A unified foundation for business analytics

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ABSTRACT

Synthesizing prior research, this paper designs a relatively comprehensive and holistic characterization of business analytics – one that serves as a foundation on which researchers, practitioners, and educators can base their studies of business analytics. As such, it serves as an initial ontology for business analytics as a field of study. The foundation has three main parts dealing with the whence and whither of business analytics: identification of dimensions along which business analytics possibilities can be examined, derivation of a six-class taxonomy that covers business analytics perspectives in the literature, and design of an inclusive framework for the field of business analytics. In addition to unifying the literature, a major contribution of the designed framework is that it can stimulate thinking about the nature, roles, and future of business analytics initiatives. We show how this is done by deducing a host of unresolved issues for consideration by researchers, practitioners, and educators. We find that business analytics involves issues quite aside from data management, number crunching, technology use, systematic reasoning, and so forth.

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1. Introduction

According to a study by Gartner, the technology category of "analytics and business intelligence" is the top priority of chief information officers, and comprises a $12.2B market [1]. It is seen as a higher priority than such categories as mobile technology, cloud computing, and collaboration technology. Further, Gartner finds that the top technology priority of chief financial officers is analytics [2]. Similarly, in studies involving interviews with thousands of chief information officers, worldwide, IBM asked, "which visionary plan do you have to increase competitiveness over the next 3 to 5 years?" In both 2011 and 2009, 83% of respondents identify "Business Intelligence and Analytics" as their number-one approach for achieving greater competitiveness. Among all types of plans, this is the top percentage for both years. To put this in perspective, consider 2011 results, in which business intelligence and analytics exceeds such other competitiveness plans as mobility solutions (ranked 2nd at 74%), cloud computing (ranked 4th at 60%), and social networking (ranked 8th at 55%) [3]. IDC reports that the business analytics software market grew by 13.8% during 2011 to $32B, and predicts it to be at $50.7B in revenue by 2016 [4,5].

It appears that a driver for this growth is the perception or realization that such investments yield value. Across a set of ROI cases, Nucleus Research finds a $10.66 payoff for every $1.00 spent on analytics applications – suggesting that such applications can be very attractive investment routes for chief financial officers [6]. Although business analytics is hardly all and everything for managers dealing with modern complexities, it is a big deal for them – becoming increasingly adopted in practice and emerging as an urgent challenge when it comes to improving business processes and outcomes [7,8].

On the academic front, the literature shows that analytics,[1] when narrowly viewed as an application of mathematical and statistical techniques, has long been studied in business schools under such titles as operations research/management science, simulation analysis, econometrics, and financial analysis. From this same relatively narrow viewpoint, it has been practiced to varying degrees by business organizations, resulting in substantial practical benefits. However, the literature also reveals that there has been relatively little *introspective* investigation of business analytics as a field of study. As a rough gauge, for instance, in journals of the business administration fields, articles with the term "analytics" in the title have been relatively rare, although a marked upswing can be observed over the last few years. Given the rise of analytics degree programs in business schools and the very extensive resources being poured into business analytics (BA), it seems prudent and timely to step back to investigate the big picture – as a foundation for organizing, positioning, guiding, and propelling future BA studies and applications. As a step in this direction, we develop a BA foundation that is a relatively unifying and inclusive characterization for understanding the nature, impacts, and potential of business analytics from both theory and practice standpoints.

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[1] When this paper uses the term "analytics" it should be understood as referring to business analytics, unless indicated otherwise.

The BA foundation scopes out three dimensions and six perspectives. Further, it introduces a framework that identifies and links building blocks that are fundamental to study, research, and application of business analytics. As such, the business analytics foundation advanced in this paper functions as an initial ontology for the emergent BA field – a language that people can share for discourse about the business analytics universe, and a mental model for organizing one's understanding of business analytics phenomena and possibilities. The ontology is, of course, subject to modification as the BA field grows and matures.

We begin by briefly outlining the heritage of business analytics. Against this historical background, we ask where BA is going. BA phenomena are seen as occurring in a three-dimensional space of domain, orientation, and technique. Within this space, there are diverse perspectives about the nature of BA as a field of study. While each is compelling, they are not unified into a single, broad, encompassing view that offers systematic guidance for shaping the future of BA as a field of study. We contend that until there is a cohesive unifying view, BA is likely to remain fragmented into developments within respective perspectives, and may become dominated by one or another of them without recognizing value inherent in the other views. Accordingly, we advance a conceptual framework that is a synthesis of six diverse classes of BA perspectives that appear in the literature. Initial indications of the framework's value are demonstrated by using it to generate examples of analytics issues worthy of further study by practitioners, researchers, and educators. Finally, a brief application of the framework is provided to illustrate its components and suggest its relevance to BA practice.

2. The business analytics heritage

Insight into the nature of business analytics can come from an examination of its heritage [9]. Generally, today's conventional views of BA are concerned in some way with operating on data, with an aim of supporting business activities (e.g., decision making). The operations may involve examination, calculation, or inference. From a technological perspective, such operations date as far back as the "dawn of the computer age" in the 1940s and 1950s (www.fico.com/analytics) with efforts such as the Kerrison Predictor (a computerized, fully-automated, anti-aircraft fire control system; 1940), the Manhattan Project (the use of Monte Carlo simulation to predict the course of nuclear chain reactions; 1944), and the first computerized weather forecast models (1950). They also include such 1950s developments as the Logic Theorist, using heuristic methods to infer problem solutions [10], and the mechanization of solving optimization problems [11].

Subsequent commercialization of related technology included such milestone developments (www.fico.com/analytics) as solving the shortest-path problem which transformed routing and logistics (1956), FICO's use of predictive modeling to assess credit risk (1958), the Black–Scholes model for optimal stock options pricing (1973), and the release of Visicalc, the first commercial tool for model-based decision support system (DSS) development (1979). Since then, the use of computers to operate on data to aid decision making has been a central aspect of DSS research and practice for over 30 years [12,13] resulting in a variety of tools that support business intelligence and business analytics initiatives. Today, DSSs that use data, procedures, and reasoning to solve problems have become so commonplace on the Web that they are largely taken for granted by their users (e.g., consumers).

Although the term "Business Intelligence" is often credited to H. Dressener, an analyst at Gartner (e.g., see [14]), in fact the term was first coined in 1958 by IBM computer scientist H. P. Luhn [15]. Modern-day business intelligence (BI) and its technologies evolved from DSS concepts and advances [16], most notably, the Executive Information System (EIS) paradigm. The typical setup for a BI system centers on a large data store holding highly *structured data* – typically in the form of data warehouses and/or data marts. BI software allows various kinds of operations with these data, ranging from "simple reporting, to slice-and-dice, drill down, answering ad hoc queries, real-time analysis, and forecasting…perhaps the most useful of these is the dashboard," plus such facilities as data mining, scenario analysis, business performance measurement, and business activity monitoring [16]. Such operations are undertaken at the discretion of decision makers, "with the objective of improving the timeliness and the quality of the input to the decision process."

Expanding on this, there is the move toward dealing with massive collections of relatively *unstructured data* such as audio, video, clickstream, and text. This takes BI (and its analytics aspects) into creation and maintenance of new kinds of data sources/repositories and new ways for dealing with them (e.g., Hadoop, MapReduce) – with the ultimate aim of harvesting value from them in the sense of supporting knowledge acquisition, insight generation, problem finding, and problem solving to assist decision making. Accordingly, technological aspects of analytics are rooted in the decision support capabilities provided by business intelligence. But, business analytics has other roots. It is not all about technology. For instance, there is operations research. Along with applied statistics, this is where quantitative aspects of analytics are grounded – methods for building quantitative representations of situations (i.e., mathematical and statistical models), calculating solutions to such models (typically, technology assisted), and interpreting the results. However, there is far more to analytics than quantitative methods and mathematics. The world presents an abundance of unruly data, complex messes, and wicked decision problems [17,7]. Problems have qualitative aspects. Their data may be non-numeric and their solutions may rely on logic, reasoning, inference, and collaboration.

The importance of qualitative analysis has long been recognized. For instance, Ackoff [18] points out that quantification "depends on qualification. What is qualified at one stage may be quantified at another; but at any stage some qualitative judgments are required" and that progress depends on improving one's abilities to qualify. Killman and Mitroff [19] points out that there is "an important class of variables that have been slighted in the literature of OR/MS, qualitative variables." Mingers [20] summarizes a variety of qualitative methods for transforming data into decisions, arguing that they are especially applicable as candidates for coping with situations where insufficient quantitative data are available, decision problems are unstructured or semi-structured, or active participation of stakeholders is advisable. These methods include cognitive mapping, strategic choice analysis, decision conferencing, soft systems methodology, robustness analysis, and nominal group technique.

In sum, modern-day BA is rooted in the ongoing advances of systems to support decision making. These advances include increasingly powerful mechanisms for acquiring, generating, assimilating, selecting, and emitting knowledge relevant to making decisions. Given its decision support heritage, business analytics necessarily partakes of and exploits these mechanisms. The knowledge that must be processed ranges from qualitative to quantitative and BA is concerned with operating on both knowledge types, as appropriate for the decision at hand. The situation in which decision support occurs may be well-structured or, at an opposite extreme, complex and outright wicked. Following suit, we can expect BA to be applied in both kinds of situations. Today's importance of BA reflects the complex situations in which organizations find themselves: decisions need to be made in the face of change that is relentless and rapid, knowledge that can be massive and eclectic, some variables that are largely unknown or little understood, and competition that is fierce and global.

3. Whither business analytics?

Watson [9] observes "We all know that analytics is a hot topic. It would be hard to miss the large number of books, articles, research reports, Webinars, and survey findings that suggest its importance. Despite the recent attention, I feel that analytics is not fully understood. There are many incorrect, imprecise, and incomplete understandings." He goes on to share his thoughts about business analytics, concluding that it is not simply a buzzword or hype. Subsequent sections of this paper lend strong support to Watson's conclusion and contribute to better understanding analytics as a legitimate field of study and practice.

Accepting that BA is not ephemeral, it is sensible to ask where this emergent movement is heading. Davenport et al. [21] offers several specific predictions about this, including big data analytics changing the information technology landscape, fast growth of cloud-based predictive analytics, rise of analytics asset management as a major challenge, methods of text and social media analytics entering the mainstream, and continued growth in demand for analytics talent. Betser and Belanger [22] suggest that technology factors for BA's future include data stream management, cloud, mobile, bandwidth, non-SQL databases, and new forms of data. As another take, Forrester expects important unfolding issues to include self-service analytics, pervasive analytics, social analytics, scalable analytics, and real-time analytics [23].

Broadly, analytics appears to be pervading all business administration disciplines. Each can apply analytics practices/technologies in the context of transforming evidence into insights and decisions. While BA may increasingly become ingrained in this or that discipline, we argue that it can retain an identity of its own with respect to education, practice, and research. For instance, degree programs in analytics exist, job announcements for BA positions are commonplace, and conferences devoted to BA have appeared.

Beyond speculating on the future, we advocate that a valuable prelude is the creation of an inclusive foundation on which analytics developments, prognostications, and visions can be built. This foundation is not a listing of some software packages, or mathematical/statistical techniques, or applications. It must be fundamental, recognize business analytics dimensions (domains, orientations, and techniques, for example), appreciate the complementary diversity of perceptions about business analytics, and provide a framework to provoke and position thinking about BA. It must offer means for describing what we need to investigate and understand about the conduct of analytics, the resources that enable/facilitate it, the manipulations of those resources, the influences that constrain and guide it, and its impacts (both actual and potential). Existence of such a foundation furnishes a basis for systematic advances in research, education, and practice pertaining to BA. Here, we articulate a foundation in terms of three dimensions, six classes of perspectives, and a unifying framework that relates those perspectives to each other.

4. Some dimensions of analytics

An examination of the literature suggests that analytics can be studied along several distinct, albeit complementary, dimensions. A summary of some of these is indicative of the richness of analytics phenomena. In brief, consider the three dimensions of domain, orientation, and technique.

4.1. Domain

This dimension refers to subject fields in which aspects of analytics are being applied. Domains and sub-domains include traditional business administration disciplines: marketing, human resources, business strategy, organization behavior, operations, supply chain systems, information systems, and finance. At a more detailed level, analytics may be applied to a topic within any of these disciplines. For instance, one domain is marketing analytics, while retail analytics is a sub-domain. Business analytics domains include:

- Web Analytics [24,25]
- Google Analytics [26]
- Software Analytics [27,28]
- Crisis Analytics [29,30]
- Knowledge Analytics [31]
- Marketing Analytics [32,33]
- Customer Analytics [34,35]
- Service Analytics [36]

- Human Resource Analytics [37,38]
- Talent Analytics [39]
- Process Analytics [40]
- Supply Chain Analytics [41,42]
- Risk Analytics [43]
- Financial Analytics [44]

Generally, those who work in one of these domains tend not to reference works of researchers in others, although it should be possible for researchers across domains to learn from one another. This principle may be broadened to include findings from non-business domains such as learning analytics or medical analytics. It would be useful to investigate the extent to which there is a core of analytics concepts common to all domains. The framework devised later is offered as a unifying core for understanding the full scope of BA.

4.2. Orientation

This dimension refers to a direction of thought. It is an example of what could be considered as part of a business analytics core. Its components are not peculiar to one or another business domain. Perhaps the most frequently discussed orientation is predictive analytics. This involves means for predicting what may or will occur (e.g., [45,46]). Predictive analytics has been identified as part of a three-fold taxonomy introduced in 2010 by the global consulting house, Capgemini, the other two orientations being descriptive analytics and prescriptive analytics [47–50]. Each of the three aspects in this orientation taxonomy is concerned with *what analytics does*; that is, we think about analytics in terms of description, prediction, or prescription.

There are other orientation taxonomies. Consider, for instance, an alternative four-fold orientation. Think about analytics in terms of *what is made by an analytics effort*. Such effort can make **S**ense of a situation, make **P**redictions, make **E**valuations, or make **D**ecisions. We call this the SPED taxonomy and contend that each of its four kinds of products is distinct from the others – having value in its own right. For instance, SWOT analysis makes an evaluation of strengths–weaknesses–opportunities–threats, but does not make predictions, interpretations, or decisions. Using analytics for benchmarking is another example of making evaluations. Note that one SPED component can also be an ingredient in the production of another. For instance, a decision may be based on sense (i.e., perceived meaning, interpretation) of a situation, predictions relative to possible actions/changes in the situation, and evaluations of possible outcomes [51]. Or, sense of a situation may depend on decisions about what factors to consider, predictions about future events, and evaluations of potential relationships among factors or events.

Taking a third kind of orientation, we might think about *analytics benefits*. Drawing on knowledge management theory, an understanding of analytics orientation may be susceptible to the PAIR model, which holds that there are four primary avenues a knowledge management initiative can traverse enroute to competitiveness: **P**roductivity, **A**gility, **I**nnovation, and **R**eputation [52]. If we accept that analytics is a knowledge-intensive activity, then the PAIR model suggests that analytics can be oriented toward enhancing an entity's productivity, agility, innovation, and/or reputation.

Orientation taxonomies, such as those suggested here, can be complementary. Each gives us a way for structuring the examination, investigation, and implementation of analytics – in whatever subject domain is of interest.

4.3. Technique

This dimension refers to the way in which an analytics task is performed and, it too, can be viewed from multiple perspectives. For instance, some analytics techniques are technology-based, while others are practice-based. One may also differentiate between the use of

quantitative techniques, qualitative techniques, and hybrids [53,54]. Yet another view differentiates between techniques for dealing with structured, semi-structured, and unstructured situations [55].

Techniques may also be differentiated based on specific mechanisms used for analytics, such as approaches to data mining [56,57], text mining [58,59], audio mining [60,61], online analytical processing [62,63], data warehousing [64,65], query-based analysis [66,67], dashboard analytics [68,69], visual mining [70–72], and so forth.

5. The core of business analytics

While dimensions, such as the three above, characterize the broad landscape of BA possibilities, there is a more fundamental aspect of the analytics core. This central focal point involves answers to: What is business analytics? What is the rationale/purpose for undertaking business analytics initiatives?

To begin to answer these questions, we have assembled the published views of a set of business scholars, paying particular attention to inclusion of diverse vantage points that are representative of what exists in the business literature. We consider, here, views that are broadly applicable, rather than those concerned with specific applications and domains. The accumulated definitions span the past 10 years, with the preponderance being more recent – following the 2007 book that popularized business analytics [73]. As previously noted, we do not look at usage of the term in non-business fields.

Table 1 displays perceptions about what BA is, along with rationales authors give for adopting BA in an organization. The definitions are organized into several classes based on their similarity. Before considering each cluster and synthesizing a framework from them, we observe a dual theme that pervades all of the definitions: The phrases "fact-based" and "decision" (or "decision making") appear repeatedly. As an alternative to "fact" some definitions allude to "data." Thus, in spite of

Table 1
Business analytics.

Class	Definition of BA	Rationale for BA	Source
A Movement	1. "…culture, where fact-based decision-making is encouraged" and rewarded	successful deployment of data warehouses, so they are "more easily diffused in an environment"	[89]
	2. "management philosophy" through which "insights can be gained and decision making improved" based on a "rich set of data"	"to support and optimize the capability that is the main driver of a company's value and competitive advantage"	[90]
	3. "movement …. driven by technically literate executives who make fact-based decisions, the availability of good data, a process orientation to running an enterprise, and improved software for data capture, processing, and analysis"	"improve the overall process or decisions associated with process roles"	[91]
A Collection of Practices & Technologies	4. "a subset of what has come to be called business intelligence: a set of technologies and processes that use data to understand and analyze business performance"	"compete on making the best decisions"	[73]
	5. "a group of tools that are used in combination with one another to gain information, analyze that information, and predict outcomes of the problem solutions"	"allow for informed decision making"	[92]
	6. "a wide range of techniques and technologies" that "make it easier to get value, meaning, from data"	"simplify data to amplify its meaning"	[93]
A Transformation Process	7. "more than just analytical methodologies or techniques used in logical analysis. It is a process of transforming data into actions through analysis and insights in the context of organizational decision making and problem solving"	"improve the overall process or decisions associated with process roles" "decisions and insights obtained from analytics are implemented through changes within enterprise systems"	[91]
	8. "process of transforming data into actions through analysis and insights in the context of organizational decision making and problem solving"	"better decision making"	[48]
	9. "the scientific process of transforming data into insight for making better decisions"	"better decisions"	[82]
A Capability Set	10. "extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions"	"compete on making the best decisions"	[73]
	11. "the use of analysis, data, and systematic reasoning to make decisions … the most analytical firms and managers employ a combination of techniques, both quantitative and qualitative" "an organizational capability that can be measured and improved"	"to make better decisions and take right actions" "help your managers and employees make better decisions, and help your organization perform better"	[54]
	12. "a company's use of its databases, explicative and predictive models and fact-based management to drive its decisions and actions"	"…better guide the exclusively human decisions and provide automated decisions in some tasks"	[42]
	13. "The use of data and related insights developed through applied analytics disciplines (for example, statistical, contextual quantitative, predictive, cognitive and other models) to drive fact-based planning, decisions, execution, management, measurement and learning. Analytics may be descriptive, predictive or prescriptive."	"create competitive advantage"	[88]
	14. "discipline of applying advanced analytical methods ranging from descriptive to predictive to prescriptive modeling"	"better decision making"	[83]
Specific Activities	15. "accessing, aggregating, and analyzing large amounts of data from diverse sources to understand historical performance or behavior, or to predict— or manage—outcomes"	"rapid implementation of new ideas, products, and services, which result in greater profits and shareholder value"	[94]
	16. "examine and manipulate data to drive positive business actions"	"users can make well-informed, fact-based decisions to support their organizations' tactical and strategic goals"	[95]
A Decisional Paradigm	17. the "part of decision management" that involves "logical analysis based on data to make better decisions"	"create more value for customers and more profit for companies"	[96]
	18. "data-driven decision making" rather than "ignore the evidence and make our strategic decisions based on anecdotes and guesses… simply because harvesting the right data to inform our decisions is more complex than it might first appear"	"improve decision making" "true value … is the result of knowing which data elements to combine and compare in order to produce new knowledge … we must not assume that simply exposing raw data results in good decision making"	[97]

notable differences in perceptions about the nature of business analytics, there is near consensus that whatever definition is adopted, it involves the notion of fact-based decision making.

This shared element of business analytic definitions is subject to tweaking. The first tweak involves introduction of "evidence" as an element of these definitions. For instance, Pfeffer and Sutton [74] have advanced the idea of what they call "evidence-based management" (also see [75]). Although not using the term "analytics," they examine and advocate initiating evidence-based management movements in organizations – adopting a culture or philosophy in which a proposed change is met with requests for (1) evidence about its need and efficacy, (2) clear description of logic, and (3) explanation of sources behind the evidence; this allows it to be examined for relevance, faulty reasoning, and unreliability. Further, they advocate openness to experimentation and encouragement for continuous learning as important aspects of an evidence-based culture. In a similar vein, Rycroft-Malone et al. [76] hold "that 'evidence' in evidence-based practice should be considered to be 'knowledge derived from a variety of sources that has been subjected to testing and has found to be [relevant] credible' ([77], p. 311)."

Because the "evidence-based" notion is more fully developed and encompassing than "data-based" or "fact-based" terms, we suggest that the Table 1 definitions can be enhanced by substituting "evidence" for "fact" or "data" terms, where "evidence" includes hard facts, reliable measurements, justified estimates, well-reasoned approximations, unbiased observations, credible explanations, authoritative advice, and the like. It does not include arbitrary or unfounded beliefs, guesses, opinions, speculations, conjectures, suspicions, or hearsay. A body of evidence is not driven by desires, emotions, politics, or ideology; nor is it a captive of preconceptions. This evidentiary enhancement to the concept of BA allows analytics to draw on inputs about which there is not absolute certitude – as happens, for instance, when hard facts are simply unavailable (e.g., with what-if analysis, simulation modeling, when using sales-force estimates, or drawing on expert opinions). Further, as noted by Simon [78], problem recognition and solution often occur within the confines of bounded rationality, limiting completeness and precision of "fact" gathering a priori. That is, in the real world, obtaining and demonstrating absolute facts about all relevant factors can be too costly, too late, or infeasible.

A second tweak involves the "decision making" term. While decision making is certainly a key facet of business, a manager is also concerned with solving more than decision problems. This suggests there are other kinds of management problems that may benefit from analytics. From the SPED taxonomy, we expect that a manager can also produce evidence-based solutions to problems of making sense, making predictions, and making evaluations. For instance, there are sense-making problems, whose solutions are not decisions, but rather meaning/understanding. "Problem solving" is a richer, more flexible term, as it also recognizes types of problems that are not decisional. Accordingly, we contend that analytics definitions, such as those in Table 1, can be enhanced by substituting "problem solving" for "decision making."

In addition to solving a problem, there is also the essential act of recognizing a problem – recognizing occasions for making sense, predictions, evaluations, and decisions. As with problem solving, problem recognition may be more, or less, evidence-based. Accordingly, we suggest that analytics definitions can be enhanced by including the concept of "problem recognition" as well as "problem solving."

Going forward, we adopt a general core characterization of business analytics as being concerned with *evidence-based problem recognition and solving that happen within the context of business situations*. While consistent with, and underlying, the varied definitional perspectives in Table 1, this broader working definition of BA allows a more inclusive view of diversity in kinds of evidence considered (beyond just hard facts), diversity in kinds of problems managers address (aside from decisional), and diversity in aspects that are addressed (both recognizing and solving).

5.1. Core perspectives on evidence-based problem recognition and solving

Table 1 shows a structuring of the core analytics concept into six classes, each reflecting a particular definitional perspective. The six classes result from our interpretive "factor analysis" of the various definitions based on the emphasis found in each. While there may be some cross loading, the classes are conceptually distinct. Although related and complementary (as subsequently illustrated in a BA framework), no one of them is an instance of another and no one of them is a simple amalgam of others.

5.1.1. A movement

From the first perspective (exemplified by definitions 1–3), *BA is seen as being a movement*. It involves a mind-set in which evidence-based problem recognition and solving governs an entity's strategies, operations, and tactics. The entity can be individual, organizational, inter-organizational (e.g., supply chain), or societal. When an analytics movement is in place, problem recognition and solving are fed by evidence, within the scope of bounded rationality. Evidence is the driver in dealing with problems. It is not ignored, handled in a haphazard way, or treated as an afterthought. When an analytics movement is in place, evidence is not cherry-picked to support a preconception or tossed away if it does not. In an analytics movement, philosophy, or culture, evidence is deemed more important than dogma, politics, fashionability, or personal agendas. We might speculate that, by freeing an organization from such (oftentimes dysfunctional) forces, a BA movement fosters creativity, encourages collaboration and knowledge sharing, and focuses efforts within a realistic, not fictitious, portrayal of situations.

When an organization commits to a BA movement, it lives and breathes evidence-based problem solving (and recognizing) as a foundation for its actions and existence. As definitions 1 and 2 suggest, this commitment means that an entity's *culture* and *philosophy* are imbued with a mind-set of evidence-based problem solving. For such an organization, adoption of an analytics philosophy and cultivation of an analytics culture are essential for implementation of a BA movement. This mindset is considered essential to pursuing its vision and achieving its mission.

From this analytics-movement perspective, a variety of issues confront practitioners, researchers, and educators. They need to study such questions as how to define and instill a BA philosophy, how to create and sustain BA culture, how to determine the antecedent factors and competitive impacts of a successful BA movement, and what are ways to measure progress and success when engaging in a BA movement.

5.1.2. A collection of practices and technologies

In the second class (exemplified by definitions 4–6), *BA is seen as being a collection of practices and technologies*. This is a very different focus than that of the first class. The collection can exist without an imperative of a BA movement, although its deployment may be less effective in the absence of such imperative. Here, "practices" refers to how things get done when it comes to operating on evidence – with goals of increasing understanding, making predictions, generating new valuable knowledge, and so forth. We take these practices to include an organization's acquisition, assimilation, selection, generation, and emission of knowledge (i.e., evidence, in the present context) in the face of various managerial, resource, and environmental influences [79].

In the modern world, operations on evidence may be digital – in whole or in part. However, technological solutions do not exist for all problems and, for others (e.g., involving relatively "small" data or "simple" analysis), can be "overkill." Recalling our earlier discussions on the technique dimension of analytics (Section 4), BA techniques may be technology-based, and/or practice-based. More often than not, today, the two are combined.

Moreover, BA practices do not always deal with number crunching. Indeed, most – as much as 80% [80] – of an organization's data or knowledge base is not at all numeric. Yet, such evidence is still subject to BA practices and technologies. Therefore, with regard to the technique dimension of analytics, BA techniques may be quantitative, qualitative, or combinations. The technique dimension also differentiates between techniques for dealing with structured, semi-structured, and unstructured situations. Number crunching helps with some, but not all, situations.

The practices-and-technologies perspective is perhaps the most commonplace view of BA. It is held by technology vendors and by those who regard analytics as something (e.g., number crunching) they have been doing for decades. Yet, there are still important, open-ended issues to consider. Among the issues that confront practitioners, researchers, and educators are: what should exist in a particular practice-and-technology collection, whether there is value in coordinating the collection with a BA movement approach (and how so), how to encourage and manage adoption, ways to measure deployment effects, what factors are antecedents of a successful deployment, how the collection is affected by advances in BA technologies, and what is the relationship between massive data and the selection of appropriate techniques – especially statistical analysis techniques [81].

5.1.3. A transformational process

In the third class of definitions (exemplified by 7–9), *BA is seen as being a process of transformation*. Evidence is transformed via some process into insight or action. Presumably, a transformation process employs some mix of practices and technologies operating on some body of evidence and is influenced by some culture. In this perspective, the focus is on the process that drives, coordinates, controls, and measures the transformation. What is of interest from this perspective is the what, why, when, and how of the transformation. However, there is no mention of handling evidence acquisition, storage, and maintenance and handling the processors (human and digital) required for performing transformations and using results. We suggest that requisite evidence and processor management should be recognized as an important aspect in design and execution of a transformation process.

In a survey of INFORMS membership (over 1800 respondents), Liberatore and Luo [48] find that the transformation-process view is tied with the capability-set view (discussed below) in terms of the extent of match with individual members' views on what analytics is. The other four views identified in Table 1 were not studied in the survey. Further, a 2012 poll by INFORMS finds that 72% of voting members largely concur with the definition: "the scientific process of transforming data into insight for making better decisions" [82].

From the transformational-process perspective, practitioners, researchers, and educators face a variety of issues. A central issue is how to design a process that transforms evidence into insights that make sense of a situation or decisions that drive actions taken in the context of a situation. How are the SPED elements incorporated and coordinated within the process? What are the design requirements and criteria for evaluating the process? The PAIR model may give some guidance on this point. Those who study BA as a transformational process also face questions about how to muster sufficient resources to make process execution practical, how to measure process performance, what steps to take for ensuring process control, and how to infuse creativity into an evidence-based transformational process.

5.1.4. A capability set

In the fourth class (exemplified by definitions 10–14), *BA is seen as being a set of capabilities*. These are competencies possessed by an organization and its processors. They determine what can be done in the way of evidence-based problem recognition and solving. Definitions belonging to the capability-set perspective suggest inclusion of processors' skills for managing evidence, using models, and logical reasoning. Collectively, definitions 10–14 indicate that BA capabilities can include:

- Using techniques that are quantitative, qualitative, and combinations
- Using statistical techniques
- Using systematic reasoning
- Working effectively with models that are:
  o Descriptive/Explanatory,
  o Predictive, or
  o Prescriptive
- Working effectively with evidence (e.g., databases, click-streams, documents, sensors, maps)

The extent of BA capabilities can vary, and there is no guarantee that existence of a particular capability will result in the full use of that capability. For instance, an organization may possess the capability to execute certain technologies, but lack those technologies (conversely, possessing a technology says nothing about the degree of a firm's capability for effectively applying that technology).

The definitions are explicitly concerned with capabilities for executing collections of practices and technologies. However, implicitly, BA capabilities are not limited to an organization's potential for executing its repertoire of practices and technologies: there is also some degree of capability for effectively coordinating the use of such skills in the course of problem finding and solving. They include capabilities of innovation, improvisation, and imagination involved in building a culture, designing processes, or conducting specific activities such as evidence acquisition. The framework introduced later suggests that possessing processors with such capabilities is necessary for a BA movement to flourish and BA transformations to happen. It is a capability set that influences what BA transformational processes will be built, and that functions as both means and constraints on what a BA movement can accomplish.

From the capability-set perspective, central issues confronting practitioners, researchers, and educators are specifically what a capabilities portfolio should look like, what the relative weightings of inherent competencies should be, and how must the desired capability profile be built and refreshed [7]. One also faces questions about the measurement, shelf-life, and costs of alternative capabilities, and the impacts of a capability portfolio on competitiveness. Investigation of this last point should be cognizant of possible relationships of BA with dynamic capabilities, operational capabilities, and improvisational capabilities – all of which are recognized as important competitive factors [83,84].

5.1.5. An activity type set

From the fifth perspective (exemplified by definitions 15–16), *BA is seen as being a set of specific activity types for operating on available evidence*, rather than being a set of broad competencies. According to the definitions, these four activities are accessing, examining, aggregating, and analyzing evidence. The framework introduced later suggests that specific types of evidence-manipulation activities are important to consider in design of a transformation process. Various patterns of such activities, along with execution of various practices and technologies, are what enable transformations from evidence to insight or decision.

Beyond the four above-mentioned manipulations, there may well be other activities that are relevant, or other ways of thinking about or classifying manipulation activities. For instance, the knowledge chain theory identifies five first-order activities for manipulating evidence (i.e., acquiring, generating, assimilating, selecting, emitting knowledge) and four second-order activities of measuring, controlling, coordinating, and leading manipulation actions [52]. From the specific-activities perspective, issues confronting practitioners, researchers, and educators pertain to arranging them into the design of transformational processes, ways to measure and control efficacy of the activities, how to ensure security, integrity, and regulatory compliance during the performance of analytics activities, and what factors are antecedents of successful activity execution.

5.1.6. A decisional paradigm

In the sixth class (exemplified by definitions 17–18), *BA is seen as being a decisional paradigm*. It is said to be an approach to decision making – distinct from other approaches, such as naturalistic decision making [85–87] – or is perceived as part of decision making. It is possible that one paradigm supports another and that paradigms may mutually conflict. The "analytics" decisional paradigm may be seen as an umbrella concept that covers a combination of definitions 1-16.

From the decisional-paradigm perspective, a variety of issues confront practitioners, researchers, and educators. A central issue is whether such a paradigm is appropriate, in light of an organization's analytics *movement* maturity and its analytics *capabilities*. If so, then design of a *transformational process* incorporating attendant specific *actions*, implemented via selected *practices and technologies*, can proceed. There is also a need to study such questions as what are the situational traits that make BA suitable for a given organization, how to attain and sustain buy-in for this paradigm, ways to integrate BA with other decisional paradigms, avoiding misuse of analytics, and so forth.

5.1.7. Rationale for analytics

The "Rationale" column in Table 1 identifies several reasons for pursuing BA. These can be consolidated and summarized to give the following rationales for business analytics:

• Achieve a competitive advantage
• Support of an organization's strategic and tactical goals
• Better organizational performance
• Better decision outcomes
• Better or more informed decision processes
• Knowledge production
• Obtaining value from data

In principle, these same factors can be seen as being endogenous variables whereby outcomes of an organization's BA efforts can be measured and as a basis for gauging efficacy realized from:

1. Nurturing an analytics *movement*
2. Adopting a *decisional paradigm* that stresses analytics
3. Building and growing a managed set of analytics *capabilities*
4. Designing analytics processes for *transforming* evidence into insights, decisions, and actions
5. Conducting specific evidence-manipulation *activities* needed within an analytics initiative
6. Executing analytics *practices and technologies*

Above, we have identified a variety of unresolved, and perhaps heretofore unidentified, issues for each of these six perspectives. Based on that discussion, it appears that, when considering BA, all six perspectives deserve attention by researchers, practitioners, educators, and students. Ignoring any of them renders an organization vulnerable to sub-par, even unacceptable, outcomes from BA initiatives. However, there are additional considerations beyond those indicated in any of the definitions in Table 1. These arise because of relationships that exist among the six perspectives.

5.2. A unifying foundation for understanding business analytics

Building on the six definitional perspectives of BA, we introduce a foundational framework that encompasses all of them *and* their relationships. This framework is a super-perspective that both covers and unifies the rich collection of analytics definitions. It is designed to be consistent with, and inclusively supersede, the specialized characterizations of business analytics. As such, the business analytics framework (BAF) serves as an organizing device for practitioners to use in planning and evaluating their analytics initiatives, a generative mechanism for researchers to use in identifying and designing their analytics investigations, and a guiding template for educators to use for positioning topics and ensuring full coverage in their
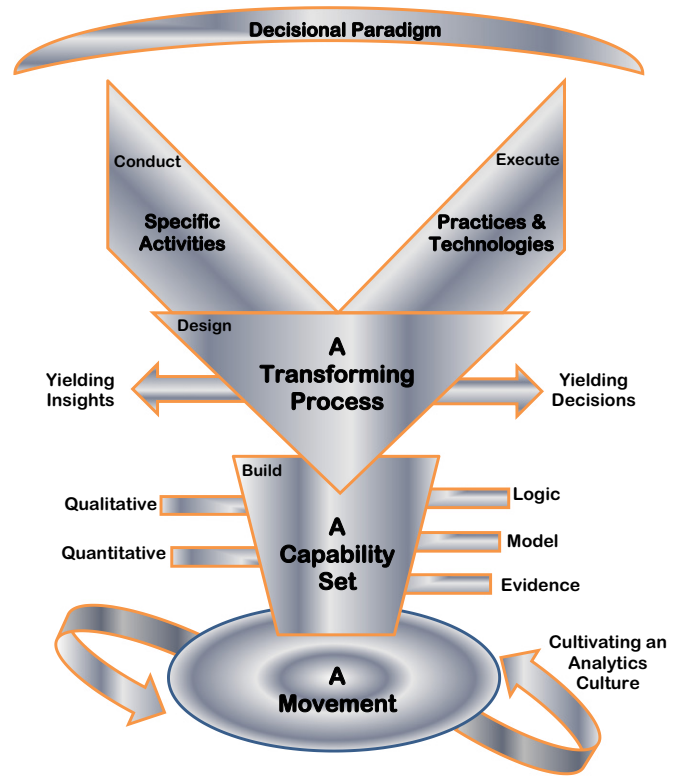

Fig. 1. Business analytics framework (BAF).

analytics curricula. Fig. 1 portrays the BAF, showing a particular arrangement among the six building blocks. To avoid BA attempts that are insular, piecemeal, out-of-sync, or defective, certain *alignments* between blocks are essential.

At the base, we have a BA movement grounded in a rationale, such as implementing a strategy, achieving a mission, or fulfilling a purpose. The movement is powered by a philosophy and culture in which evidence-based problem solving (and recognition) is of high priority. Adopting an analytics philosophy and cultivating an analytics culture become core values. Along with other values such as transparency, integrity, excellence, and accountability, they ultimately shape *how* things get done. The resultant conduct and execution of BA determines *what* things get done (e.g., what decisions get made, what evaluations are produced, what predictions are devised, what sense is made of a situation).

A movement will not 'move' without a suitable capability set. Without requisite competencies, BA philosophy and culture are to no avail. Conversely, a strong set of capabilities to use for BA will be relatively ineffective when there is no movement to apply these competences in a consistent, committed, coordinated, purposeful fashion. It follows that a strong alignment between an organization's BA movement and its set of BA capabilities is necessary. As the BAF portrayal in Fig. 1 indicates, intentions inherent in the movement need to fit realities inherent in the capability set. Thus, the BAF generates such questions as how to effect and sustain not only a BA movement, but also an alignment between the movement and the capability set. For instance, one might ask which comes first, the movement or the capability set, what are the antecedents of alignment, what constructs are able to explain this kind of BA alignment, and who is involved in overseeing the alignment of BA capabilities with a BA movement. Such questions of analytics alignment deserve careful study, because correct answers may well impact whether an analytics-centered decisional paradigm can be effective, or even feasible. Each of these questions can be studied from a descriptive or prescriptive standpoint.

Now, looking at the capability set itself, the BAF indicates that an organization possesses some mix of competences for handling both quantitative and qualitative evidence in the course of problem solving (and recognition). Further, skill at both quantitative and qualitative modeling is necessary. Then, there is the need for competence at logical reasoning in the treatment of evidence and models. These categories of competencies are suggested by Table 1 definitions for the capability-set perspective.

Enumerating competencies within each category is far beyond the present scope, but a few examples include interpretation of competitor actions, distilling the message buried in vast data about behaviors of web site visitors, reasoning about governmental regulations in order to make recommendations, solving optimization or other modeling problems, gathering knowledge of supplier development strategies, adeptness at identifying novel sources of evidence, and expertise in understanding the factors relevant to facilities siting. It is up to an organization to build a capability set suitable for its own situation. This construction is guided by answers to such questions as what analytics-support capabilities are needed/desired, in what proportions, for how long, at what cost, and when? The construction, which is ongoing, is performed in alignment with the BA movement – shaping, buttressing, and/or emanating from the movement.

The BAF in Fig. 1 shows that the building of a capability set is also performed in alignment with a transformational process(es). This can work in two directions. A BA process for transforming evidence into insights or decisions may be designed subject to BA capabilities on hand. Conversely, the transformational design can inform the building of capabilities, by identifying capability requirements. When there is a mismatch between capabilities and process, the BA movement is unlikely to bear fruit. In the interest of avoiding a mismatch, there is a need to study such questions as what are the antecedents of alignment between building BA capabilities and designing evidence-based transformational processes, what constructs are able to explain this kind of BA alignment, who participates in ensuring the alignment of BA capabilities with BA transformations, and so on. Again, each of these questions can be studied from descriptive or prescriptive standpoints.

The transformational-process component of the BAF may be left to serendipitous, ad hoc exercise of capabilities. However, this may be less effective than conscious design and sustained application of processes for transforming evidence into insights (interpretations, predictions, evaluations) and decisions. In the BAF, a transformational-process design specifies procedures and/or rules that operate on evidence and are performed with analytics capabilities. Such a design is a mechanism for coordinating, controlling, and measuring analytics work. Procedures and rules not only harness analytics capabilities, but also are designed in terms of conducting specific kinds of activities and executing practices and technologies. In Fig. 1, this is indicated by the building blocks protruding from the transformational process component. Here, again, alignment is important.

In this case, the nature and degree of alignment is inherent in transformational-process designs. These indicate how to handle dependencies among specific evidence-manipulation activities (e.g., knowledge acquisition, knowledge assimilation) and within portfolios of practices (e.g., variants of lessons-learned techniques, Delphi-based methods) and technologies (e.g., data warehousing system, data mining software). As with other alignments within the BAF, there are questions that deserve study, including possession of requisite BA practices/technologies for accomplishing a transformation, whether the capabilities set furnishes competences for executing them, what patterns of evidence-handling activities are effective for accomplishing a transformation, and which practices/technologies to invoke within these activities.

Overall, successful adoption of BA as a decisional paradigm depends on the BAF alignments. Moreover, in the BAF, application of capabilities is neither opportunistic nor ad hoc. Rather, in keeping with an organization-wide BA philosophy and culture, such capabilities are applied as a matter of course and routinely whenever and wherever necessary.

5.3. A brief BAF application

Here, we apply the BAF to illustrate its concepts and to demonstrate its relevance for practitioners in planning and evaluating their analytics initiatives. The illustration involves a study whose findings are based on anecdotes (e.g., McKesson, BAE Systems, Pfizer) and a large-scale survey conducted by MIT and IBM researchers [88]. The survey involved 4500 managers and executives from organizations in over 120 countries and 30 industries. Its goal was to understand how organizations could use BA to achieve greater competitiveness. One finding is that organizations can take one of two paths to become highly sophisticated or advanced users of analytics: specialized or collaborative. The specialized path uses a wide range of analytics skills and tools to improve operations within individual business units or functional areas. This usually leads to pockets of analytical prowess within an organization. On the other hand, the collaborative path uses analytics broadly across business units and functional areas to bring the entire organization to the same level of excellence in analytics sophistication. To demonstrate the versatility of the BAF, we describe the key features of these paths using the six BAF building blocks.

Both paths are described as being anchored in a data-oriented culture that underscores a pattern of behaviors, practices, and beliefs that are consistent with the principles of analytical decision making. This is in line with the BAF's *movement* building block, which we have positioned as the base of any BA initiative. Additionally, both paths follow a *decisional paradigm*, being presented as pervading every business decision, from strategy formulation to day-to-day operations. As organizations strive toward analytic sophistication, they are seen as equipping themselves to manage, understand, and act on data. This is what the BAF refers to as a *capability set*. Along a specialized path, for example, capabilities discussed include those of staying abreast of new advances in analytics and applying them to meet the newest data challenges, such as capabilities for mining real-time data from the Internet or from unstructured email content.

Depending on the capability set that is built, Kiron et al. [88] differentiate between two kinds of processes that can move organizations forward with analytics. In BAF parlance, these are alternative approaches for *transforming* evidence into insights or decisions. A propensity toward understanding data to explain what is happening, and why, leads an organization to design a specialized transformation process. In contrast, a collaborative transformation process is designed by organizations to enable and facilitate flows of suitable evidence to individuals throughout the enterprise for exercising their capabilities for making decisions analytically. Each kind of transformation process relies on conducting *specific activities* by executing various *practices and technologies*.

For organizations on a specialized transformational path, Kiron et al. [88] identify the specific activities of analyzing patterns, identifying trends, and discovering anomalies, albeit within silos of functional areas or organizational units. They indicate that performing such activities involves advanced analytics technologies (e.g., predictive modeling) and proven practices (e.g., Six Sigma). In BAF terms, a specialized transformation process is designed with the flexibility to accommodate various configurations of these kinds of activities and adoption of these kinds of practices/technologies. Further, the BAF implies that among the organization's many analytics-related capabilities there are some appreciable degrees of competences in conducting these kinds of activities and in adopting these kinds of practices/technologies.

In contrast, the collaborative path of transformation is designed so that evidence is readily available and accessible to meet specific needs of individuals in the organization. Practices include techniques for integrating data and insights distributed across the organization.

Technologies, such as common data platforms, data visualization tools, and dashboards, allow individuals to perform such specific activities as generating snapshots of enterprise performance or developing "what-if" scenarios to manage daily operations and shape future strategies. In BAF terms, a collaborative transformation process is designed with the flexibility to accommodate various configurations of the specific activities and the adoption of these kinds of practices/technologies. Further, the BAF implies that among the organization's many analytics-related capabilities there are some appreciable degrees of competences in conducting the activities and in adopting the practices/technologies to accomplish a collaborative transformation consistent with enterprise objectives.

The BAF is derived from multiple academic perspectives on what BA is – perhaps themselves derived from what other academics have had to say or from what their authors observed in practice. The result is a unification and subsumption of these perspectives. But, to what extent does the BAF connect with the world of practitioners? The survey-based and anecdote-based study by Kiron et al. [88] examines behaviors and experiences of firms engaged in successful business analytics initiatives. By applying the BAF to their study, we have some practice-based evidence that the BAF constructs are consistent with the real world. Via actual examples provided by independent researchers, we show that all of the BAF constructs are illustrated in practice. Our examination of the Kiron study does not reveal any substantial concepts that are missing from the BAF. It does, however, reveal that many of the issues and questions generated from the BAF in Sections 5.1 and 5.2 have not been identified, addressed, or answered. Accordingly, we suggest that the BAF serves not only as a theoretical foundation for understanding business analytics, but also as a guide that can benefit practitioners as they grapple with the launch and operation of their own analytics initiatives.

We contend that the BAF is sufficiently promising to warrant further investigation and application. One starting point for this would be identifying extensions, modifications, and refinements to the BAF by examining its capacity to characterize BA initiatives in specific firms. Although beyond the scope here, the real-world examples highlighted by Kiron et al. [88] could be examined through the BAF lens. A series of case studies can be performed, using the BAF to structure interviews or focus groups with practitioners regarding their own BA experiences and views. The objectives would be to refine or more fully develop the framework, to detail ways in which it can be applied in practice, and to uncover empirically-grounded propositions about BAF for theory development and hypothesis testing.

6. Discussion

The business analytics framework can be adapted in several ways. A few examples are discussed here. For the most part, they involve restricting the framework in various ways or collapsing aspects of the framework to eliminate their distinctions. Such adaptations are at the discretion of the BAF user, although we caution that they reduce the resolution and richness relative to full-scale adoption.

6.1. The evidence tweak

Consider the tweak in Section 5, where we use the term "evidence" instead of commonplace "data" or "facts." There is nothing in the BAF, or overall BA foundation, that prevents a reader from replacing the concept of evidence with "data" or "facts." However, this results in a restricted appreciation of business analytics.

The term "data" frequently carries with it a connotation of referring to quantitative evidence. By adopting the term "evidence," we are more neutral, intentionally avoiding such a connotation, and allowing that qualitative evidence can also be used in problem solving. Further, unlike the "fact" term, "evidence" allows a BAF user to set his/her own threshold for what qualifies as evidence, in contrast to the absolute certainty

required for considering only facts. Another rationale for adopting "evidence" is to be consistent with the evidence-based management movement emanating from Stanford researchers. This connection positions future research in which analytics can learn from evidence-based management, and vice versa.

The notion of data, whatever meaning is ascribed to it, is subsumed in the notion of evidence. In the interest of greater generality and completeness, we choose to use of the "evidence" term. While one may substitute the "data" term, the foundation designed here would need to be interpreted in a more restrictive manner.

6.2. The problem tweak

A second tweak brings problem recognition and problem solving into the fore, overshadowing decision making. We observe that much of the BA heritage is rooted in efforts to support the making of decisions. Further, most of the definitions in Table 1 seem oriented specifically toward decisional problems, although other orientations (e.g., sense-making problems) are identified in some definitions. Nevertheless, because our design is driven by the literature, a unifying foundation necessarily accommodates the multiple kinds of orientations. This leads to a working definition of BA that does not dismiss additional non-decisional viewpoints about the bounds and nature of BA. We advocate (and construct) a more inclusive/expansive appreciation of BA as a field of research, study, and practice. The BAF, thus, advances a richer and more-detailed system of core perspectives and considerations for the BA field – while still accommodating the support of decisional problems.

As a related point, explained in Section 5, examination of literature characterizing BA shows that it is sometimes regarded as *being* a kind of decisional paradigm. This is distinct from a notion of defining BA by *following* a decisional paradigm. Recall that there are other (non-BA) paradigms of decision making, such as the political or ideological. Moreover, the literature shows that BA is regarded in ways other than serving as a decisional paradigm. Not concerned exclusively with decisional problems, they recognize that other kinds of problems exist (e.g., sense-making, evaluation, and prediction) and that BA can be helpful in dealing with those problems. This suggests that the BAF may be capable of extension that recognizes it as also being a sense-making paradigm, evaluation paradigm, or prediction paradigm.

Thus, in the interests of a unifying foundation, one cannot restrict the characterization of BA to a decision-making heritage or paradigm. Any such restriction would result in characterizing a special case of BA.

6.3. Other definitions

As another example of adapting the BAF, a reader may prefer some other definition of BA. Examples are shown in Table 1. For instance, one may conceive of analytics as a transformation from structured or unstructured data into data that are in some way quantified for analysis. This paper develops a more general core characterization of business analytics: *evidence-based problem recognition and solving that happen within the context of business situations*. Notice that this is not the result of expanding "**the** definition" of BA. A crucial observation, on which the paper is based, is that "**the** definition" of analytics does not exist. The fact that many definitions prevail is one motivator for designing a unified foundation that encompasses diverse characterizations in a way that unifies what they have to offer. One of the key contributions of this paper is to break out of a narrow conception of analytics. We adopt an inclusive view that takes advantage of the varying conceptions and emphases found in the literature (including transformation views). This view accommodates specialized conceptions that may be preferred or advocated by others, albeit at the sacrifice of a more complete picture provided by the BAF.

6.4. Practitioner fit

The inclusive BA foundation we develop is also able to encompass multiple perspectives of BA practitioners and multiple kinds of BA initiatives. We do not confine ourselves to particular mindsets about BA practice or initiatives (e.g., number crunching). Our research suggests that excluded considerations may well include actual or potential activities and issues involving the treatment of evidence – activities and issues that are important/useful/essential to successful analytics initiatives.

We suggest that what people are doing in the field can be viewed through the lens of the unified foundation. That is, any instance of BA in the field fits into the foundation and is subsumed by it. Examination of how it fits may well reveal unforeseen ways in which a field instance can be extended or refined, allowing practitioners to go beyond what is currently being done, by relating it to other analytics facets.

We expect that the BAF is applicable to many domains, both within and outside of business. It is beyond the present scope to compare BA with such other fields of study, but we contend a careful investigation would reveal that the foundation advanced here is not a replication of other fields, and may well contribute to a better understanding of those fields.

6.5. Component collapse

Each component of the BAF is amenable to further research and development. On the other hand, some readers may be inclined to collapse multiple extant components into a single component. This can be done, but very likely at the expense of clarity. For instance, one may prefer to collapse the collection of practices and technologies into the capability set component, arguing that the latter subsumes specific practices and technologies. The literature notes, however, that these are distinct notions. The distinction is acknowledged in the BAF introduced here (and explained using the example described in Section 5.3).

We cannot claim that a capability set subsumes the specific practices and technologies any more than we can claim that the movement component, say, subsumes a capability set. Capabilities are not limited to a potential for executing a firm's repertoire of practices and technologies. For instance, a BA capability set may include capabilities of innovation or improvisation involved in building a culture, designing transformation processes, or conducting specific activities such as evidence acquisition. Setting aside this point, we must recognize that a firm may possess capabilities to execute certain technologies, but lack those technologies. Conversely, possessing a technology says nothing about the degree of a firm's capability for effectively applying that technology; it may at any point in time be non-existent, modest, or without parallel.

As the paper contends, alignments among elements of the BAF are important considerations. Misalignments of a capability set with a set of technologies/practices should be of particular note to management, as they can suggest opportunities for, and obstacles to, improving a firm's BA initiatives/results. We cannot just assume that such alignment exists, much less that one subsumes the other.

7. Conclusion

This paper builds on prior research to design a relatively comprehensive and holistic characterization of business analytics as a real-world phenomenon, a subject for investigation, an approach to decision making, and an area for business education. It examines roots, progress, needs, and issues pertaining to the current state of analytics. We identify three kinds of analytics dimensions and six distinct classes of analytics perspectives. We use a synthesizing approach to design the Business Analytics Framework, which accounts for the six classes being complementary and points out important alignments that are needed. One contribution of the BAF, along with the three attendant dimensions, is the provision of a unifying, inclusive foundation for building an understanding of what is involved in the study of BA – effectively amounting to an ontology that researchers, practitioners, and educators can use to communicate about, and frame their ideas about, business analytics. Another benefit of this foundation is its provocation of a host of un- or under-investigated BA issues for researchers to explore and for practitioners to take into account. Many of these are brought out in Sections 5.1 and 5.2.

For BA to actually work in an organization, there are issues quite aside from data management, number crunching, technology, systematic reasoning, and so on. These added issues pertain to whether an organization is ready to adopt BA as a decisional paradigm, or whether such an attempt is likely to languish. Key factors suggested are awareness and commitment to the organization's vision, mission, and strategy; an analytics-friendly culture; a management philosophy that understands and supports the use of business analytics; techniques for avoiding evidence being trumped by anti-analytics factors such as apathy, apprehension, coercion, envy, fashion, or ideology. In sum, this paper takes an initial step toward building a foundation for the study, operation, and investigation of analytics-intensive organizations.

Acknowledgement

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