain this variable for future research, but that the coding needed to be more fine-grained than the current binary scoring. In future work, we propose to use a five-point Likert-type scale for this variable.

(b) As shown in row 13 of Table 1, despite Davenport and Harris’s (2007) and Davenport et al.’s (2010) strong arguments that one cannot successfully do business analytics without employing analytical people, only 19% of our customer-success stories mentioned analytic people. Our conclusion here is that Davenport et al.’s arguments still make sense: people without an analytic mindset are unlikely to use analytic resources effectively. Therefore, we decided to retain this construct in the BASM for future research.

(c) As shown in row 14 of Table 1, despite Seddon et al.’s (2010) strong arguments that overcoming organizational inertia is a key to success with Enterprise Systems, only 21% of our customer-success stories mentioned ideas related to this construct, and most of those references were to training. One explanation for this low score is that persuading people to shift from a “gut feel” to an evidence-based approach to decision making is not hard. But this seems unlikely. In fact, in our experience, organizational change is always hard (Kotter 1996). Therefore, we decided that this construct (Overcoming Organizational Inertia) is likely to be an important variable for explaining success with at least some BA efforts in future. So we decided to retain this construct, too, in the BASM for future research.

5 CONCLUSION

In this paper we set out to answer the question “*Through what mechanisms does business analytics contribute to business value?*”. Our answer to this question is the business-analytics success model (BASM) shown in Figure 4. This model was developed by identifying from the recent literature a number of models of key factors that affect business value from business analytics, then grouping and reorganizing the factors identified into what seemed to us to be a coherent process model (Figure 4, Panel A) and variance model (Figure 4, Panel B) of key factors that affect how business value is created through use of business analytics. The resultant BASM in Figure 4, together the explanation that surrounds it, is the primary contribution of the paper. The BASM combines insights from some very fine research into processes and factors that lead to benefits from business analytics, as well as insights from the strategic management literature and the broader Enterprise Systems literature.

Finally, although much more rigorous testing is clearly necessary, the empirical test results summarized in Table 1 provide preliminary support for many parts of the model. Support for the process-model part of BASM was very strong. Support for the variance model was less strong, but given the limitations of the data (customer-success stories published on software-vendor websites), support for the importance of most factors in the model was sufficiently strong (the factor was mentioned in more than 30% of stories) to justify their continued use in future research. Even for the three factors that were not mentioned frequently in Table 1, both logic and evidence provided in Davenport and Harris (2007) and Davenport et al. (2010) tells us that each of the three factors is worth retaining in the BASM.

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