Communications of the Association for Information Systems

Volume 46 Article 28

6-2020

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Toomas Tamm
The University of New South Wales, toomas.tamm@unsw.edu.au

Peter B. Seddon
The University of Melbourne

Graeme Shanks
The University of Melbourne

Recommended Citation

Tamm, T., Seddon, P. B., & Shanks, G. (2020). How Do Different Types of BA Users Contribute to Business Value?. Communications of the Association for Information Systems, 46, pp-pp. https://doi.org/10.17705/1CAIS.04628

Communications of the Association for Information Systems

Research Paper DOI: 10.17705/1CAIS.04628 ISSN: 1529-3181

How Do Different Types of BA Users Contribute to Business Value?

Toomas Tamm
UNSW Business School
UNSW Sydney
toomas.tamm@unsw.edu.au

Peter B. Seddon
School of Computing and Information Systems
The University of Melbourne

Graeme Shanks
UQ Business School, The University of Queensland
School of Computing and Information Systems
The University of Melbourne

Abstract:

To explain how different types of business analytics (BA) users contribute to business value, we propose a new variance model called organizational benefits from business analytics use (OBBAU). The model captures three key mechanisms through which two distinct types of BA users drive organizational benefits: 1) data scientists providing advisory services, 2) end users using BA tools, and 3) both data scientists and end users creating and enhancing BA tools. To build the OBBAU, we thoroughly reviewed the BA and IS literatures and interviewed 15 BA experts.

Keywords: Business Analytics (BA), Business Intelligence (BI), Data Analytics, Data Scientist, End User, Organizational Benefits, Business Value, Analytics Use, Decision Making.

This manuscript underwent peer review. It was received 07/15/2019 and was with the authors for 1 month for 1 revision. Indranil Bose served as Associate Editor.

1 Introduction

Since about the mid-2000s, we have seen massive and increasing interest worldwide in “business analytics” (BA), “data analytics”, “business intelligence” (BI) (Waller & Fawcett, 2013), and, more recently, artificial intelligence (AI) (Benbya, Pachidi, Davenport, & Jarvenpaa, n.d.). These concepts have many possible definitions (e.g., Holsapple, Lee-Post, and Pakath (2014) identify 18 different definitions for BA). In this paper, we view data analytics and BA as synonyms that refer to using data to make sounder, more evidence-based business decisions (Davenport & Kim, 2013, p. 3; Holsapple et al., 2014; INFORMS, n.d.)[1] and regard AI and BI as examples of BA tools (i.e., digital technologies that enable BA by either augmenting or substituting for humans in organizational decision making). Such technologies include automated decision algorithms, applications for statistical analysis, visualization, online analytical processing, data mining, and data warehouses (Brynjolfsson & McAfee, 2017; Negash, 2004).

BA and related technologies have been at or near the top of the list of CIO priorities in Gartner’s annual global surveys since about 2005 (Gartner, 2005; Howard & Rowsell-Jones, 2019; Swan, 2012). Leading enterprise software vendors have made multi-billion dollar investments to add or enhance BA capabilities of their product portfolios (e.g., Oracle bought BI firm Hyperion, IBM bought Cognos and SPSS, SAP bought BusinessObjects, Adobe bought Omniture, and many companies have built enterprise systems based on in-memory database technologies). Numerous universities and professional organizations have begun to offer an ever-growing list of degrees and certification in BA (e.g., Swanstrom (2019) has collated a list of more than 600 such degrees).

Clearly, organizations and society more broadly have much interest in BA. Several factors seem to generate this interest, such as 1) the ready availability of enormous computing power (Reed & Dongarra, 2015); 2) much-improved analytics software (Davenport & Patil, 2012); 3) the increased availability of “big data” (McAfee & Brynjolfsson, 2012), which includes real-time data from sensor arrays, click streams, and social media; 4) greater acceptance and understanding of analytics in large organizations (McAfee & Brynjolfsson, 2012); 5) increased availability of powerful mobile computing devices such as smartphones and tablets, and 6) the sense that most benefits from previous computing revolutions—such as enterprise systems and outsourcing—have been won, so organizations now need to turn to greener pastures to achieve an IT-based competitive advantage. Consequently, many in the business community view BA as the “next big thing” (Brynjolfsson & McAfee, 2017; McAfee & Brynjolfsson, 2012).

However, just as “good data won’t guarantee good decisions” (Shah, Horne, & Capellá, 2012), good BA tools do not guarantee good decisions. Rather, the way people use these tools and data to gain insights and the way that BA-using organizations make and implement decisions drives organizational benefits. While many studies on BA benefits realization recognize the importance of using BA (e.g., Clark, Jones, & Armstrong, 2007; Mikalef, Pappas, Krogstie, & Giannakos, 2018b; Seddon, Constantinidis, Tamm, & Dod, 2017; Torres, Sidorova, & Jones, 2018; Wixom, Yen, & Relich, 2013), surprisingly little research has examined BA use and users in depth. For example, Clark et al. (2007) identified BA user knowledge, commitment, and involvement in BA tool development as key drivers of BA use and resultant benefits, but they did not examine the nature of this involvement or the knowledge required in detail. Wixom et al. (2013) highlighted BA use and pervasive use as key drivers of business value but focused more on enabling BA tools and data than BA users. Building on Davenport, Harris, and Morison (2010), Seddon et al. (2017) identified BA use (“use analytic capabilities”) as the source of BA value, argued that technical and human BA capabilities enable BA use, and identified three types of BA users. However, they did not reveal much about what these BA users actually do. Ghasemaghaei, Ebrahimi, and Hassanein (2018), Mikalef, Boura, Lekakos, and Krogstie (2019), and Torres et al. (2018) recognized “analytical skills”, “human skills”, and “BI&A personnel expertise”, respectively, as key antecedents of strong BA capabilities but did not explore what the relevant skills entail or how BA users apply them. Similar limitations apply to many other studies on BA value (e.g., Hartono, Santhanam, & Holsapple, 2007; Holsapple et al., 2014; Popovič, Hackney, Coelho, & Jaklič, 2012; Visinescu, Jones, & Sidorova, 2017). In reviewing the BA benefits literature, Trieu (2017) reached a similar conclusion in noting that “remarkably little attention has been paid to concepts of effective use in the BI literature” (p. 120).

[1]After analyzing 18 different definitions of BA, Holsapple et al. (2014) conclude with the following definition: “we adopt a general core characterization of business analytics as concerned with evidence-based problem recognition and solving that happen within the context of business situations.” Two other definitions similar to ours are as follows: “By analytics, we mean the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and add value” (Davenport & Kim, 2013, p. 3); and “Analytics is defined as the scientific process of transforming data into insight for making better decisions” (INFORMS, n.d.).

Despite the limited number of studies focused specifically on BA use and users, the literature does offer some valuable, though fragmented, insights on these themes. For example, Davenport et al. (2010) and Seddon et al. (2017) have provided some foundations for differentiating between BA user types. Emerging practitioner resources for data scientists provide useful insights into the skills and capabilities that these professionals require (e.g., Granville, 2014; Harris, Murphy, & Vaisman, 2013; Patil, 2011; Viaene, 2013). Case studies that examine organizational BA adoption and benefit realization provide glimpses into BA use in specific contexts, such as banking (Shollo & Galliers, 2016), healthcare (Wang, Kung, & Byrd, 2018), manufacturing (Dremel, Herterich, Wulf, & vom Brocke, 2018), and software development (Canossa, El-Nasr, & Drachen, 2013; Kim, Zimmermann, DeLine, & Begel, 2016; Tim, Hallikainen, Pan, & Tamm, 2018). These and other studies also provide useful insights into some enablers (e.g., Wixom et al., 2013), challenges (e.g., Deng & Chi, 2012; Vidgen, Shaw, & Grant, 2017), and/or tensions (e.g., Günther, Rezazade Mehrizi, Huysman, & Feldberg, 2017) that affect BA use.

Motivated by the strong and growing importance of BA and the current state of knowledge, in this paper, we focus on providing a more rich and detailed explanation of the fundamental mechanisms through which BA use contributes to business value. In other words, we focus on "unpacking" BA use and argue that one first needs to distinguish between two different types of BA users: data scientists (Patil, 2011) and end users (Rockart & Flannery, 1983). While both these BA users leverage BA tools to gain insights that lead to decisions, actions, and organizational benefits (Seddon et al., 2017), the work they do differs in nature. We explore how both end users and data scientists create business value through BA use and address the following research question (RQ):

> **RQ:** How do different types of BA users contribute to business value?

This paper proceeds as follows. In Section 2, we discuss our qualitative theory-building methodology, which involved thorough reviewing the BA and related IS literature and interviewing 15 BA experts. In Section 3, we present the insights that emerged from our theory building, including types of BA users and BA use, the organizational benefits that result from their BA use, and enablers of benefit realization (including BA tools, data, and user competencies). Then, we synthesize these insights into a model we call organizational benefits from BA use (OBBAU). In Section 4, we discuss how this new model contributes to our knowledge about organizational benefits from BA. Finally, in Section 5, we reflect on opportunities for future research.

2 Research Method

Before arriving at the focus that we describe in Section 1, we wanted to more broadly understand the current state of knowledge on BA value realization. For our initial search, we began with a broad Google Scholar search using various related terms, such as "business analytics", "business intelligence", "analytics benefits", "data mining", "data warehouse", "digital dashboards", "management information systems", "decision support systems", "knowledge discovery", and "OLAP".

Based on this initial literature search, we became interested in BA users and competencies and, more specifically, in explaining the underlying mechanisms (Mingers, 2004) through which different types of BA use create organizational benefits. This issue seemed essential to BA value realization, yet we could find relatively little research on the topic. At this point, we repeated the search using keywords specific to this focus, such as "analytics use", "analytics competencies", "analytics capabilities", "data scientist", and "data analyst". We also explored papers cited by and citing the most relevant papers in the Google Scholar search results to identify additional resources. Overall, we continued to find few studies that focused specifically on BA use and effective use. However, we did find insightful pieces of the puzzle across the BA literature, which we synthesize and integrate into the theory-development sections that follow.

As little research has addressed BA use and effective use, we decided to adopt a qualitative theory-building approach using expert interviews to gain further empirical insights about the topic. More specifically, we build on insights from 13 one-hour interviews with 15 BA experts in Australia. We used two key criteria for selecting our interviewees: 1) background diversity (to obtain rich perspectives on BA use) and 2) depth of individual experience (to maximize insights gained from each interview). First, to broadly understand BA use types and matters related to BA use, we focused on interviewing individuals from diverse BA-related backgrounds. As Table 1 shows, our sample included a data scientist and a BA manager (for an organizational perspective on BA use), recruiters specialized in hiring data scientists and BA professionals (for insights into various BA roles and competencies), BA tool vendors (for insights into current BA tool capabilities and use), and BA industry analysts and consultants (for a broad perspective on current trends and key issues in effective BA use). Second, in identifying individual interviewees, we focused on the depth and uniqueness of their BA-related expertise. We usually sought the most senior person at the organization in our area of interest. The interviewees had significant experience in BA and some had gained renown as leaders locally and internationally. Most worked for large, global organizations among the leaders in their industry. As Table 1 shows, our sample included vice presidents, partners, and BA practice leaders responsible for BA services and technologies at their respective organizations, a managing director and recruitment director responsible for hiring BA professionals, and an independent consultant who had founded and led several BA user groups and industry associations.

We conducted semi-structured interviews to benefit from our interviewees' diverse backgrounds and perspectives and to understand BA use as richly as possible (Myers & Newman, 2007; Walsham, 1995). Since we interviewed experts with detailed knowledge about many organizations, we could more broadly cover different contexts than we would have been able to through in-depth case studies, while, with the semi-structured interviews, we could tease out nuances and explanations that we could not have achieved with a survey. We audio-recorded and transcribed all but one interview[2] for later analysis, which resulted in 259 A4-sized transcript pages.

We analyzed the data and conducted theory building in a highly iterative way that broadly followed the open, axial, and selective coding phases (Neuman, 2005). We usually conducted the first analysis—a debrief in which we reflected on key insights—directly after each interview. The research model emerged gradually as we collected data, systematically analyzed the transcripts, and frequently revisited the literature. Once we arrived at what we believed to be the final model, the first and second author independently analyzed all 13 transcripts again to verify how we had initially interpreted the data relating to the emerging hypotheses. These two authors reconciled any differences in their analyses through discussion until they agreed on the judgments that we report in Table 5.

Table 1. Interviewee Profiles

ID	Role	Organization
I1*	BA recruitment director	Recruitment firm A
I2*	BA recruitment specialist	
I3	Managing director	Recruitment firm B
I4	BA user group leader and consultant	Self-employed
I5	BA practice leader (AU)	Industry research firm A
I6	BA practice leader (Global)	Industry research firm B
I7	Partner and BA practice leader (AU & NZ)	Consulting firm A
I8	Partner and BA practice leader (AU)	Consulting firm B
I9	BA practice leader (VIC)	Consulting firm C^
I10	Vice president (AU & NZ)	Enterprise software vendor A^
I11#	Head of innovation and strategy (AU & NZ)	Enterprise software vendor B
I12#	Vice president for BA (Asia Pacific)	
I13	BA practice leader	Enterprise software vendor C
I14	Data scientist	Telecommunications firm
I15	Analytics leader	Logistics firm

*, #: Two interviewees in the same interview
^: These organizations specialized in BA (i.e., BA products/services served as their key revenue source.
AU: Australia, NZ: New Zealand, VIC: Victoria (Australian state).

Finally, to reduce the risk of misinterpretation, we circulated copies of the preliminary analysis results to all interviewees. Several interviewees replied with various positive comments about the report. None raised any concerns about our interpretation. Further, the interviewees' seniority, the wide range of their interests and specializations, and the fact that we double-coded the interview transcripts increase our confidence in our findings. We discuss these findings and provide illustrative interviewee quotations in Section 3.

[2] I15 preferred that we not record the interview. Therefore, all three authors took notes during the interview that we compared and consolidated in a debrief session following the meeting.

3 Toward a Model of Organizational Benefits from BA Use

In this section, we synthesize the insights from our theory building and then present the resultant model of organizational benefits from BA use (OBBAU). We focus on explaining the underlying mechanisms (Mingers, 2004) through which BA use leads to organizational benefits. In order to explain BA benefit realization, we begin with differentiating between two key types of BA users in Section 3.1. We identify three key mechanisms through which BA users contribute to organizational benefits: 1) data scientist advisory services (Section 3.2), 2) end user analytics (Section 3.3), and 3) BA tool creation (Section 3.5). We also identify two key enablers of BA benefit realization: 1) quality of BA tools and data (Section 3.4) and BA user competencies (Section 3.6).

3.1 Two Types of Business Analytics Users

In this paper, we differentiate between two distinct types of BA users: data scientists and analytics end users. Data scientists are analytics professionals who provide evidence-based insights on various structured and unstructured questions to an organization's senior managers. They also help organizations embed such insights into operational systems. Analytics end users are business users throughout an organization—from senior executives down to the shop floor—who use BA tools. Such people typically have good business knowledge but frequently do not have strong statistical or analytics skills. These users help an organization realize benefits from BA through very different mechanisms.

3.1.1 Data Scientists

Data scientists[3] predominantly focus on using BA tools to better understand cause and effect in an organization and its environment. Davenport and Patil (2012) describe data scientists' work as coaxing "treasure out of messy, unstructured data" (p. 70) and making "discoveries while swimming in data" (p. 73). In less colorful language, data scientists use the scientific method (Popper, 1959) and abduction (Peirce, 1903) to build evidence-based causal models of phenomena that an organization has interest in, such as models of the drivers of organizational revenue and cost streams. For example, data scientists may focus on predicting bankruptcy (Olson, Delen, & Meng, 2012), predicting customer churn (Lee, Lee, Cho, Im, & Kim, 2011), optimizing supply-chain management (Cai, Liu, Xiao, & Liu, 2009), identifying new software functionality (Patil, 2011), assuring software quality (Kim et al., 2016), and so on. In performing such work, data scientists may use many types of quantitative and qualitative techniques, but they typically use a combination of powerful BA tools for interactive visualization, data mining, predictive modeling, prescriptive modeling, simulation, and optimization.

We can distinguish at least four roles that data scientists play in BA use (see Table 2). The first two roles are "advisory" because they involve providing advice on unstructured and semi-structured problems (Adam, Fahy, & Murphy, 1998) to managers who make the actual decisions. The third and fourth roles focus on building BA capabilities ("BA tool creation") for both end users and data scientists themselves to use in the future. Of the two latter roles, the BA tool creation role involves working with IT project teams to develop tools or products (e.g., dashboards) for both business end users to use in a routine or ad hoc manner or for decision automation. In some cases, creating such tools involves embedding insights from data-scientist advisory work, such as customer-segmentation insights, into operational processes, such as distinct types of marketing campaigns (Davenport et al., 2010). It may also involve efforts to help create decision automation tools, such as training supervised learning systems and/or validating the accuracy of unsupervised learning systems (Jordan & Mitchell, 2015).

Different organizations have experimented with various ways to organize their data scientists (Kim et al., 2016; Patil, 2011). Some place data science capabilities in their head office, some place them in specific business units, some source them from consulting firms (e.g., to meet occasional demands for ad hoc analyses), and some organize them using a combination of these approaches (Accenture, 2013; Schüritz, Brand, Satzger, & Bischhoffshausen, 2017). Each approach comes with its own strengths and weaknesses (Günther et al., 2017; Someh, Songhori, Wixom, & Shanks, 2018). Organizations sometimes call the organizational unit responsible for data scientists an "analytics center of excellence" (Accenture,

[3] Patil (2011) says that he and Jeff Hammerbacher coined the term "data scientist" around 2008 because they needed a new title to describe their teams of analytics professionals at LinkedIn and Facebook, respectively. The term took off. By 2012, Davenport and Patil (2012) described the data scientist role as "The Sexiest Job of the 21st Century". By early 2016, Google Scholar had indexed over 4,100 papers that contained the term "data scientist" and, by mid-2019, that number had grown above 23,000.

2013; Schüritz et al., 2017), “business intelligence competency center” (BACC/BICC) (Davenport & Harris, 2007, p. 29; Foster, Smith, Ariyachandra, & Frolick, 2015), or simply a “business analytics team”.

Finally, one needs to remember that, no matter how clever and insightful an organization’s data scientists, it only gains benefits when it applies the insights they generate (Dietrich, Plachy, & Norton, 2014; Seddon et al., 2017; Viaene, 2013). If the organization does not trust its data scientists, the individuals who sponsor professional analytics lack the organizational clout to exploit the insights, or other impediments to action exist, the time and money spent on data scientists’ work may be wasted.

Table 2. Data Scientist Roles

Data scientist role	Description
Providing advice on unstructured problems (Advisory role)	Conducting ad hoc analytical projects, which an important but broad business question that the organization does not yet fully understand often triggers. For example, building a financial model to help an organization decide on bidding price for a proposed corporate acquisition or “data prospecting” (i.e., using data-mining tools to try to uncover previously unrecognized patterns in data).
Providing advice on semi-structured problems (Advisory role)	Solving more routine problems, such as identifying the best way to segment customers for targeted marketing or developing a credit-scoring algorithm for a bank.
Supervising BI projects (BA tool-creation role)	Supervising how an organization embeds BA capabilities, which include insights from the first two roles above, into operational systems. Examples might include implementing active-dashboard systems for end users to repeatedly use, supervising efforts to train machine-learning algorithms, or supervising efforts to embed credit-scoring algorithms for automated decision making into a bank.
Contributing to BI platform planning (BA tool-creation role)	Providing advice to the IT function on toolset selection, data warehousing requirements, data quality, data capture from external sources (e.g., social media), and so on and generally working to ensure that a high-quality BI platform is available to help an organization use BA.

3.1.2 Analytics End Users

Researchers and practitioners have widely used the term “end-user computing” (Rockart & Flannery, 1983) for decades. We adopt the term analytics end user (which we use interchangeably with the term “end user” henceforth) to refer to hands-on business users of BA (i.e., any individual that uses BA tools other than data scientists, which includes senior executives, business managers, first-line supervisors, and clerks). Such people include Davenport and Harris’ (2007) “analytical executives” and “analytical amateurs”, but most end users would probably not describe themselves as analytical anything. They typically see themselves as business professionals in their respective domains and use BA tools only when they require data to inform a decision that they need to make as part of their job. In doing so, they may use conventional reports, spreadsheets, dashboards, scorecards, online analytical processing (OLAP), visualization tools, “productionized” BA[4], and/or ad hoc queries using either desktop or mobile devices. Insights from data scientists (e.g., decisions about market segmentation) may frame the way that these tools present the information to end users. Increasingly, business users are both expected to and interested in using BA tools for improving their decisions (Kiron, Prentice, & Ferguson, 2014).

We can distinguish at least three roles that end users play in BA use (see Table 3). The first two roles involve end users using BA tools to support organizational decision making. Here, end users use BA tools in “self-service” mode to gain insight. The third resembles data scientists’ “BA tool-creation role” (see Table 2) whereby end users contribute to building stronger BA toolsets for use in their organization.

As with the data scientist role, one needs to remember that, no matter how clever and insightful an organization’s analytics end users, only when it applies the insights they generate does it gain benefits (Seddon et al., 2017). If end users lack the organizational clout or if other impediments to action exist, their BA use will not produce much value to the organization.

[4] “Productionized” BA means embedding BA algorithms (often based on insights from the organization’s data scientists) into production IT systems for routine use (e.g., using insurance risk algorithms as an integral part of selling a new insurance policy). Many AI applications exemplify productionized BA.

Table 3. Analytics End User Roles

Analytics end user role	Description
Self-directed BA use (End use role)	Conducting self-directed ad hoc analytical projects while likely using less sophisticated tools (e.g., spreadsheets and OLAP tools) and more readily available data (e.g., structured data from corporate databases) than the tools that data scientists use.
Using analytics embedded in routine organizational processes (End use role)	Using reports, dashboards, and embedded BA functionality (possibly created as a result of insights from data scientists) as part of routine decision making (e.g., in insurance claims analysis (seeking to prevent fraud) or in conversations with call-center customers). One should note that to embed BA in routine processes, organizations need to make a large investment in BI platform infrastructure, data extraction, and data quality to enable end users to easily and securely use BA.
Participating in BA development projects (BA tool-creation role)	Contributing as users to designing and specifying analytics capabilities to meet their decision-making needs. An example might include working with a project team to specify the key performance indicators and data that should be presented in dashboards or standard reports.

3.2 Organizational Benefits from Data Scientist Advisory Services

The first mechanism through which BA users drive BA value involves data scientists—including third-party (outsourced) providers—providing advisory services to decision makers throughout their organization. This mechanism corresponds to the first and second roles in Table 2. In these roles, data scientists 1) conduct ad hoc analytical projects, which an important but broad business question that the organization does not yet fully understand often triggers (i.e., addressing unstructured problems (Adam et al., 1998)); and/or 2) solve more routine problems. Organizations expect their data scientists to use both their problem-solving skills (Newell & Simon, 1972; Pretz, Naples, & Sternberg, 2003) and the analytical tools and data available to them in combination to provide insights (Bowden, Jung-Beeman, Fleck, & Kounios, 2005; Sternberg & Davidson, 1996). These insights may help the firm reduce costs and/or provide better products/services to its customers and, thus, achieve a competitive advantage. Issues that organizations might call on data scientists to address include segmenting customers, identifying key drivers of customer churn, detecting fraud, improving credit-scoring algorithms, improving software functionality, and so on. Such advisory services often require data scientists to use sophisticated techniques and data that their organization's BI platform provides. Famous examples in which data scientists have created organizational benefits include improving Netflix's movie recommendation algorithm by 10 percent (Netflix, 2019) and helping Barack Obama to secure the victory in the 2012 U.S. presidential campaign (Issenberg, 2012, 2013).

All the BA experts we interviewed discussed some aspects of organizational benefits from data scientist advisory services. Some interviewees expressed the view that predictive analytics (Delen & Demirkan, 2013) in particular has a lot of promise as a source of benefits from such services. Since most individuals we interviewed had quite a strong relationship with the data scientist role, we do not find it surprising that many believed strongly in its value potential. More importantly, however, the interviewees also provided clear explanations and examples to back up their views:

> *We had [an analytics] group at the airline [that] analyzed information from the data warehouse relative to load factors. So how many people are on a particular flight from one place to the other, where do they buy their tickets, and how much profit did the company make out of it? And one of the analysts took it upon himself to do a little bit more digging.... It didn't matter what ticket it was, they paid 50 bucks [commission to travel agents]. Well, then the analyst came to the conclusion that well, hang on, ...in this particular case..., we basically own the route. Why are we paying these guys 50 bucks commission when there is no alternative? ...A golden query—they saved something like $20 million a year.* (I7)

> *They basically set up a consortium of UK insurers. ...And the power with doing that was not in each of the individual companies' data, but by bringing it all together. ...From that they were able to identify—and this was I believe using neural networks—to show associations with people..., [where an] individual was claiming on multiple policies across the different [insurers]. ...I know that they did uncover some big fraud rings.* (I9)

Despite their overall optimism about the value that data scientists provide, our interviewees generally expressed skepticism about the value potential of highly exploratory data "prospecting" because such searches for "the needle in the haystack" can be very expensive with an unknown return. Rather, they suggested that data scientists usually need clearly defined questions and a business case to maximize the likelihood that they will create value:

> *In the big world of how much data is being sent out compared to the value of analyzing that data and getting that insight, you're ploughing through several, several haystacks for that one needle and somebody's got to pay for those haystacks. …We're looking for evidence where having insights that are delivered through big data analysis will actually pay for what it took to collect and analyze that data. We're not interested in collecting and storing and churning through the data just for the heck of it.* (I7)

> *[Here's] a bunch of data, see if you can find something in it. Which we've found just doesn't work. You need to be very, very focused on a problem or problems that you're looking to solve.* (I9)

Although decision makers in an organization may on some occasions choose not to act on insights that data scientists provide, based on the above insights, we posit that, overall:

> **H1a:** The greater the extent to which data scientists provide high-quality advisory services (which includes providing advice on 1) unstructured and 2) semi-structured problems), the greater the organizational benefits from BA use.

3.3 Organizational Benefits from End User Analytics

The second mechanism through which BA users drive BA value involves end users at all levels in an organization using BA to make more evidence-based decisions. This mechanism corresponds to the first and second roles in Table 3. In these roles, end users 1) conduct self-directed ad hoc analytical projects using a range of tools and 2) use reports, dashboards, and embedded BA functionality as part of routine decision making.

As we explain in Section 3.1.2, organizations have increasingly made BA tools and data available to all their employees—from senior executives to front-line employees—to help inform their decisions. Employees use these tools to gain insights that lead to decisions and actions (Seddon et al., 2017) that result in organizational benefits. End user analytics includes using reporting tools, spreadsheets, and/or dashboards to inform both operational and strategic decisions. Such decisions might lead to improved customer service, better inventory planning, fewer loan defaults, fewer unexpected financial results, and so on. Further, we can expect higher-quality use to lead to greater benefits (Davenport et al., 2010).

Most individuals we interviewed also discussed the benefits that organizations gain from end users using BA, and many commented on a trend towards more analytics-savvy employees at all organizational levels. They observed that activities that have traditionally been BA professionals' responsibility have started becoming a part of end user analytics:

> *Where the analytics is embedded in the business process does make a huge difference. …Smarter processes or just more informed people that can make better decisions. [A] federal agency doing casework…did something really interesting. They just took some of the BI components out [of their data warehouse], well not out, but integrated them into the case-management environment in the right context and they saw case times reduce by 40%.* (I5)

> *[They] started an initiative last year, a pilot, for their petrol stations, so their fuel operations, to give all of their regional managers an iPad report which talked about their KPIs. So what's specific to their particular store—it could be retail, it could be fuel supply, it could be financial. How is that store performing? ...It was changing behavior in each of the stores. They were aligning to the KPIs, they were starting to work together. So why is that store over there doing better in these metrics than these stores, are they running better promotions, are they doing better staffing of their stores, etc.* (I11)

Although decision makers may on some occasions choose not to act on insights obtained from end-user use of BA, based on the above insights we posit that, overall:

H1b: The higher the extent to which end users engage in high-quality BA use (which includes 1) self-directed BA use and 2) use of BA embedded in routine processes), the greater the organizational benefits from BA use.

3.4 Technology and Data as Enablers of BA Use

The quality of the enabling technology and data strongly impacts an organization's ability to obtain benefits from BA use through the two mechanisms that we discuss in Sections 3.2 and 3.3. This quality comprises 1) BA tool quality (including hardware, software, processes, and governance (Ghasemaghaei, Hassanein, & Turel, 2017; Mikalef et al., 2018b; Seddon et al., 2017)) and 2) data quality (including its completeness, accuracy, timeliness, and accessibility (Price & Shanks, 2005)). These BA tools and data need to be fit for purpose (Ghasemaghaei et al., 2017; Seddon et al., 2017; Vidgen et al., 2017) and enable easy, secure BA use (Ghasemaghaei et al., 2018). BA tools and data affect the quality of BA services that data scientists provide and how well end users use BA and, thus, the quality of the resultant decisions (Delen & Demirkan, 2013; Ghasemaghaei et al., 2018; Visinescu et al., 2017) and the benefits that organizations gain (Torres et al., 2018).

A data scientist without access to high-quality data and sophisticated statistics, modeling, and simulation tools (e.g., SAS Analytics, IBM SPSS and R) is akin to a racing car driver without a car. Moreover, because data scientists often have to address unstructured problems, they will likely require access to multiple different data sources and potentially use the data from such sources for purposes other than what it was originally collected for (Shollo & Galliers, 2016). Our interviewees frequently mentioned the IT function's reluctance or slow responsiveness in granting analysts access to data or enabling tools as impeding their work:

> *Technology is a key enabler of analytics..., particularly if you want to handle large data sets and be able to provision them quickly and on a repeatable basis. ...There are very smart, low cost tools like MicroStrategy, like ClickView, like SAS, that are, like R, very powerful tools that can very quickly be plugged into data sources and extract information and be able to do analytics without the need necessarily to even involve anyone from the IT department.* (I8)

> *I've come across organizations a number of times where they said: 'Look, frankly we spend most of our time fighting IT. You know, fighting for data or we can't get R installed, we've been waiting for five months.* (I4)

> *Throughout my whole time*[5] *I was, generally speaking, begging data [from] the IT community.* (I14)

Therefore, the ease with which one can extract data from organizational databases and the extent to which the data is stored in (or can be converted into) a standardized format also enables quality data-scientist advisory services. Our interviewees also identified the lack of high-quality data as impeding organizations from realizing value from BA:

> *We had to work with people from within consumer [area] who were experts in the database of the call records—including their dirtiness—to do this [analysis]. So it actually took me five months to do it. I mean it should have taken me three weeks but it took five months, most of which was getting the data, and three days was doing the analysis.* (I14)

End users may also leverage various BA tools that software vendors may have built, their organization's IT team may have developed, or BA projects that data scientists coordinated may have implemented. Common BA tools for end users include pre-defined dashboards embedded into enterprise applications, which organizations can typically tailor when implementing; visualization software from vendors such as Tableau, Qliktech, Spotfire, and MicroStrategy, which allow users to more flexibly and dynamically examine data individually or interactively in groups; and spreadsheet packages, which have long been a staple in end user analytics (Davenport & Harris, 2007) and include powerful BA capabilities such as real-time links to data sources, pivot tables, statistical functions, and various add-ins (e.g., Solver, and Visual Basic macros) (Albright, Winston, & Zappe, 2010), though authors such as Davenport and Harris (2007, p. 168) caution that end users can often make errors when using spreadsheets and/or use spreadsheets in scenarios that this tool does not suit.

[5] This interviewee, who had a PhD in accounting, had worked for over 20 years as a data scientist (i.e., long before anyone coined the term "data scientist").

End users lack time and expertise in assessing underlying systems' or data's quality. Therefore, high-quality tools, platforms, data, and support structures can enable end user analytics. As I11 observed:

> *BI's becoming humanized, it's becoming accessible and it's becoming trusted. But with that expectation there's also a lot of risk. Because what if you're serving up bad data, what if you're serving up poor analytics to those people? You're actually exposing people to make decisions on bad processes. …BI requires you to have a foundation that is trusted, you have to have one single semantic layer that everyone agrees to, you need to have very strong ETL processes and data management and data governance processes and you need to have your power users that help manage that environment.*

In summary, to enable high-quality BA use by both data scientists and end users, organizations often need to invest significantly in BA infrastructure, data extraction, and data quality. Further, for end users these resources need to be particularly easy to use, because they generally lack expertise in controlling for potential errors or biases in underlying data and rarely have the time to seek out and use BA tools unless they can easily access them. Since BA tools and high-quality data provide the foundation on which both data scientist and end user analytics become possible, we posit that:

> **H2:** The higher the quality of the enabling technology and data (which includes 1) an integrated BI platform; 2) application support for BA; and 3) data completeness, accuracy, timeliness and accessibility), the higher the quality of data scientist advisory services and end user analytics.

3.5 The Role of BA Users in BA Tool Creation

In the previous section, we discuss the importance of high-quality BA tools as an enabler of BA use. However, this relationship is reciprocal as BA users, in turn, have an important role to play in improving the quality of BA tools for both their own and/or their colleagues' use. Therefore, the third mechanism through which BA users drive BA value involves both data scientists and analytics end users 1) creating and improving BA tools for them both to use and 2) embedding insights from BA into operational systems that end users (perhaps not volitionally) use. This mechanism corresponds to the third and fourth roles in Table 2 and the third role in Table 3.

Specifically, it involves data scientists, end users, and IT staff working together on projects 1) to enhance their organization's BI platform (Davenport & Harris, 2007; Davenport et al., 2010), 2) to embed insights from using analytics into organizational processes (Davenport et al., 2010; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011), and 3) to provide access to high-quality data (Davenport et al., 2010). Such projects do not lead to organizational benefits directly. Rather, they contribute later when data scientists and end users (effectively) use the new BA capabilities. BA tool-creation examples include 1) the implementation of new software that delivers new analytics functionality, 2) initiatives that apply existing functionality to new decision-making areas, 3) projects to build tools to embed insights that data scientists discover from using BA into routine organizational processes, and 4) projects to provide more high-quality data to both data scientists and end users.

While data scientists and end users both play an important role in creating BA tools, they contribute differently to this process. Data scientists add value by creating and improving BA tools and guiding efforts to embed BA capabilities in operational systems by 1) supervising efforts to embed BA capabilities that they develop in their analytics initiatives (e.g., improved customer segmentation or credit risk models) into operational systems (Davenport et al., 2010) and 2) providing advice to the IT function to ensure that an organization has a high-quality BI platform and high-quality data to help all employees use BA (Davenport & Patil, 2012). End users help create BA tools in a way that resembles how users contribute to most other IT projects (i.e., they assist the project team to understand business information needs and to design solutions that address these requirements). Doing so improves the chances that the new tools are useful, easy to use, and relevant to the business.

While all of these ways in which BA users contribute to BA tool creation have value, "productizing" insights from data scientists in particular appears to be an increasingly important mechanism for organizations to realize benefits from BA. It can lead to two types of BA tools. The first type includes tools for end users to support them in their routine decision processes (e.g., Shanks and Bekmamedova (2012) describe how data scientists' insights at a large financial institution led to the development of dashboards to assist customer-facing staff in their daily interactions with customers). The second type includes tools that fully automate certain decisions, i.e., tools for algorithmic decision making (Faraj, Pachidi, & Sayegh, 2018; Galliers, Newell, Shanks, & Topi, 2017; Lindebaum, Vesa, & den Hond, 2019).

Ongoing BA tool-creation initiatives also emerged as an important factor that enables BA value in our interviews. Once an organization builds tools for routine, operational decision making, these decisions no longer require data scientists' involvement. While time and cost constraints can prohibit organizations from involving data scientists in operational decisions, embedding their knowledge in operational systems in the form of algorithms makes it available quickly and at scale, which, in turn, enables decision makers to act in a timely and well-informed fashion at the frontline. As Davenport et al. (2010, p. 121) observe, "embedding analytics into processes improves the ability of the organization to implement new insights. It eliminates gaps between insights, decisions, and actions." This is consistent with the following observations from our interviewees:

> *[If] it's solving a really big problem and it's worth doing as just one-off is fine. But I think you'll get the most value by creating your model, solving the problem, getting into a production state, getting the business using it on a daily basis and then iterating back to check that the model's still running, still producing those results because businesses change quite rapidly.* (I9)
>
> *Far too many people view BI as being a project but it's actually a program, it's not a project [in] the traditional sense. …Yes, the first iteration might be, but for BI to be successful it has to be a program that has ongoing longevity and executive sponsorship.* (I10)
>
> *The more valuable part is to use that routine, that algorithm or whatever it was, that this [data scientist] found and say, alright, how about every time we get a claim in, we run it through this algorithm or this engine. …That way you stop it and analyze it before the money goes out the door.* (I7)

Because BA tool-creation projects can enable an organization to increase how well and how sophisticatedly both data scientists and end users use BA, we posit that:

> **H3:** The more effective the BA tool-creation initiatives (which include 1) the number of ongoing BA initiatives, 2) data scientists' supervising BI projects, 3) data scientists' contributing to BI platform planning, and 3) end users participating in BA development projects), the higher the quality of the enabling technology and data available to BA users.

3.6 Competencies as Enablers of BA Use and Tool Creation

Researchers have widely acknowledged human competencies (which include cognitive ability, knowledge, motivation, creativity, and skills relevant to a job task (Spencer & Spencer, 1993)) as a key determinant of the quality of the work they do (Hunter & Hunter, 1984; McClelland, 1973; Sandberg, 2000). In this section, we examine the key BA user competencies and how these competencies affect each of the three BA benefit mechanisms (i.e., 1) the quality of data scientist advisory services, 2) the quality of end user analytics, and 3) the effectiveness of BA tool creation).

3.6.1 Competence of Data Scientists

Data scientists require the following competencies: 1) strong statistical analysis, computing, and data-manipulation skills (Davenport & Patil, 2012; Debortoli, Müller, & vom Brocke, 2014; Mikalef, Giannakos, Pappas, & Krogstie, 2018a; Power, 2016); 2) research skills (Mikalef et al., 2018a; Power, 2016), which includes the ability to explore and test cause-and-effect explanations; 3) curiosity (Davenport & Patil, 2012; Vidgen et al., 2017); 4) a deep understanding of the enquiry context (i.e., the business domain) (Davenport & Harris, 2007; Debortoli et al., 2014; Waller & Fawcett, 2013); and 5) strong communication and interpersonal skills both for liaising with the business domain experts (Viaene, 2013) and for conveying BA insights convincingly to business stakeholders (Kim et al., 2016; Patil, 2011). Due to the nature of data scientists' work, many of these competencies overlap with the competencies that doctoral researchers (Kim et al., 2016), statisticians, and econometricians require.

Our interviewees expanded on several of these competencies. A data scientist needs strong technical skills in statistical methods, modeling, and data visualization and the ability to extract and convert data for analytics purposes. They also agreed that finding analysts with the right technical skills does not pose the greatest challenge. Rather, the greatest challenge involves finding data scientists who have not only the necessary technical skills but also research skills, business and domain knowledge, and interpersonal and communications skills. For example, two interviewees observed that:

> *The most successful all-rounder analyst…has got the technical and academic smarts to be able to delve into the data, be able to develop some really effective analytical solutions, but then understand how and why that can be used within a business. Rather than just stop at the numbers but somebody who can actually interpret that information and use that to address a problem.* (I1)

> *In business, I've found nothing more useful in my background than my research training but that's partly also a function of the particular roles that I was given. So the ability to determine a relevant context for the problem, you know, contextualize a problem and sharpen the problem statement, articulate some questions, interrogate stakeholders as to their particular views.* (I14)

Based on the insights we discuss above, we posit that:

H4a: The higher data scientists' competence (which includes 1) technical skills for statistical analysis, computing, and data manipulation; 2) research skills and curiosity; 3) business and domain knowledge; and 4) interpersonal and communications skills), the higher the quality of their advisory services.

3.6.2 Competence of Analytics End Users

End users can use BA in two ways: 1) based on curiosity (the first role in Table 3) and 2) by using algorithms that data scientists create and operational software embeds (the second role in Table 3). Both ways require user competence, though the former more closely resembles an elementary data scientist role. The competencies that end users need to use BA effectively include the ability to 1) understand BA-based insights' opportunities and limitations relevant to their role and responsibilities, 2) engage in basic exploratory analytics (e.g., interrogate data using spreadsheets, basic tailoring of dashboard reports, etc.), and 3) effectively interpret and incorporate data-driven insights into their daily decision making (Davenport & Harris, 2007).

Both prior research and our interviewees mostly focused on data scientists' competencies (an issue we discuss further in Section 5). However, our interviewees did highlight that end users are becoming increasingly BA savvy. Therefore, many analytics tasks have begun to move from the specialist data scientists' domain to the mainstream end user domain. As two interviewees said:

> *There's been a bit of a line of thinking that, you know, you need to be a Harvard PhD maths graduate to actually be able do this. …But actually the greater weight of movement here will be from business people becoming more analytically savvy.* (I8)

> *The expectation has moved up the value chain of what self-service means. A few years ago, the things that the tools that are being delivered now [are used for], would come out of what's now become fashionably known as the Data Science department…. If you went back five years and or even maybe a little longer, seven or eight years, and you went to a marketing department and said: "Tell me about basket analysis", they'd go: "What are you talking about?".* (I10)

Furthermore, unlike data scientists, organizations often do not hire end users based on their BA skills, which means that analytics end users' competence may in fact warrant special attention. For example, Deng and Chi's (2012) findings suggest that insufficient relevant competencies may represent the predominant reason that prevents end users from effectively using BA (whereas, for data scientists, the common impediments generally relate to BA tool quality). Case studies on organizations transitioning towards more evidence-based decision processes highlight the importance of end user training as one of the first steps on the journey towards improving how effectively and how extensively end users use BA (Dremel et al., 2018; Tim et al., 2018).

Based on these insights, we posit that:

H4b: The higher analytics end users' competence (which includes their 1) awareness of BA opportunities and limitations, 2) ability to interpret BA insights, 3) basic exploratory analytics skills, and 4) readiness to act on BA insights), the higher the quality of their BA use.

3.6.3 Competence in BA Tool Creation

Just as competencies affect the quality of data scientist advisory services and the quality of end user analytics, they also affect the effectiveness of BA tool creation. While many skills that data scientists and end users need in a tool-creation role overlap with the skills that they require when using BA, our data suggests that certain skills may be unique to a tool-creation context.

Regarding data scientist competencies, 1) systems integration skills (I4), 2) IT development skills (I9 and I15), and 3) the ability to engage effectively with the IT function (I4) appear to be at least more important in, if not unique to, the BA tool-creation context. Additionally, when creating prescriptive BA tools, business process management skills may have high importance (I6). As two interviewees elaborated:

> *Prescriptive stuff is really when you start to get into…what we're calling intelligent business operations. So once again, this is more of your real time analytics…. There's a lot more skills around business process skills and business process management skill involved in that prescriptive area.* (I6)

> *You've created your model, you've got a great model that you think's going to work and you can sort of prove that but then the next step is to actually be able to what I call productionize and put it into the business systems where you want it to be working. And that also is a level of skill that's required. So you need to understand some of the project methodologies—whether that's using Agile or standard waterfall processes—but you need to take that model and be able to productionize it and help the business use it.* (I9)

Furthermore, some skills that data scientists commonly need to effectively provide advisory services may have a different role or emphasis when they create BA tools. For example, data scientists need the ability to engage with the end user community in both contexts. However, the contexts have different desired key outcomes: end users' ability and willingness to act on the advice in the former and end users' ability and willingness to leverage the resulting BA tool in the latter. These two distinct outcomes may require different influencing skills, since users choose whether to adopt data scientists' advice largely at a particular point in time (and, hence, the choice may be more amenable to active persuasion) but adopt a BA tool over time (and, hence, achieving behavior and/or habit change often has greater importance). As an interviewee said:

> *What sort of skills do you need with operational analytics? …Well, building predictive models for accuracy, deploying predictive models. …And then what are the soft skills? The soft skills are really all about coordinating with IT. Please give us the data, please don't choke us ('cause IT loves doing that). Coordinating with the trigger-pullers, the end users. Please use these insights, we're not here to make you obsolete, we're not here to make you feel stupid, this computer thing is here to help you. You know, winning people over, playing all these sort of lateral politics. And then integrating everything electronically as well, getting a whole lot of systems to talk to each other.* (I4)

Based on these insights, we posit that:

> **H5a:** The higher data scientists' competence, the more effective their organization's BA tool-creation initiatives.

Regarding end user competencies, our data remained mostly silent on skills specific to the BA tool-creation context. The only related insight emerged from I13, who discussed the importance of BA users understanding what one can achieve with BA (which converges with the competence about understanding BA-based insights' opportunities and limitations that we discussed in relation to H4b):

> *If someone's got a reporting requirement, …they have a pretty good idea when they talk to you about what they want to do. In [the predictive analytics] area, they don't know what is possible. So they know they've got a problem and you've got to try and understand the problem and drill down on the problem before we can structure a solution.* (I13)

The lack of related discussion could mean that 1) end users have more homogenous skills in using BA and creating BA tools, 2) our interviewees had more interest in and/or knowledge about data-scientist competencies (i.e., the lack of discussion could constitute a limitation in our data), or 3) end users' skills largely do not affect BA tool creation. In our opinion, the third explanation is the least plausible. Although end users might play a less prominent role in creating BA tools than data scientists, at the least, some competencies that we discuss in relation to H4b should be important for effectively participating in BA tool creation as well (as the above insight from I13 suggests). Therefore, for completeness and as a foundation for future research, we tentatively also posit that:

H5b: The higher analytics end users' competence, the more effective their organization's BA tool-creation initiatives.

3.7 A Model of Organizational Benefits from Business Analytics Use (OBBAU)

In this section, we consolidate the key insights from the preceding theory-building sections regarding the mechanisms through which BA users contribute to business value. We summarize these insights, based on both our empirical findings and literature synthesis, in the organizational benefits from business analytics use (OBBAU) model in Figure 1 and define the constructs in this model in Table 4. We frame the OBBAU as a variance model (Langley, 1999); that is, its seven constructs are defined as variables, and the arrows in Figure 1 (with the labels H1a to H5b) indicate a variance relationship between the constructs. Table 5 summarizes which interviews provided insights towards formulating each hypothesis. A "Y" in a cell in Table 5 indicates that the specific interview supported the formulation of the respective hypothesis. For reasons that we explain in Section 3.6.3, we also include H5b in the OBBAU despite the limited empirical support in our data.

In a nutshell, we argue that, to more deeply understand how organizations realize benefits from BA, we need to differentiate between two types of BA users: data scientists and analytics end users. We propose three key mechanisms (Mingers, 2004) through which BA users drive BA value: 1) data scientists providing advisory services to organizational decision makers (H1a), 2) analytics end users using BA tools in self-service mode (H1b), and (3) both data scientists and analytics end users contributing to improving enabling BA tools (H3). The third mechanism delivers value indirectly by enhancing the enabling capabilities for H1a/b. The OBBAU model also recognizes the impact that data scientists' and end users' competencies (H4a, H4b, H5a and H5b) have on the value that organizations realize through these three key mechanisms.

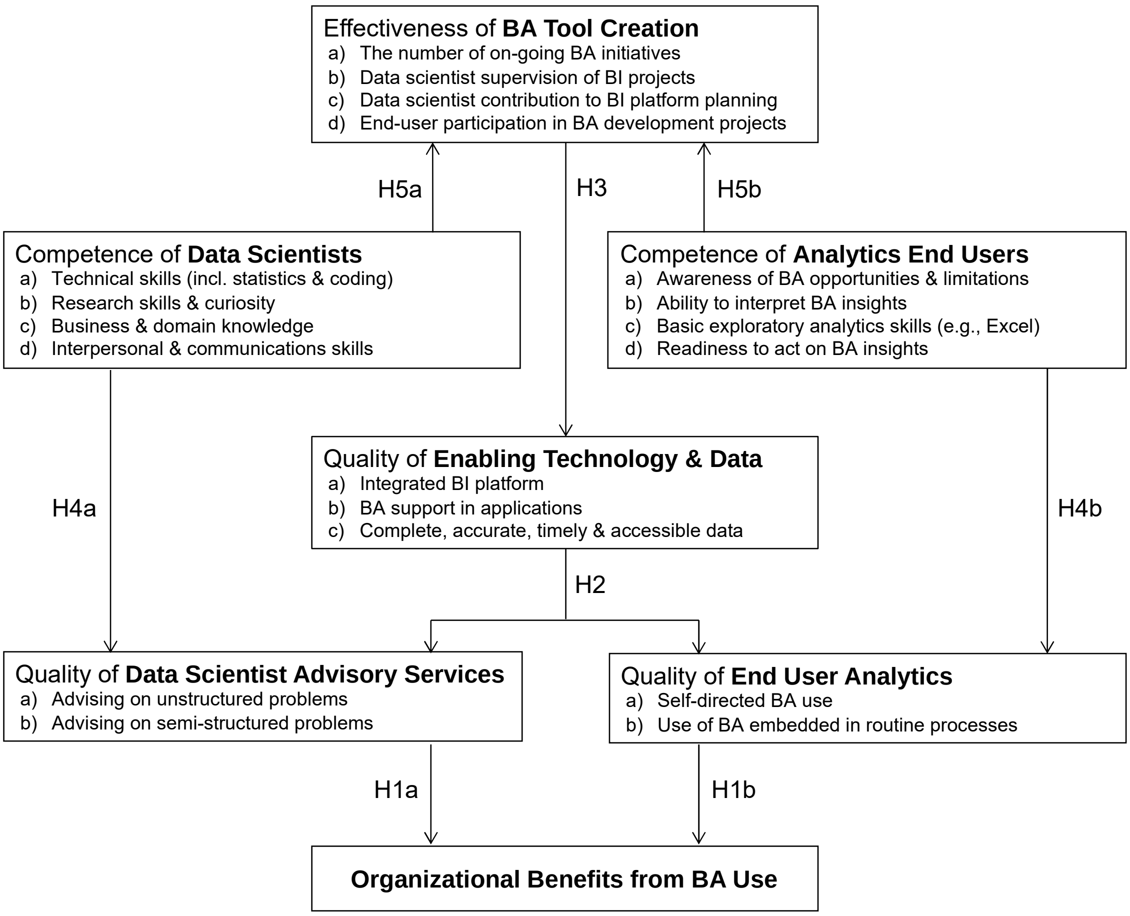

Figure 1. The Organizational Benefits from Business Analytics Use (OBBAU) Model

Table 4. Definition of Concepts in the OBBAU Model

Concept	Definition
Effectiveness of BA tool creation	Measures how effectively an organization continuously improves the tools that enable its BA efforts, which includes 1) the number and scope of ongoing projects to improve the BI platform, to provide new analytics tools, and/or to provide high-quality data to both data scientists and end users and 2) the level of engagement of relevant BA stakeholders in that process.
Quality of enabling technology and data	Measures the quality of 1) the platforms that enable BA (including hardware, middleware, and data stores), 2) BA applications (including functional fit and ease of use), and 3) data (including completeness, accuracy, timeliness, and accessibility) that support easy, secure, and timely BA use in the organization.
Competence of data scientists	Measures data scientists' ability to perform and communicate the results of their analytics work, which includes 1) technical skills (e.g., cognitive ability, quantitative analysis skills), 2) curiosity and research skills (e.g., ability to explore and test cause-and-effect explanations), 3) domain knowledge (e.g., of industry trends, strategic levers, organizational factors), and 4) interpersonal and communication skills.
Competence of analytics end users	Measures end users' ability to perform analytical tasks, which includes 1) knowledge of when and where to source relevant data, 2) basic analytical skills (e.g., working with spreadsheets and drilldown reports), and 3) the ability to correctly interpret and act on BA insights.
Quality of data scientist advisory services	Measures the quality of decision support that data scientists provide to organizational decision makers on both ad hoc and routine business problems, which includes accuracy, relevance, timeliness, and appropriate presentation of such advice.
Quality of end user analytics	Measures how well end users use BA to support their daily decision making on both ad hoc and routine business issues, which includes 1) appropriately using BA tools and 2) making correct inferences on the best course of action based on the results.
Organizational benefits from BA Use	An overall measure for the organizational value of the insights, decisions, and actions that flow from BA use, assessed from senior management's perspective.

Table 5. Hypotheses that Emerged from the Interviews

ID	Role	H1a	H1b	H2	H3	H4a	H4b	H5a	H5b
I1*	BA recruitment director (recruitment firm A)	Y		Y	Y	Y			
I2*	BA recruitment specialist (recruitment firm A)								
I3	Managing director (recruitment firm B)	Y		Y		Y			
I4	BA user group leader and consultant (self-employed)	Y	Y	Y	Y	Y	Y	Y	
I5	BA practice leader (AU) (industry research firm A)	Y	Y	Y	Y	Y			
I6	BA practice leader (global) (industry research firm B)	Y	Y	Y	Y	Y		Y	
I7	Partner and BA practice leader (AU & NZ) (consulting firm A)	Y	Y	Y	Y	Y	Y	Y	
I8	Partner and BA practice leader (AU) (consulting firm B)	Y	Y	Y	Y	Y	Y		
I9	BA practice leader (VIC) (consulting firm C)	Y	Y	Y	Y	Y		Y	
I10	Vice president (AU & NZ) (enterprise software vendor A)	Y	Y	Y	Y	Y	Y		
I11#	Head of innovation and strategy (AU&NZ) (enterprise software vendor B)	Y	Y	Y	Y	Y	Y	Y	
I12#	Vice president for BA (Asia Pacific) (enterprise software vendor B)								
I13	BA practice leader (enterprise software vendor C)	Y	Y	Y	Y		Y		Y
I14	Data scientist (telecommunications firm)	Y	Y	Y		Y			
I15	Analytics leader (logistics firm)	Y	Y	Y	Y	Y		Y	
	*, #: two interviewees in the same interview.								

4 Discussion

With this study, we contribute to the literature by integrating both empirical insights and those from the BA literature to develop a foundation to better understand BA use and how organizations realize benefits from it. The OBBAU model that emerged from our theory-building process highlights three different ways in which two types of BA users (i.e., data scientists and analytics end users) use BA tools to deliver organizational benefits.

Even though researchers widely recognize the importance of BA use in the benefits-realization process, little research has examined BA use and effective use in detail (Trieu, 2017). However, three closely related streams in the BA literature contain useful pieces of the puzzle. In this paper, we build on and synthesize the insights on BA users and use types from these studies and extend them through our empirical findings.

The first literature stream that provides insights on BA use involves studies on BA benefits realization. These studies provide insights into either overall BA benefits realization or some of its key elements and often highlight BA skills/competencies, quality of BA tools and data, and BA use as essential components in that process (Ghasemaghaei et al., 2017; Seddon et al., 2017; Torres et al., 2018). However, these studies do not usually differentiate between types of BA use and frequently also do not investigate the required competencies or BA tool/data quality in depth. The OBBAU integrates these important components in BA use and extends these prior studies by differentiating between BA user types and types of BA use.

The second literature stream includes in-depth case studies that examine BA benefits realization in a particular organizational setting (Shollo & Galliers, 2016; Tim et al., 2018; Wang et al., 2018). Although these studies do not typically focus on BA use types, they often contain valuable industry-specific examples of BA use in their case descriptions. Davenport and Harris' (2007), Davenport et al.'s (2010), Davenport and Kim's (2013) studies represent notable exceptions: these studies build on multiple case studies and explicitly differentiate between "analytical professionals" and "analytical amateurs". The OBBAU extends these studies by further examining BA use types and proposing a model of how they lead to value.

The third literature stream examines the nascent data science profession. Many studies in this stream focus on data science practice (Davenport & Patil, 2012; Granville, 2014; Patil, 2011; Viaene, 2013), though some also examine data science education (Asamoah, Sharda, Hassan Zadeh, & Kalgotra, 2017; Mikalef et al., 2018a). These books and papers provide valuable insights on data scientists' work (and particularly the competencies they require). The OBBAU leverages these insights but also illustrates the important role that analytics end users play in BA benefits realization.

In addition to contributing to the theoretical understanding of BA benefit realization, we believe the OBBAU model also has useful implications for practice by highlighting some key issues that organizations need to consider to maximize benefits from BA. First, organizations need to understand and recognize the different but complementary roles that data scientists and analytics end users play in providing benefits from BA. Second, the three mechanisms we highlight (i.e., data scientist advisory services, end user analytics, and BA tool creation,) each require not only different competencies but also different enabling organizational and IT capabilities. Finally, timely access to high-quality data is a critical enabler of any kind of analytics activity.

5 Future Research

Researchers have many rich opportunities to investigate types of BA users (including their characteristics and competencies), BA use, and how they lead to organizational benefits. First, as we focus on building theory in this study, we would suggest that future research test the OBBAU model with independent data. Our study relies on a relatively small sample of BA experts. Using a larger and more diverse sample may provide additional insights. In particular, researchers may find it beneficial to include end users from a diverse range of roles to address the relatively limited insights into analytics end user competencies (which we discuss further in the next paragraph). Methodologically speaking, researchers could also conduct in-depth case studies to more deeply understand the OBBAU constructs and the mechanisms that underlie their interrelationships, or they could survey the two types of BA users to obtain additional evidence about the extent to which the OBBAU model's knowledge claims are generalizable.

Second, while researchers have opportunities to explore both data scientists' and end users' BA use and competencies, it appears that they have overlooked end users in particular amid the recent excitement about the emerging data science profession. Indeed, we found as much in our findings in that only six of our 13 interviews discussed the analytics end user competencies and how they affect BA use (H4b). Yet, as we note in Section 3.6.2, the interviews also suggest that business users have learned to use BA with greater sophistication, while some studies suggest that end user competencies may be a key impediment to their effective BA use (Deng & Chi, 2012). Therefore, we believe that analytics end user competencies have more importance than Table 5 may suggest. Future research could examine both the importance and the types of end user competencies that organizations need to realize value from BA.

Third, comparing the value from BA tool creation and advisory analytics warrants further empirical examination. Our interviewees had differing opinions about the relative value of the advisory services that data scientists provide (i.e., H1a) compared to their contributions to creating BA tools for end users to use for operational analytics (i.e., path H3 to H2 to H1b). For example, I9 believed that, in most cases, "productizing" the analytical insights by embedding them in operational systems led to greater organizational benefits, which concurs with the rising organizational interest in algorithmic decision making (Galliers et al., 2017; Lindebaum et al., 2019). Conversely, I4 viewed data scientist advisory services as more important due to the potentially transformative nature of the insights such services can produce. I8 believed that both mechanisms have importance though for different reasons: "Analytics can be very powerful at a point in time to help clients discover value. [On the other hand, productization creates] …sustainable, repeatable processes for analytics. That again is a major industry in its own right.". While we lean towards the latter perspective based on our findings, we believe this issue would benefit from further investigation.

Fourth, and somewhat related to the third opportunity, examining data scientist and end user competencies specific to the context of BA tool creation represents another promising avenue for future research. Our data indicates that, at least for data scientists, effectively contributing to creating BA tools requires skills beyond those required to effectively provide advisory services. However, overall, we obtained limited insights into these specific skills from our data. Furthermore, our data remained largely silent on what competencies end users need to effectively participate in creating BA tools. Future studies could help further both BA theory and practice by explicating the competencies required in the BA tool-creation context and, thereby, provide a foundation for improving these initiatives.

Finally, while we focus on examining BA users' roles, other managerial and technological factors also affect BA benefits, such as analytic leadership (Davenport & Harris, 2007; Davenport et al., 2010; Watson & Wixom, 2007), the effect of organizational power and politics on the analysis process (Günther et al., 2017) and/or on the ultimate decisions taken (Eisenhardt & Zbaracki, 1992; Hambrick & Mason, 1984), and also the external environment's characteristics (Mikalef et al., 2019). Future studies could examine whether such factors have a different impact for different types of BA users and/or BA use.

We hope that the OBBAU model encourages other researchers to join the journey in better understanding the different types of BA users and use and that it acts as a useful stepping stone for such future research.

Acknowledgments

Australian Research Council (ARC) grant DP0987003 supported the research we report in this paper. We presented an earlier version of this paper at ICIS 2013 (see http://aisel.aisnet.org/icis2013/proceedings/KnowledgeManagement/14/).

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About the Authors

Toomas Tamm is Senior Lecturer in Information Systems and Technology Management at the UNSW Business School of UNSW Sydney and was previously Research Fellow in the School of Computing and Information Systems at The University of Melbourne. Prior to entering academia, he worked in the retail and services sector as a sales consultant, web editor, and project manager. His research seeks to enable organizations make better digitally-enabled decisions, and revolves around two closely interrelated areas: 1) strategic technology investment decisions (particularly the related decision processes and approaches for improving these processes and outcomes, such as enterprise architecture) and 2) digitization of organizational decision making (especially how to balance the strengths of humans and decision support and automation technologies to improve organizational decision-making).

Peter B. Seddon is an Honorary Professorial Fellow in the School of Computing and Information Systems at The University of Melbourne, Australia. He was an academic at The University of Melbourne for 38 years. He currently has a Google Scholar H-index of 41 and over 11,000 Google Scholar citations to his work. He was a Senior Editor for *MIS Quarterly* from 2005 to 2008 and Program Co-chair for PACIS 2011. His major research interests are evaluating information systems success, packaged enterprise-application software, IT management, strategic decision making, IT outsourcing, business analytics, and research methodology.

Graeme Shanks is Professor in the UQ Business School at The University of Queensland and Professorial Fellow in the School of Computing and Information Systems at The University of Melbourne. He was previously Associate Dean Research and Professor in the Faculty of Information Technology at Monash University. Before becoming an academic, he worked for a number of private and government organizations as a programmer, systems analysts and project leader. His research interests focus on the management and impact of information systems, data analytics, enterprise architecture and conceptual modeling. He has published the results of his research widely in leading information systems journals and conferences.