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Big Data Analytics: Opportunity or Threat for the Accounting Profession?

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ABSTRACT: Contrary to Frey and Osborne's (2013) prediction that the accounting profession faces extinction, we argue that accountants can still create value in a world of Big Data analytics. To advance this position, we provide a conceptual framework based on structured/unstructured data and problem-driven/exploratory analysis. We argue that accountants already excel at problem-driven analysis of structured data, are well positioned to play a leading role in the problem-driven analysis of unstructured data, and can support data scientists performing exploratory analysis on Big Data. Our argument rests on two pillars: accountants are familiar with structured datasets, easing the transition to working with unstructured data, and possess knowledge of business fundamentals. Thus, rather than replacing accountants, we argue that Big Data analytics complements accountants' skills and knowledge. However, educators, standard setters, and professional bodies must adjust their curricula, standards, and frameworks to accommodate the challenges of Big Data analytics.

Keywords: data analytics; Big Data; automation; management accounting; financial accounting; auditing.

I. INTRODUCTION

Continuous progress in artificial intelligence and machine learning, coupled with a growing ability to analyze Big Data, has increased the threat that a large spectrum of jobs will be computerized in the future (Brynjolfsson and McAfee 2014; Ford 2015; Frey and Osborne 2013). This threat may be particularly salient for accountants. Frey and Osborne (2013) predict, based on task characteristics, a 94 percent likelihood that accounting and auditing jobs will eventually become automated. Data analytic techniques applied to Big Data (hereafter, Big Data analytics) have the potential to replace many of the tasks traditionally performed by accountants and auditors. Entry-level accounting and auditing tasks, such as the posting and collection of accounts receivable, have already become automated. In the near future, more complex tasks currently performed by accountants, such as business analysis, external reporting, and auditing, may become automated as well, due to the routine nature of these tasks and the lack of machine inimitable skill requirements associated with these tasks (Frey and Osborne 2013). This begs the following question: in the era of Big Data analytics, are accountants and auditors obsolete, as Frey and Osborne (2013) suggest, or do Big Data analytics bring new opportunities for accountants to uniquely create value?

The threat that Big Data analytics will replace many of the tasks traditionally performed by accountants may be particularly salient in the auditing context. For example, instead of relying on traditional sampling techniques to perform tests of details, automated processes could examine entire populations for unusual patterns and anomalies. In place of auditors sending out manual confirmations, a blockchain type of technology could enable automatic confirmations. A consensus is emerging among academics that once access to Big Data analytic techniques becomes ubiquitous in business, users of financial statements will expect audited financial statements on demand, necessitating a shift from traditional sample-based auditing to continuous "auditing by exception," where data analytic techniques direct auditor attention on a real-time basis to "instances where the

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data does not match the auditor's expectations based on his or her knowledge of the client's business" (Earley 2015, 496; Krahel and Titera 2015).

Furthermore, in the future, public accounting firms may face competition for the provision of audit services from nonaudit firms. Advances in data analytic and data visualization techniques will make it easier for non-accountants with data analysis competencies to obtain audit evidence and complete financial statement audits by applying data analytic techniques to Big Data (Brown-Liburd, Issa, and Lombardi 2015; Earley 2015). Within the audit community, there is the sentiment that if accounting firms do not exploit opportunities or neutralize threats made possible due to emerging technologies, then existing tech firms such as Google or FinTech start-ups may seize the opportunity to enter the audit market. This would increase the already-intense competition among accounting firms for the provision of audit services.

Although many accounting tasks may be subject to automation, it seems less likely that the entire profession is threatened with technological unemployment (see Mokyr, Vickers, and Ziebarth [2015] for a literature review).[1] As suggested by Autor (2014, 2015), many professions consist of a bundle of tasks that, collectively, are not easily automatable, and we maintain that accounting is one of those professions. Consistent with findings regarding past computerization (Arntz, Gregory, and Zierahn 2016; Spitz-Oener 2006), rather than replace the profession, we maintain that data analytics and Big Data will instead change task structures within the accounting profession, and this will provide opportunities for accountants to leverage their existing skills in conjunction with newly acquired ones.

As educators, we often teach incoming accounting students that "accounting is the language of business." Just as mastery of a language allows one to understand and interact with native speakers of a language, mastery of accounting grants an ability to interpret and understand concepts native to a business environment. This ability is central to accountants' capacity to add value in a world of Big Data. The advantage inherent in understanding the language of business is the ability to think holistically about the information presented rather than responding in a formulaic way. Big Data presents many opportunities to businesses, but in order to effectively leverage those opportunities and truly generate value from Big Data, businesses require individuals who understand not only Big Data and their analyses, but firm fundamentals and business strategy. As the CEO of the American Institute of Certified Public Accountants (AICPA) states:

> Big Data has increased the demand for information management specialists, while dramatically increasing the potential for visionary professional growth and positioning. CPAs are perfectly suited to take a leadership role in deciphering and using Big Data to achieve strategic business goals. (Melancon 2012, para. 7)

The objective of this paper is to explore the ways in which Big Data represents both an opportunity and a threat to the accounting profession. Further, we will examine the ways in which accountants can play a strategic role in the world of Big Data. Like all attempts to anticipate the future, the challenge of making meaningful predictions increases the further we aim into the future. Given this inherent difficulty and our implicit objective to identify factors/attributes that could make the next generation of accountants more resilient to job automation, our horizon is approximately ten years. This choice reflects the number of years needed—undergraduate education and practical experience—until the current accounting-bound high school graduates enter their most productive years. Firms seeking to reduce costs will naturally leverage Big Data analytics to replace easy-to-automate tasks commonly performed by entry-level employees. As this trend continues, accountants should complement their existing strong financial understanding with expertise in utilizing data analytics and interpreting Big Data.

The main contribution of this paper is to illustrate that, although Big Data analytics do present legitimate threats to the accounting profession, Big Data analytics also bring opportunities for accountants to add value to firms in new and interesting ways, some of which we will illustrate. As such, predictions that Big Data analytics will spell doom for the accounting profession (e.g., Frey and Osborne 2013) need not prove prophetic.

The remainder of the paper is organized as follows. In Section II, we will present a conceptual framework in which we identify the areas where accountants have an advantage in the coming world of Big Data analytics, as well as the areas where accountants are better suited to playing a support role to data scientists. Sections III, IV, and V will then explore in greater detail specific ways in which accountants can take both lead and support roles in three functional areas of accounting—management, financial, and audit. Section VI will discuss implications for education, standards, and accounting firms, as well as the limitations of our work and suggestions for future research, and Section VII provides concluding remarks.

II. CONCEPTUAL FRAMEWORK

As depicted in Figure 1, we propose a conceptualization of data analytics broadly along two dimensions: data type and analysis approach. Within the broad dimension of data type, two distinct subcategories are important. Data can be either

[1] Mokyr et al. (2015, 32) characterize technological unemployment as the "widespread substitution of machines for labor."

FIGURE 1
Data Analysis in a Pre- and Post-Big Data World

		Data: Structured	Data: Unstructured
Analysis Approach	Problem-Driven Analysis (Supervised Machine Learning)	Problem-driven analysis on structured data *(pre-Big Data)*	Problem-driven analysis on unstructured data *(post-Big Data)*
	Exploratory Analysis (Unsupervised Machine Learning)	Exploratory analysis on structured data *(post-Big Data)*	Exploratory analysis on unstructured data *(post-Big Data)*

structured or unstructured. Structured data refers to data that are typically generated through the firm's transaction processing systems, such as point-of-sales systems (POS), inventory management system, and customer/supplier relationship management system (CRM and SCM). Unstructured data originate from a wide variety of sources such as Facebook, Twitter, and YouTube, and they may be in various forms such as text, audio, and video. Structured data are highly organized such that they can easily be included in a traditional relational database. Conversely, unstructured data, which represent by far the largest portion of extant data, refers to data that lack the organizational rigor of structured data (Beath, Becerra-Fernandez, and Short 2012; Davenport, Barth, and Bean 2012; Gandomi and Haider 2015).

The dimension of analysis type can also be broken down into two subcategories: analysis can be either problem-driven or exploratory.[2] Using a problem-driven approach, problems are identified, hypotheses are formalized regarding potential causes, and solutions are developed to specifically address those problems. This approach to analysis is akin to theory-driven hypotheses testing. For example, in an accounting setting, the problem of determining an appropriate selling price for a product would often begin with product costing analysis, such as the identification of the product's direct and indirect costs.

In contrast to problem-driven analysis, exploratory analysis involves summarizing large datasets to understand the data's main characteristics independent of formal hypothesis testing. For example, data mining—a form of exploratory analysis—is defined as the process by which useful patterns, exceptional or unusual records, and relationships are discovered within large volumes of data. Data mining is highly technical and leverages tool sets from statistics, artificial intelligence, and database management (Clifton 2009).

Due to the highly technical nature of exploratory analyses, data scientists have a comparative advantage and, therefore, should take a lead role with respect to exploratory analysis. Given the complexity of this rapidly evolving approach to data analyses, it is unlikely that accountants will displace data scientists to dominate exploratory analyses. However, we assert that accountants still have a role to play with respect to exploratory analyses:

[2] An alternative approach would be to consider the analysis from a machine learning standpoint and make the distinction between supervised machine learning versus unsupervised machine learning. In supervised machine learning, we start with a set of observations that are already labeled/classified. For example, in a regression analysis or classification problem, we have the values of the dependent variable and the goal is to fit the best model in order to make predictions. In unsupervised machine learning, the dataset is not labeled. We rely on techniques such as clustering analysis or deep learning in order to capture and describe the underlying pattern.

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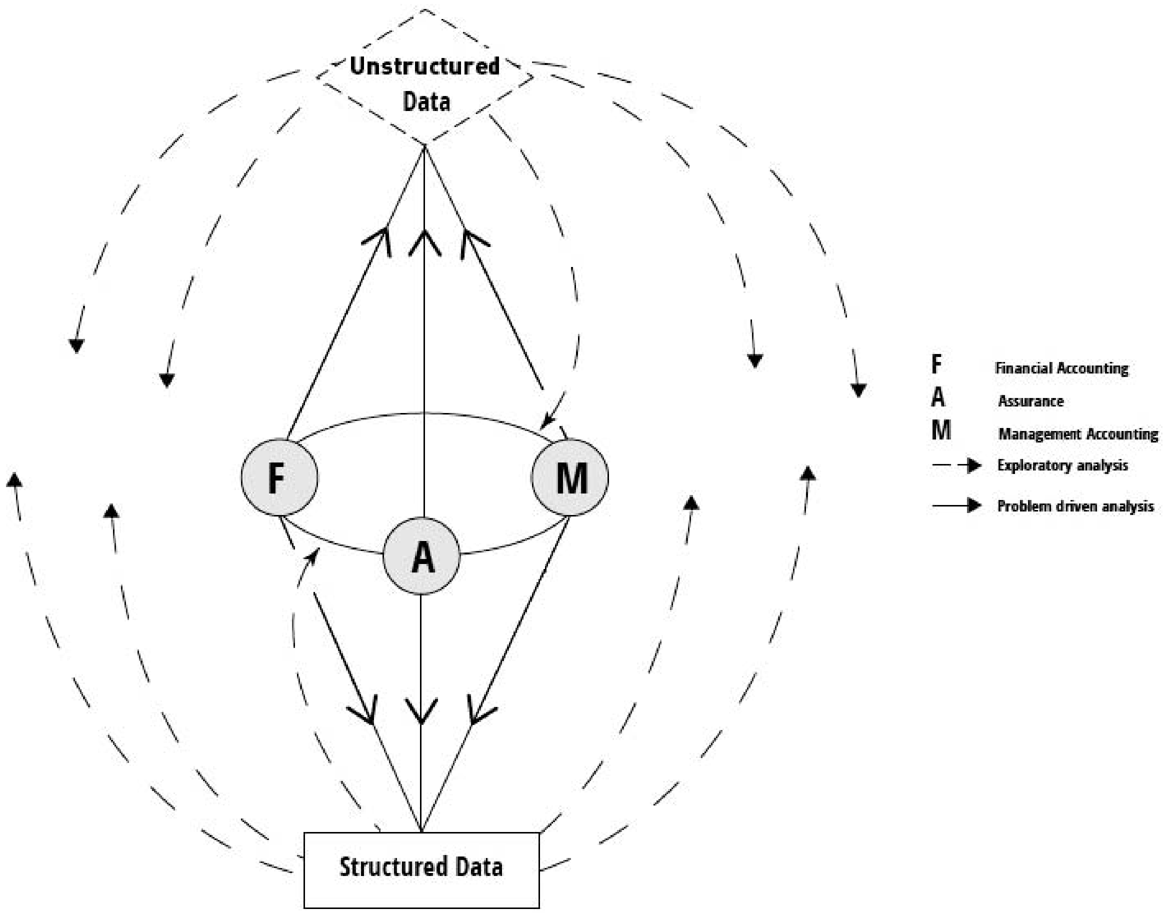
FIGURE 2
Analytic Data Flow Model



> In the context of unsupervised [machine] learning, there is no . . . direct measure of success. It is difficult to ascertain the validity of inferences drawn from the output . . . One must resort to heuristic arguments not only for motivating the algorithms . . . but also for judgement as to the quality of the results. (Hastie, Tibshirani, and Friedman 2009, 487)

Accountants' strong business acumen provides them with an ability to filter out irrelevant and draw attention to relevant content to be included in exploratory analyses, as well as assist in interpreting the results of any analyses within a business framework. By recognizing relationships among the data and how those factors impact firm financial performance, accountants continue to help firms achieve their financial objectives.

This conceptualization of the two different types of data, as well as the two different types of analysis and how they relate to three functional areas of accounting—management, financial, and audit—can be seen in the Analytic Data Flow Model in Figure 2. In the model, the directional solid arrows represent problem-driven analysis. Each of the three nodes representing functional areas of accounting (financial, management, and assurance) has solid arrows going to each of the two types of data (structured and unstructured). The arrows go from the nodes to the data because with a problem-driven approach, an accountant uses domain-specific knowledge in their functional area to guide their approach in data analyses. For example, a financial accountant who wishes to know the year-end sales figure will go to the underlying structured data and aggregate it into a single useful number. An auditor may analyze tweets to capture customer sentiment toward a new product release in order to assess whether sufficient provisions for sales returns have been set aside for potential recalls.[3]

[3] We thank Glen Gray and Greg Shields for this suggestion.

In contrast to problem-driven analysis, exploratory analysis is represented by dashed arrows that branch out from each of the two data types. Two features of these arrows are important. First, arrows go from the two data types to the functional nodes. With an exploratory approach, a data scientist does not have strong *ex ante* predictions about the results of their data analysis (Hastie et al. 2009, 487). Instead, data scientists attempt to interpret the results of their analyses to discover knowledge encoded in the data. This difference in the directionality of the arrows underlies one of the arguments we will make in this paper. Problem-driven analysis is often best suited to those who possess domain-specific knowledge, understand the problem, and can generate strong *ex ante* theory-driven hypotheses to test (i.e., accountants). By contrast, exploratory analysis, which is data-driven, is best suited to those who understand data and can uncover knowledge encoded in the data (i.e., data scientists).

The other important feature of these arrows is that not all of the arrows eventually make it to one of the accounting nodes. Exploratory analysis focuses on letting the data speak for themselves, and not everything the data have to say will be useful or relevant to decision makers. This underlies another argument we make in this paper. Although exploratory analysis is best suited to data scientists, accountants, who possess domain-specific knowledge, will play a critical supporting role in guiding exploratory analysis, as well as helping in the correct interpretation of the results of exploratory analyses.

In subsequent sections, we argue that accountants are already well acquainted with the data analysis of the pre-Big Data world—problem-driven analysis on structured data. In a post-Big Data world, problem-driven analysis of unstructured data will become increasingly important, as will exploratory analysis of both structured and unstructured data. We argue that because accountants already have domain-specific knowledge and skills in the arena of analyzing structured data with a problem-driven approach, they will be able to leverage those competencies to contribute meaningfully to the problem-driven analysis of structured and unstructured data in a Big Data world. Therefore, the problem-driven analysis of unstructured data is where accountants should focus the majority of their effort and attention in order to contribute and create value in a post-Big Data world. By contrast, exploratory analyses of both structured and unstructured data will primarily be the domain of data scientists. To ensure that accountants are not replaced entirely by data scientists, it falls on the accounting profession to make its value understood as problem-driven analyses begin using increasing amounts of unstructured data.

Importantly, in considering opportunities and threats to the accounting profession within this framework, it is important to move beyond the narrow definitions of accountant and accounting provided in prior research. For example, while Chenhall (2003, 129) defines management accounting narrowly as "a collection of practices such as budgeting or product costing," a broader definition of management accounting as "the process of supplying the managers and employees in an organization with relevant information, both financial and nonfinancial, for making decisions, allocating resources, and monitoring, evaluating, and rewarding performance" (Atkinson, Kaplan, Matsumura, and Young 2011, 2) better reflects the nature of management accounting as it is taught in business schools. We advocate defining management accounting broadly.

Following Horngren, Harrison, Smith Bamber, Lemon, and Norwood (2002, 2), we define accounting as an "information system that measures business activities, processes that information into reports and financial statements, and communicates the findings to decision makers." This broader conceptualization is in line with how practicing accountants already brand themselves. For example, CPA Canada (2017) defines accountants as "dedicated professionals who focus on strategic and financial management." The Institute of Management Accountants (IMA) describes accounting professionals as "essential to financial management, organizational development, and the achievement of strategic goals" (http://www.imanet.org/about-ima/our-mission). If accountants do not broaden their data analysis competencies to conform to these descriptions of accounting professionals, then they risk being left behind or replaced by data scientists.

The next three sections of this paper will discuss how accountants in each of three functional areas of accounting—management, financial, and audit—can create value in a Big Data world. For each of these three functional areas of accounting, we will discuss what changes we can expect as Big Data proliferates more widely and how accountants should react to these changes to ensure the accounting profession continues as a going concern.

III. MANAGEMENT ACCOUNTING

In the late 1960s, the pursuit of costing accuracy seemed foolhardy since the costs associated with greater accuracy far outweighed the benefits (Kaplan 2006). Over the last few decades, technological developments have led to an explosion of available information and a collapse in the cost of storing and retrieving information to the point where costing accuracy is "economical and almost routine" (Kaplan 2006, 128). Unfortunately, this explosion of information does not necessarily lead to better decisions. For instance, Kaplan (2006) noted that an abundance of information can result in business units expanding product lines and supplier networks without consideration of how these initiatives affect each other and the firm. Thus, continuous improvement efforts, which appear to be valuable, may be "orthogonal or subtractive rather than additive and complementary" (Kaplan 2006, 128).

Big Data analytics could offer a solution or aggravate this problem. By using a combination of structured and unstructured data, organizations can achieve more useful insights than they can by relying on structured data alone. For example, organizations assessing customer service quality could measure response times to customer inquiries. While precise and objective, this type of structured data does not reflect service quality from the customer's point of view. Combining structured data gathered regarding response times with unstructured customer sentiment data provides organizations with a deeper understanding of problems as they are perceived by the customer (Sperková, Vencovsky, and Bruckner 2015). Emerging technologies such as blockchain and the Internet of Things may provide users with an abundance of data. However, Big Data potentially contains large amounts of useless and/or unreliable data (Ramirez, Brill, Ohlhausen, and McSweeny 2016), which challenges organizations attempting to leverage Big Data into actionable plans and take advantage of emerging opportunities. To quote Venkataraman, CFO and COO of Syncsort:

> Over the next decade, Big Data has the potential to be a real game-changer. But it's just rows and columns on a spreadsheet without the right tools. We have gone from a world in which firms have too little data to a world in which firms have so much data they have difficulty making sense of these data and drawing insights from them. (Thomson 2015, 7)

Using more data can increase the power of analysis, but it fails to remove inaccuracies or biases present in Big Data. Furthermore, with sufficiently large datasets, finding spurious correlations is unsurprising.[4] Although data scientists possess skills to conduct exploratory analyses that identify correlations and patterns in the data, accountants' ability to understand the language of business provides them with the capability to identify and interpret relevant data that can be turned into implementable strategies.

The function of management accounting has evolved from focusing primarily on budgetary control, costing, and variance analysis to developing and implementing strategies that foster increased firm performance while managing risk (Ramli, Sulaiman, and Zainuddin 2015). Management accounting "helps an enterprise to develop and implement its strategy" (Atkinson et al. 2011, 5). Thus, accountants must understand "what managers do, the information managers need, and the general business environment" (Garrison et al. 2012, 3).[5] This provides accountants with opportunities to develop expertise in strategy formulation and implementation, monitoring the attainment of strategic objectives, as well as recommending and taking corrective action where required.

Although the origin of accounting is unknown, Luca Pacioli, dubbed the Father of Accounting, is credited with authoring the first publication of the double-accounting method in 1494. Over time, financial accounting standards emerged as the result of statutory requirements, and management accounting information relied upon accounting information designed for financial reporting purposes. To meet their information needs, accountants developed skills to draw on and interpret information from multiple sources.

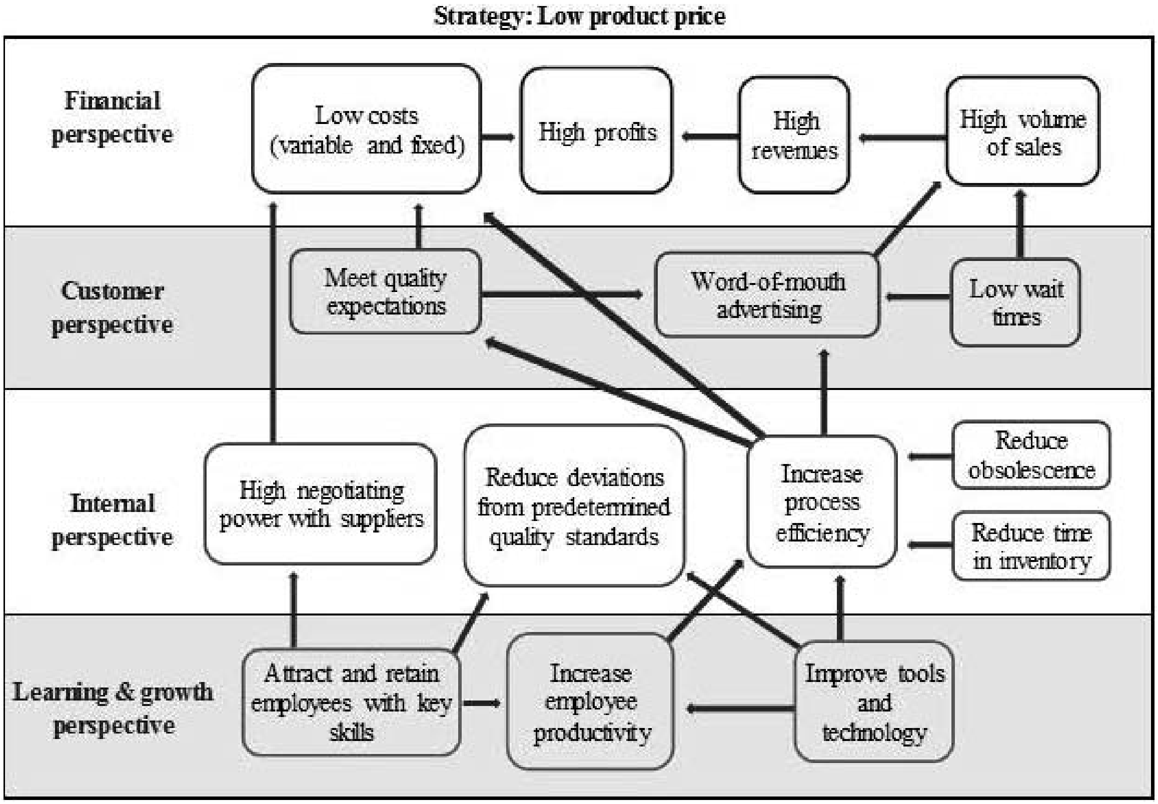
As noted by Gordon, Cooper, Falk, and Miller (1981), in the early 1980s, accountants were incorporating data external to their firms in their pricing decisions. In fact, Simmonds (1982) credits accountants' skill of gathering, merging, and interpreting data from a variety of sources as a significant reason for their central role in firms' strategy development and execution. Managers find that traditional financial measures alone are insufficient for forecasting future financial success (Kaplan and Norton 1992). Greater value can be generated by moving beyond these traditional measures. For example, Trax Technology Solutions (Singapore) is able to drill down sales revenues and operating/sales expenses of individual products to a specific salesperson and link them to website traffic, time of day, and geographical location of users to optimize labor allocation (Katz 2014). This information helped develop key performance indicators that align employee incentives with the firm's strategic objectives. In doing so, Trax Technology Solutions applied a problem-driven approach to identify relationships among the structured data and interpret this information through the lens of the firm's financial objectives. This example demonstrates the adaptability of accountants to incorporate data not traditionally included in their analyses, such as website traffic.

Along with playing an active role in strategy formulation, accountants contribute to strategy implementation and monitoring. Accounting tools, such as the sample Balanced Scorecard (BSC) depicted in Figure 3, provide a framework for examining an organization from multiple perspectives and seeing how factors in each perspective contribute to a firm attaining its strategic objectives. For decades, accountants have been involved with developing BSC metrics and devising techniques for monitoring performance. Traditionally, performance on BSC measures have been captured using structured data (e.g., sales revenues, customer satisfaction surveys, product defect rates).

[4] For examples of spurious correlations, see Vigen (2017).

[5] Malmi and Brown (2008) distinguish between management accounting systems (MAS) and management control systems (MCS) and suggest that management accounting is part of MAS. They define MAS as systems designed solely for decision-making purposes, whereas MCS are designed to control or influence the behavior of others. Recognizing that some systems may be used for both purposes, Atkinson et al. (2011) refer to these systems collectively as management accounting and control systems (MACS). Consistent with our broad definition of management accounting, we conceptualize MCS and MAS as part of management accounting.

FIGURE 3
Sample Balanced Scorecard and Strategy Map for a Hypothetical Company



Using Big Data analytics, accountants can broaden their monitoring techniques to include unstructured data that may provide the potential to identify areas of improvement and opportunities. For instance, sentiment analytics based on Facebook data can be merged with existing accounting data to develop sophisticated models. As an example, Best Buy already knew that people disliked their "restocking fee." However, using software to monitor social networking and the ability to merge these data with internal sales data revealed that this sentiment was very strong among their most valuable customers. This understanding led Best Buy to drop almost all restocking fees (Murphy 2011). This example highlights how accountants can extend their problem-driven approach to include analysis of unstructured data, thereby identifying underlying causes, recognizing the potential ramifications, and developing plans to mitigate adverse impacts.

The potential of the Internet of Things and Industry 4.0 to revolutionize production and logistics is staggering.[6] To facilitate flexible operations, data capturing firms' manufacturing and business processes (e.g., production quality, labor costs) may be continuously communicated within an organization and with external parties along the value chain to create a vast and complex network of suppliers, producers, and customers (Drath and Horch 2014). To support this network, firms will need to develop new processes capable of continuously monitoring, analyzing, and interpreting data (Davenport et al. 2012). Given accountants' ability to recognize and assess how various performance measures reflect effective operations as they relate to a firm's strategic operations, gaining data analytics skills to use data generated by Industry 4.0 provides accountants with additional tools to monitor operations and product quality, discover opportunities to reduce costs, and meaningfully contribute to decision making (Dai and Vasarhelyi 2016).

With respect to quality control monitoring, text and/or voice analysis of customer phone calls and emails can help accountants identify troublesome product or service features and make recommendations that lead to a timely resolution. For firms concerned with sustainability issues as they relate to the customer perspective, content analysis of social media postings

[6] According to Wikipedia, Industry 4.0 is the fourth industrial revolution (after mechanization, mass production, and automation), which includes cyber-physical systems, the Internet of Things, and cloud computing. Industry 4.0 originated as the digital transformation of manufacturing into connected factories that support smart decentralized manufacturing, self-optimizing systems, and a digital supply chain.

can inform accountants of whether members of the public believe a firm is effectively meeting its corporate social responsibility objectives. As these examples highlight, accountants can engage in analysis of unstructured data to monitor firm performance in many settings.

With expertise in strategic planning, accountants are able to identify key competitive factors idiosyncratic to the firm, select appropriate measures of those factors, and effectively communicate that information throughout the organization. Thus, accountants possess valuable business acumen that firms can leverage for the attainment of their long-term objectives. Due to their familiarity with financial information and firms' systems and structures, Kaplan (2006) maintains that accountants have a strategic advantage over others, such as economists, in leveraging technological developments.

Going forward, rather than see their role diminish, accountants may see their responsibilities grow. As problems arise, accountants can use their business knowledge to incorporate both structured and unstructured data into their analyses. With respect to exploratory analyses, accountants can collaborate with data scientists by recommending content to explore, both structured and unstructured, and then interpret the results in light of the firm's strategic objectives. In the next five years, the availability of Big Data, coupled with data analytics, has the potential to make "the finance function . . . a strong, formidable strategic partner to operations and sales. Finance is the natural gatekeeper of data, as information normally flows through the function" (Katz 2014, 20).

IV. FINANCIAL ACCOUNTING

Financial accountants have long contributed to their firms' strategic objectives and decision-making processes. As far back as the early 20th century, financial accountants were using DuPont Analysis to help firms better understand financial data and how to interpret those data through a strategic lens to improve decision making. DuPont Analysis is an early instance of financial accountants engaging in a problem-driven approach of structured data. Specifically, financial accountants were analyzing structured financial statement data to understand drivers of a firm's profitability. Financial accountants can still analyze financial statement data, as well as data related to the financial statements to help with the strategic decision-making process, but in a world of Big Data, they will need to move beyond simple tools like the DuPont framework.

As a starting point, recent research in accounting provides insight with respect to how accountants can introduce unstructured data to their problem-driven analyses. Traditional economic models hold that firms with a concentrated customer base will lack bargaining power and suffer decreased profits as a result.[7] Patatoukas (2012) uses structured and unstructured data to test the hypothesized negative relationship between customer base concentration and firm performance. He does so by using textual information from firm disclosures about major customers in order to test the hypothesis that a concentrated customer base negatively impacts firm performance. In contrast to conventional economic wisdom, he finds that, although the relationship between customer base concentration and gross margin is negative, the effect on net income is positive due to decreases in selling, general, and administrative expenses. This provides one example of how an individual with an understanding of accounting can use a problem-driven approach to model the relationship between customer base concentration and net income. This model can now be leveraged by firms to increase income by increasing customer base concentration.

For many firms, using Big Data in this manner may prove quite profitable (Patatoukas 2012). However, if decision makers do not understand firm fundamentals, then following this strategy blindly could be disastrous. That is why it is important that financial accountants take a leading role in the decision-making process—they understand the data that make up a firm's financial statement and how those data relate to firm strategy. For example, consider a firm that has high margins because it is following a product differentiation strategy. For that firm, sacrificing gross margin to increase net income may be perfectly reasonable. In contrast to a high-margin firm, imagine a firm that already has thin margins because it is pursuing a cost leadership strategy. That firm may be unable to continue as a going concern if gross margins drop any lower. Thus, it is important for financial accountants to take a leading role in the decision-making process as they understand not only the trends suggested by Big Data analytics, but also the underlying mechanisms for those trends as they relate to their firm's business strategy. This is why accountants are well suited to a lead role in this type of analysis. Accountants will understand when the model does and does not apply.

Another interesting example of insights yielded from problem-driven analysis of structured and unstructured data can be observed in the various new measures of competition based on accounting data (Karuna 2007; Li, Lundholm, and Minnis 2013).[8] For example, Karuna (2007) devises an interesting method for measuring product market competition, which he argues cannot be uni-dimensionally proxied for by industry concentration, as done in prior studies. This can be additionally supplemented by the work of Li et al. (2013), who use unstructured textual data to assess the level of competition based on

[7] A highly concentrated customer base refers to firms for which a large proportion of total revenue is driven by relatively few customers.

[8] The studies listed in this section are just a small sample of a growing literature. An alternative path would have been to build our examples based on textual analysis of financial reports (e.g., Li 2008, 2010; Loughran and McDonald 2011).

frequency of references to competition/competitors in the firm's 10-K. Hampton and Stratopoulos (2015) leveraged the text-mining capabilities of Capital IQ to extract the number of buyers and suppliers listed in firms' forms filed with the Securities and Exchange Commission (SEC) to generate proxies for the bargaining power of buyers and suppliers. Decision makers can leverage these findings to guide strategic firm-level decisions. For example, a firm can use Big Data analytics to identify areas with low competition as potential areas for expanding the business.

Generally, a method that can identify low-competition areas would be a useful tool for a firm deciding how to expand. However, once again, blindly following the data without understanding business fundamentals can be dangerous. For instance, an increase in sales would suggest growing market size and, therefore, an enticing low-competition area. However, what if increased sales were accompanied by decreasing inventories? This could indicate that the market is growing so fast that existing firms cannot keep up with demand, which would suggest a good area to expand into. Alternatively, declining inventories could also suggest that firms are liquidating in preparation for exiting an industry that has become undesirable to operate in due to an exogenous shock. Textual analysis of competitors' management discussion and analysis (MD&A) can be helpful in differentiating between the two scenarios, but, ultimately, having someone with domain-specific knowledge, such as an accountant, will be helpful in understanding that competition is not the only determinant of desirability.

To this point, we have discussed the importance of accountants taking a leading role for problem-driven analyses of both structured and unstructured data in the realm of financial accounting. However, an accountant's role is not limited to just problem-driven analyses. Accountants also have an important support role to play in exploratory analyses. As indicated in Figure 2, exploratory analyses can yield many potential models, but not all of them will be equally valid or useful in making decisions.

One reason that an otherwise-good model may prove untrustworthy is that the underlying data are deficient with respect to either quantity or quality. Prior research shows that investors find that Level 1 and Level 2 assets are more value-relevant than Level 3 assets (Song, Thomas, and Yi 2010). One reason for this finding is that the data available to firms are insufficient to value Level 3 assets with the same degree of accuracy as Level 1 and 2 assets. Big Data analytics represent an interesting solution to this problem. Machine learning allows a computer to use exploratory analyses to improve its own models over time, thereby ultimately developing more reliable models (Devitt 2015; SAS 2016). However, in order to do this, the computer needs some input with respect to the quality of its previous model iterations. This type of exploratory analysis is a good example of an instance where, even though it is appropriate for data scientists to take the lead, accountants can and should play a valuable support role to ensure that correct inferences are made when letting the data speak for themselves. A data scientist should work with someone who understands the business, specifically, the Level 3 assets in question, as they can provide feedback about the quality of previous model iterations as time passes and uncertainty about prior valuations is reduced. In other words, an accountant, acting in a support role, can provide important information about the validity of previous model iterations in order for the machine to develop better models in the future.

Even after every effort has been made to improve a model, Box (1976) asserts that all models are wrong, but some are useful. Therefore, managers should assess the usefulness of the many models generated via exploratory analysis when making decisions. However, knowing how to assess which models are useful and which are misleading is a difficult art. Mastering that art requires two traits: (1) an understanding of the underlying business, and (2) an understanding of the data and how they are analyzed. Both of these traits are in short supply even separately, let alone together. A global survey of executives conducted by KPMG LLP reports that 94 percent of executives identified business complexities as their greatest challenge (KPMG LLP 2011). Furthermore, executives in the same survey agreed that business complexity is likely to increase going forward. Hence, those who understand the business and its complex operations are likely to become even scarcer going forward. Similarly, the unprecedented explosion of Big Data has firms scrambling to find qualified data scientists (Orihuela and Bass 2015). This raises the question: How can firms possibly identify and hire/train people that understand the business side of the firm's operations, as well as understand data and data analysis?

To solve this problem, firms may find that accountants can be a valuable human resource. Many firms already use rotations through the accounting function as a management training ground because accountants necessarily develop a thorough understanding of the firm's operations in order to perform their jobs (Burton, Starliper, Summers, and Wood 2015). Additionally, some accountants have long used large structured datasets (Beach and Schiefelbein 2014; Ponchione 2013; Tabuena 2012) and, more recently, have moved into the realm of Big Data analytics by using unstructured data with a problem-driven approach (Peters 2015), such as the use of textual analysis of employee emails in order to detect and prevent fraud (Tabuena 2012). In other words, in addition to possessing significant domain-specific knowledge about their businesses, accountants have a long-demonstrated competency with respect to the problem-driven analysis of structured data. Accountants are further beginning to demonstrate their value in the realm of problem-driven analysis of unstructured data. Given accountants' dual competencies on the business side, as well as the data side, we think accountants are prime candidates to play a support role to data scientists in the exploratory analysis of both data types.

Notwithstanding accountants' competencies in the realm of problem-driven analysis and the potential impact accountants can have in a support role for exploratory analyses, data may be misleading because of management manipulation. In examining this possibility, it is instructive to look at one of financial accounting's most widely used models—the Jones model. Jones (1991) developed her model in order to determine whether firms managed earnings in response to import relief investigations. The fact that one of financial accounting's most widely used models was developed in response to underlying data that could not be trusted at face value highlights an important principle of data quality, not just for Big Data analytics, but for any manner of data analysis: garbage in, garbage out (Woodie 2013). In short, this principle states that if the underlying data used in an analysis are flawed, then the results of the analysis will also be flawed. A firm using Big Data analytics to differentiate itself from its competitors must be able to determine whether the data used are reliable and valuable.

The idea that the data underlying an analysis may be unreliable is not new to accountants. For example, in Jones' (1991) setting, the data provided by the firms in her sample were unreliable because firms were actively manipulating the data to attain favorable import relief. In the context of Big Data analytics, Twitter has often been used in conjunction with financial statement data to assess various aspects of company performance (e.g., Blankespoor, Miller, and White 2014; Elliott, Grant, and Hodge 2016). However, a company pursuing this methodology to gain information about competitors should first assess the value of the tweets as information (e.g., does the company being assessed engage in social media management). Therefore, although many models exist and even more can be produced to provide firms with important strategic information about their competitors, it is important that the data be analyzed by someone who understands their business model well enough to make determinations about when given models are not viable because the veracity of the underlying data cannot be trusted. Making determinations about the veracity of data is not new to accountants. In fact, auditors have long provided assurance services that do exactly that.

V. AUDITING

Much of the traditional financial statement audit is focused on using a problem-driven approach to analyzing structured data. For example, in planning tests of controls and substantive tests, the auditor's efforts are directed by the closed-ended problem of trying to obtain sufficient appropriate audit evidence. Currently, auditors typically apply their data analytic efforts on data generated by their audit clients' accounting information systems, which are limited in size and have an inherent structure. Looking toward a Big Data future, auditors must learn how to apply their problem-driven approach to data analysis on much larger datasets, and need to build competencies in analyzing unstructured data in order to stay competitive in the market for assurance services. Furthermore, auditors must be proactive and capitalize on this opportunity to secure themselves an important supporting role in the exploratory analysis of both structured and unstructured data. Public accounting firms face unique threats in the wake of the Big Data revolution in the form of potential increased competition from technology-based firms with competitive advantages in data analysis. Having said that, we maintain that the Big Data future has a place for auditors, and offers new opportunities for public accounting firms in the form of new consulting opportunities, particularly with respect to providing assurance over the veracity of unstructured data.

In the context of a financial statement audit, auditors will find it useful to update their traditional substantive tests, tests of controls, and analytical tests by applying problem-driven data analytic techniques on Big Data (Titera 2013). In the pre-Big Data world, auditors apply a problem-driven approach on structured data to assess whether financial statements are materially misstated.[9] Post-Big Data, developments in data analytic techniques will allow auditors to test entire populations of structured data at a time, as well as use non-traditional unstructured data to test hypotheses relating to financial statement assertions (Hayashi 2014; Cao, Chychyla, and Stewart 2015). However, performing substantive tests on entire populations does not negate the need for auditors. In all cases, the objective remains to generate a list of outliers that will require follow-up by an auditor with good critical thinking skills in order to distinguish between spurious and non-spurious outliers and determine whether financial statements are free from material misstatement.

Some argue that advances in models used to process and identify outliers in population-level data will improve efficiency to such an extent that the need for auditors to perform manual follow-up on outliers will be minimal (Issa 2013; Moffitt and Vasarhelyi 2013). However, it is unclear whether simply improving model efficiency will decrease the need for auditors. As auditors transition to working with Big Data, from testing samples to testing entire populations, the volume of data analyzed increases by several orders of magnitude, greatly increasing the number of exceptions that must be ruled out or examined. Furthermore, if auditors begin to incorporate unstructured data into their population-level analyses, then they will have to test any associated data streams that are used to vouch or match to the population in question for relevance and veracity, further increasing the volume of data that must be considered. In the near future, it is unlikely that this transition from sample-based

[9] Although auditing standards do not describe this process as hypothesis testing, the audit approach is consistent with formal hypothesis testing described in Section II.

testing to whole population testing will reduce the number of auditors required to obtain audit evidence. In fact, there may be a temporary increase in demand for entry-level auditors in order to process and label outliers to facilitate machine learning to improve the efficiency of these models.

Some suggest that non-accountants, such as computer scientists and other data scientists, may begin to compete with accounting firms in the audit market (Brown-Liburd et al. 2015; Earley 2015). However, unlocking the full potential of data analytics in an audit setting requires individuals who are not only well versed in Big Data analytics, but also have an intimate understanding of business (McAfee and Brynjolfsson 2012). It is this intimate understanding of business that provides auditors with a competitive advantage over data scientists in generating predictions to test using a problem-driven approach. As part of their university and firm training, auditors are provided with general business domain knowledge and training in problem-driven data analysis. As auditors gain experience performing audits, they begin to cultivate additional business domain knowledge based on their experiences that is difficult to obtain through other means (Bonner and Lewis 1990).

Tabuena (2012) argues that data analytic techniques are not completely foreign to auditors, in particular, forensic specialists, who already have experience dealing with large quantities of structured data in attempts to trace fraud. With additional training in data analytic techniques suitable for unstructured data, such as text mining, and training on the use of statistical software, these specialists, along with other members of the audit team, should be able to apply these principles of problem-driven data analysis to combinations of structured and unstructured data. As accountants continue to gain competencies in problem-driven analysis of both structured and unstructured data, they will be able to combine this with business domain knowledge to achieve high levels of efficiency and create value in the world of Big Data.

Another argument to support the assertion that the financial statement audit cannot easily be automated is that some portions of the audit involve significant subjectivity or professional judgment, making them naturally resilient to automation (Frey and Osborne 2013). For example, the choice to require management to provide going concern disclosure is a decision that involves a great deal of subjectivity. While the underlying ratio and financial statement analyses used to support this decision can be easily automated, the ultimate decision to require or not require management to provide footnote disclosure is subjective. Auditors have to judge whether there is "substantial doubt" that the audited entity will be able to continue as a going concern, and to evaluate management's plans to "alleviate substantial doubt" (PricewaterhouseCoopers LLP [PwC] 2014).

Although it is likely that in the near future, we will be able to develop models to predict whether it is more likely than not that an organization will be able to continue as a going concern, current standards are not meant to be applied formulaically (PwC 2014). Furthermore, it is less likely that we will be able to develop models that will be able to assess management's ability and intention to carry out plans to "alleviate substantial doubt" due to the idiosyncrasies in any given organization's plans and the possibility of management intentionally providing misleading information. Thus, it is likely that Big Data analyses will complement auditors' professional judgment rather than substitute for it.

Other parts of the financial statement audit that would be difficult to automate are portions of the audit requiring social intelligence (Frey and Osborne 2013). Examples include client relationship management, collection of inquiry evidence, and detecting management's intentions to commit financial statement fraud. The assessment of fraud risk, as well as detection of fraud intentions, requires an in-depth knowledge of the audit client's operations, business environment, and motivations (Peecher, Schwartz, and Solomon 2007). Although automated data analytic procedures may provide knowledge of an audit client's operations and business environment, it is difficult to automate holistic assessments of management's motivation, opportunity, and ability to rationalize financial statement fraud, as these assessments require social intelligence (Frey and Osborne 2013). Furthermore, if fraud detection were to become fully automated, then it would become largely rules-based, opening the door for fraudsters aware of these rules to alter their behavior such that fraud models fail to detect their activity. Although manual fraud-detection techniques are unlikely to uncover all, or even most, fraud, we argue that it is an invaluable complement to automated fraud-detection techniques.

Historically, the audit profession has been slow to adopt technologies that have revolutionized the business world (Alles, Kogan, and Vasarhelyi 2002; Alles 2015; Dai and Vasarhelyi 2016). However, there is ample evidence that the Big 4 public accounting firms, and the industry as a whole, have already begun to react and adapt to the advent of Big Data. For example, Deloitte LLP has announced a partnership with Kira Systems to develop text-mining software capable of machine learning in order to quickly extract information from unstructured business documents in order to support their audit and consulting practices (Deloitte LLP 2016). Similarly, KPMG LLP has announced a partnership with IBM to use IBM's Watson, a cognitive computing technology capable of machine learning, to support "judgment-driven processes" within the audit (IBM 2016). Ernst & Young LLP (EY) has already begun to plan for how Big Data and blockchain technologies will impact the financial statement audit (EY 2015, 2016). Also, PricewaterhouseCoopers LLP has made significant investments into audit technology in order to automate portions of the audit (Rapoport 2016).

This proactive attitude toward adoption of data analytic techniques, combined with difficult-to-replicate human capital that has been accumulated by public accounting firms in the form of experienced auditors possessing task-specific, sub-specialty, and client-specific knowledge, will make it difficult for tech firms to compete with accounting firms in the market for audit services. Furthermore, these proactive partnerships between public accounting firms and technology-based firms are signs that auditors are positioning themselves to play a strong supporting role in the realm of exploratory analysis using structured and unstructured data.

The above discussion deals with the resiliency of the audit profession to automation from the perspective of audit engagements. However, the advent of Big Data analytics presents many new opportunities for audit firms to expand their existing advisory practice. Warren, Moffitt, and Byrnes (2015, 404) assert that one of the first steps to enabling Big Data analyses in an organization is to "identify the data, assess their suitability for the task at hand, and decide whether the analyses should be outsourced." Although companies have already begun to collect an enormous amount of unstructured data, they are unsure about how to effectively leverage this new source of information to make better business decisions (Earley 2015). Importantly, the Federal Trade Commission (Ramirez et al. 2016) recently issued a report cautioning firms that although Big Data is useful and presents many new opportunities, there are many new sources of "hidden biases" that must be controlled for, and that firms are likely not used to dealing with these sorts of biases in structured data. Furthermore, Goes (2014) cautions that in the era of Big Data, validating data and discriminating between "malicious and valid" data will become increasingly important. Firms engaging in Big Data strategies are likely to become increasingly concerned with the quality of data used in their analyses. Hazen, Boone, Ezell, and Jones-Farmer (2014) estimate that poor data quality can negatively impact revenue by 8–12 percent and expenses by 40–60 percent. Therefore, firms will need guidance in terms of assessing the relevance and veracity of Big Data in order to generate value through its use.

Auditors are already charged with assessing the relevance and veracity of structured business data through the financial statement audit. With additional training in data analysis and experience in how to approach the analysis of unstructured data gained through auditing in the world of Big Data analytics, auditors are well positioned to help nonaudit clients assess the relevance and veracity of their unstructured business data. While accounting firms face competition from tech firms in the market to provide consulting services to businesses, accounting firms may be able to carve a niche for themselves by offering a rare combination of data analytic skills and a strong understanding of business.

VI. IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

Throughout this paper, we have argued that, although many of the routine tasks currently performed by accountants will likely be automated in the future, it is unlikely that Big Data analytics will eliminate the need for accountants altogether. In fact, we assert that Big Data analytics present opportunities for accountants to play a leading role in problem-driven analyses of structured and unstructured data and to support data scientists in exploratory analyses to create value. This argument was built on two pillars: accountants have the advantage of understanding business, and they are already accustomed to working with structured datasets and performing data analysis. Our position has implications for firms hiring talent to leverage Big Data analytics (demand side), universities and professional organizations charged with the training of the new generation of accounting professionals and the retooling of existing ones (supply side), as well as accounting standard-setting organizations, accounting firms, and vendors.

Big Data analytics present many opportunities, as well as pitfalls, for companies. To capitalize on the opportunities of Big Data while avoiding the pitfalls, companies need to utilize individuals who understand not only data analytics, but the business, as well. Current practices suggest that accountants understand the business and are already beginning to work with data scientists. As such, accountants are poised to contribute meaningfully to their firms as part of the Big Data revolution. Irrespective of accountants' qualifications for analyzing Big Data, we have also made the argument that the outcome of Big Data analytics will not exceed the quality of the data being inputted. This is a problem that can be addressed by auditors, who have long been charged with ensuring the veracity of data.

From the supply side, we consider the implications relating to skills that future accountants need to have, or existing accountants will have to acquire, in order to remain valuable in a world of Big Data analytics. In other words, what are some of the key elements of a competency map for future accountants and auditors? The starting point for the creation of such a competency map should be the understanding that we are not dealing with just one technology, but a series of interrelated technologies (Hampton and Stratopoulos 2016). For example, the transition from problem-driven analysis of structured data to unstructured data (Figure 1, top row) was fueled by the growth of Facebook, Twitter, and YouTube. However, this transition only became feasible with the emergence of cloud computing that made the storage and analysis of Big Data economical. What we have termed Big Data analytics is bound to go through another round of growth as radio frequency identification (RFID) costs go down, leading to widespread adoption of the Internet of Things. Real-time Big Data analytics will become feasible as blockchain technology matures and smart contracts are embedded in more and more processes. Last, but not least, the democratization of advanced machine/deep learning techniques will blur the lines between problem-driven and exploratory analysis of Big Data. Therefore, preparing accountants to understand and embrace emerging technologies, as well as preparing them to interact with data and computer scientists, will become a critical competency for accountants who want to play an active role in the era of Big Data analytics.

Consistent with our main proposition, we suggest that in order to develop tech-savvy accountants who will be resilient to automation, we need to focus in the following areas:

(1) Complement accounting knowledge with training in business strategy and understanding of business models. Train for a role of accounting as it applies to the firm's business model (how the firm will make money) rather than a narrow setting.
(2) Develop business analytic capabilities. This means that given a business problem, accountants should be able to identify and extract appropriate data, clean and transform the data, perform data analysis, interpret results in the context of the problem, and communicate business implications to stakeholders.
(3) Learn to work with structured and unstructured data of large size using tools that are designed for a world of Big Data. We need to take the next generation of accountants beyond Excel and Access and introduce them to tools that were developed for Big Data and/or scale to the level of Big Data (e.g., SQL, Hadoop, MongoDB, R, and SAS).
(4) Finally, understanding principles of programming (e.g., an introduction to programming languages like Python) is necessary if we want accountants to develop the ability to learn new emerging technologies in the future and be able to communicate with data and computer scientists.

We have argued that accountants are in a prime position to take a lead role in the problem-driven analysis of unstructured data. Accounting firms already employ specialists who are accustomed to working with structured datasets (Beach and Schiefelbein 2014; Ponchione 2013; Tabuena 2012). Accounting education and training needs to bolster and broaden this extant competency so that a majority of accountants, not just a handful of specialists, are comfortable with analyzing large datasets. Currently, even when working with structured data, accounting firms often leverage specialists for large datasets. With that education as a starting point, accountants will have a sizable advantage over potential entrants when the time comes to analyze large unstructured datasets with a problem-driven approach.

The role that auditors will play in the world of Big Data analytics will largely depend on the evolution of auditing standards. Some experts have expressed uncertainty over how evidence provided through analysis of Big Data falls within the audit evidence hierarchy, and whether standards will interpret evidence provided by Big Data as "anything more than indicative evidence" (Ramlukan 2015, 19). Thus, until standards are changed to consider how Big Data will fit into the financial statement audit, the suitability of Big Data techniques in replacing traditional audit methods of gathering audit evidence remains unclear. Auditors' ability to analyze 100 percent of an entity's population of data, rather than a sample, and the implications for audit standards seem to have been one of the most often mentioned benefits of data analytics. According to a recent report by the Institute of Chartered Accountants in England and Wales (ICAEW 2016, 3), this change "will affect management expectations about the focus and scope of external audit." The authors of the ICAEW report argue that had this ability been available since the 1950s, current risk-based audit standards and the concept of materiality might have not been developed.

Notwithstanding the practical implications for auditors (for example: If 100 percent of a population could be examined, and the auditor took a sample, then is the auditor more vulnerable to litigation?), making the discussion of population versus sample the focal point of the new standards is not likely to make the profession more resilient to automation. In the context of our framework, the ability to examine 100 percent of a population is still limiting auditors to the problem-driven analysis of structured data (upper-left corner of Figure 1). From a theoretical standpoint, a shift from a well-designed random sample of structured data to an entire population is going to have only a marginal effect on the level of confidence (assuming that the sample-based analysis uses an alpha of 5 to 10 percent). The threats and opportunities put forward in this study are stemming from leveraging unstructured data and using machine/deep learning techniques on structured and unstructured data. This means that we need a new generation of standards that work with structured and unstructured data and can integrate either a problem-driven or exploratory analysis. Without such a mindset, and with standards that limit auditors to the pre-Big Data era (the upper left corner of Figure 1), the gate remains open for potential new entrants (e.g., accounting technology [AccTech] start-ups) to the marketplace and to upset the auditing landscape.

We hope our paper is a useful road map for accountants and accounting firms seeking to understand how they can continue to add value for their clients and firms in a world of Big Data. However, our recommendations are forward-looking and, as such, we are unable to subject our recommendations to rigorous empirical scrutiny. This represents a limitation and we encourage firms and future research to examine the empirical validity of our recommendations. Another limitation and opportunity for future research would be to expand the scope of analysis to other areas within the accounting profession, such as tax and internal auditing. Last, but not least, a limitation and a potential opportunity for future research, as well as an opportunity for growth, in auditing would be to explore the implication of Big Data and cybersecurity.

VII. CONCLUDING REMARKS

Data analytics and Big Data will inevitably change the role of accountants, but this does not mean that accountants will become obsolete. Instead, the Big Data revolution will lead to automation of the more mundane and routine functions, allowing accountants to focus their attention on opportunities to provide value to their organizations and clients. While Frey and Osborne (2013) categorize accounting and auditing as likely to be automated due to lack of machine inimitable skills, we advance the argument that accountants possess the ability to think strategically and leverage their business knowledge to augment the value provided by Big Data analytics. In essence, we argue that accountants' skills and knowledge are complements and supplements to Big Data, invaluable to maximizing value through the use of Big Data analytics in a business setting.

Rather than see their role diminish, accountants' expertise in gathering, merging, and interpreting data from multiple sources is likely to make accountants even more valuable with the emergence of Big Data analytics. Although unstructured data provide firms with valuable information, it must be interpreted within the context of the firm. Accountants' business acumen, coupled with their strong financial knowledge and strategic planning skills, provides them with the necessary capabilities to do this—skills that are also resilient to automation. Similar to supplementing financial measures with nonfinancial measures in the BSC, augmenting structured data with unstructured data provides managers with a clearer picture.

Big Data represents a big change to the way firms will do business. Many jobs and tasks will be made obsolete through its implementation. Whether Big Data represents a threat or an opportunity to the accounting profession is up to accountants. In order to make sure accountants have a place in the world of Big Data, appropriate education and training need to occur on all levels, from university students through to the continuing education of practicing accountants. Additionally, standard-setting bodies and institutions that define best practices need to incorporate the changes inherent in a Big Data world into their guidelines and recommendations. Accounting will have to change in response to Big Data, and we are optimistic about its future.

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