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Impact of business analytics and enterprise systems on managerial accounting

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ABSTRACT

The nature of management accountants' responsibility is evolving from merely reporting aggregated historical value to also including organizational performance measurement and providing management with decision related information. Corporate information systems such as enterprise resource planning (ERP) systems have provided management accountants with both expanded data storage power and enhanced computational power. With big data extracted from both internal and external data sources, management accountants now could utilize data analytics techniques to answer the questions including: what has happened (descriptive analytics), what will happen (predictive analytics), and what is the optimized solution (prescriptive analytics). However, research shows that the nature and scope of managerial accounting has barely changed and that management accountants employ mostly descriptive analytics, some predictive analytics, and a bare minimum of prescriptive analytics. This paper proposes a Managerial Accounting Data Analytics (MADA) framework based on the balanced scorecard theory in a business intelligence context. MADA provides management accountants the ability to utilize comprehensive business analytics to conduct performance measurement and provide decision related information. With MADA, three types of business analytics (descriptive, predictive, and prescriptive) are implemented into four corporate performance measurement perspectives (financial, customer, internal process, and learning and growth) in an enterprise system environment. Other related issues that affect the successful utilization of business analytics within a corporate-wide business intelligence (BI) system, such as data quality and data integrity, are also discussed. This paper contributes to the literature by discussing the impact of business analytics on managerial accounting from an enterprise systems and BI perspective and by providing the Managerial Accounting Data Analytics (MADA) framework that incorporates balanced scorecard methodology.

1. Introduction

Over the years, the role of management accountants has significantly changed. Serving the purpose of assisting and participating in decision making with management, modern management accountants work from four aspects: to participate in strategic cost management for achieving long-term goals; to implement management and operational control for corporate performance measure; to plan for internal cost activity; and to prepare financial statements (Brands, 2015). As business competition has increased tangentially with technology development, the scope of managerial accounting has also expanded from historical value reporting to more real time reporting and predictive reporting (Cokins, 2013).

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While enterprise systems provide improved effectiveness and efficiency of management accountant tasks, studies indicate that management techniques have not changed significantly (Granlund and Malmi, 2002; Scapens and Jazayeri, 2003). The argument is that management accounting principles and standards used by organizations prior to the implementation of enterprise systems have not changed. To provide more relevant and valuable information to management in this highly technical business environment, management accountants should be further utilizing all of the functions of the enterprise system (e.g. descriptive, predictive, and prescriptive data analytics; big data from both internal and external sources; and financial and non-financial information) rather than considering the system merely as a more powerful calculator.

The purpose of this paper is to discuss the potential impact of enterprise systems, big data, and data analytics on managerial accounting and to provide a framework that implements business analytics techniques into the enterprise system for measuring company performance using the balanced score card (BSC) framework from a management accounting perspective. While some literature describes the impact of business analytics on management accounting (Nielsen, 2015; Silvi et al., 2010), little research discusses using business analytics for measuring a company's performance in an enterprise system environment (Nielsen et al., 2014).

This paper contributes to the literature in several ways. First, this paper discusses the impact of business analytics on managerial accounting from an enterprise system perspective. Although some researchers have proposed a BSC framework for management accountants to apply business analytics (Nielsen, 2015; Silvi et al., 2010), few have examined this issue within the enterprise systems context. Second, this study proposes the Managerial Accounting Data Analytics (MADA) framework that incorporates the BSC framework for management accountants to utilize data analytics for corporate performance measurement. Lastly, attributes related to the implementation of a MADA framework (i.e. business intelligence context, data quality and integrity) are discussed to build the connection of the MADA framework and modern business practice.

The paper is organized as follows: The next section discusses the changing role of management accountants and the impact of enterprise systems on managerial accounting. The development of business analytics and big data, as well as their impact on enterprise systems are reviewed next, followed by the development of the proposed Managerial Accounting Data Analytics (MADA) framework. This MADA framework is then applied in the Business Intelligence (BI) environment, followed by a discussion of relevant issues. The paper concludes by briefly expanding on suggestions for future research.

2. Changing role of managerial accounting

2.1. *Management accountant's role*

Evolving from its traditional emphasis on financially-oriented decision analysis and budgetary control, modern managerial accounting encompasses a more strategic approach that emphasizes the identification, measurement, and management of the key financial and operational drivers of shareholder value (Ittner and Larcker, 2001). The goal of management accounting is to provide managers with operational and financial accounting information. Management accountants serve the role of participating in strategic cost management for achieving long-term goals; implementing management and operational control for corporate performance measurement; planning for internal cost activity; and preparing financial statements (Brands, 2015). To support this intended role, the main obligations of management accountants can be classified into (1) preparing financial statements; (2) measuring the company's performance; and (3) providing decision related information (Cokins, 2013).

With ERP systems and powerful business analytic tools that provide enterprises the ability to interpret and analyze various types of data (such as internal/external, structured/unstructured and financial/nonfinancial), it is crucial for management accountants to adjust their responsibility to help companies gain competitive advantage (Nielsen, 2015). In the preparation of financial statements, management accountants use accumulated historical values to report the financial situation of the company. However, in a business world that requires more timely and relevant information, financial statements usually are not an ideal source of information for decision-making by management as they are backward looking, reporting on past events rather than providing the forward-looking data needed for running the business. Modern management accountants assist management with measuring firm performance from internal data and providing decision related information from both internal and external data. Not only should management accountants provide descriptive reports to answer questions about prior events, they also need to make predictions including consequences for uncertainty and risk in decisions (Nielsen, 2015).

To fulfill these challenging tasks that help the business stay competitive, management accountants now can use business analytical tools to conduct prescriptive analysis to support decision makers against the uncertainties. For example, an optimization model could allow accountants in a manufacturing company to choose among different raw material vendors that could reduce cost and boost revenue (Taleizadeh et al., 2015). It is suggested that management accountants should transgress the boundaries of management accounting and interact with non-accountants to solve practical problems (Birnberg, 2009). Cokins (2013) highlights seven trends that are occurring in management accounting: (1) expansion from product to channel and customer profitability analysis; (2) management accounting's expanding role with enterprise performance management (EPM); (3) the shift to predictive accounting; (4) business analytics embedded in EPM methods; (5) coexisting and improved management accounting methods; (6) managing information technology and shared services as a business; and (7) the need for better skills and competency with behavioral cost management. In summary, management accounting has broadened its domain from conventional financial reporting to also including performance measurement and strategic decision making. Specifically, management accounting has extended its traditional focus to include identifying the drivers of financial performance, both internal and external to the business. New and revolutionary non-financial metrics and approaches have been added to management accounting functions, with an impact that is still being studied by academics and practitioners (Silvi et al., 2010).

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2.2. ERP systems

Enterprise Resource Planning (ERP) systems are organization-wide and integrated information systems that are capable of managing and coordinating all the resources, information, and functions of a business from shared data stores (Kallunki et al., 2011). Since ERP systems can integrate transaction-based corporate information into one central database and allow that information to be retrieved from different organizational divisions (Dechow and Mouritsen, 2005), they can improve the capability of management accountants to fulfill the aforementioned roles by providing management with access to relevant and real-time operational data in the support of decision making and management control.

Early research suggests that ERP systems have limited impact on management accounting (Granlund and Malmi, 2002). One of the reasons is that the implementation of ERP systems focuses on improving the efficiency of the financial reporting process and not changing the nature of that process, even though change could be obtained through the design and implementation of a system that integrates the operations of the entire organizations (Sangster et al., 2009). That is, management accountants consider the ERP system as a powerful tool for report generation and neglect its potential in process control and corporate performance analysis.

For a successful ERP implementation, Grabski et al. (2009) point out that the nature of management accounting's role should be changed dramatically, whereby the management accountant becomes a business advisor who takes proactive steps to aid executives and decision makers. Specifically, they describe the interactive relationship between ERP systems and management accountants as follows (Grabski et al., 2009,[1] pp. vii–viii):

“1. When management accountants are involved in an ERP system implementation, there is an increased likelihood of the implementation being a success.

2. The impact of the ERP system on the role of the management accountant is related to the perceived success of the system implementation, with more successful implementations exhibiting the more dramatic changes to the role.

3. While all ERP implementations results in changes in the tasks performed by management accountants, a successful ERP implementation results in a significant change in the management accountant's tasks, they become business partners not just data providers.

4. A successful ERP implementation results in both increases in data quality and quality of decision-making, and in additional time for management accountants to become involved in value-adding tasks rather than mundane data recording and information reporting tasks.

5. Management accountants in an ERP environment need a strong understanding of the business and the business processes, significant interpersonal skills, leadership skills, decision-making skills, analytical skills, planning skills and technical skills.

6. The role of management accountants in an ERP environment is more that of a business advisor to top management than that of a traditional management accountant.”

Furthermore, Scapens and Jazayeri (2003) propose that with the ability of ERP systems, management accountants have the potential to report more forward-looking (predictive) information and to provide more direct support to business managers with the computerization of many traditional accounting tasks. For management accountants to be able to provide more predictive reports, the data available to support such analyses may need to be more varied and voluminous – that is, big data.

3. Big data and business analytics

Big data and business analytics now influence almost every aspect of major companies' decision making, strategic analysis, and forecasting (Griffin and Wright, 2015). On any given day, a business might create, purchase, extract, collect, process, and analyze millions of data elements from external and/or internal sources to maintain competitive advantage. Big data and business analytics are no longer the domain of a few initial innovators and adopters; they are ubiquitous for any business that wants to remain competitive (Davenport, 2006). Since management accountants traditionally utilize information generated from accounting records to assist business managers, it is anticipated that the availability and use of big data and analytics by businesses will impact the managerial accounting profession. However, first it is necessary to understand big data and business analytics in the internal business environment and its context.

3.1. Impact of big data on the business enterprise system

Big data could be regarded as data sets so large or unstructured that they cannot be processed and analyzed easily using most database management systems and software programs (Warren et al., 2015). Big data in its entirety can originate from traditional transaction systems as well as from new unstructured sources such as emails, audio files, internet click streams, social media, news media, sensor recordings, videos, and RFID tags (Zhang et al., 2015). Big data has become characterized by four qualities or the four V's: immense Volume, high Velocity, broad Variety, and uncertain Veracity (Laney, 2001; IBM, 2012).

Historically, business and accounting data reported transactions and other structured data, such as orders, sales, purchase orders, shipments, receivables, personnel information, time sheets, and inventory. This data is predictable, orderly, and familiar to businesses. This type of data stands in contrast to big data. Where the former data was structured in rows and columns, the latter data

[1] Executive summary of Grabski et al. (2009). *Management accounting in enterprise resource planning systems* available at http://www.sciencedirect.com/science/book/9781856176798.

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that is not structured and may seem overwhelming to work with due to the volume, variety and data type. The emergence of big data has changed the management accountant's task. A business utilizing big data would have invested significant resources to collect, process, prepare, and eventually analyze it and consequently expects deeper insights and knowledge as results.

Essential for any type of data, beyond being big or not, is that it be of high quality (Chae et al., 2014). High quality data is complete, precise, valid, accurate, relevant, consistent, and timely (Redman, 2013). Research shows that high quality data is an important business resource and asset (Chae and Olson, 2013; Redman, 1996) and has tremendous impact on an entity's performance (Forslund and Jonsson, 2007; Gorla et al., 2010). Poor quality data of any type and from any source can negatively impact the management accountant's work, rendering forecasts to be in error. Valuable analysis and forecasts are a result of the most appropriate analytical approach(es) applied to high quality data (Redman, 1998). Or, as stated by Davenport et al. (2010, pg 23): "*You can't be analytical without data, and you can't be really good at analytics without really good data*."

3.2. *Classification of business analytics*

Business analytics is 'the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their operations, and make better, fact-based decisions' (Davenport and Harris, 2007, pg 7). The recently proposed three dimensions of domain, orientation, and techniques (Holsapple et al., 2014) are useful for understanding the scope of business analytics. Domain refers to the context or environment in which the analytics are being applied. Orientation describes the outlook of the analytics – descriptive, predictive, or prescriptive. And finally, techniques refer to the analytical processes of the domain and orientation. The feasibility of the application of any one technique is decided not only by its orientation, but also by the available data.

For this discussion, the domain dimension is business management. Management accountants in this domain are expected to create systems that align with management duties and goals. The three dimensions of orientation (descriptive, predictive, prescriptive) should now be clarified to gain an understanding of their potential in the managerial accounting domain. The differing orientations of these dimensions are partly due to the availability of different types of data in conjunction with various techniques and the capabilities of enterprise systems to handle big data.

3.2.1. *Descriptive analytics*

Descriptive analytics answers the question as to what happened. It is the most common type of analytics used by businesses (IBM, 2013) and is typically characterized by descriptive statistics, Key Performance Indicators (KPIs), dashboards, or other types of visualizations (Dilla et al., 2010). Descriptive analytics summarize what has happened and which also forms the basis of many continuous monitoring alert systems, where transactions are compared to benchmarks and thresholds are established from ratio and trend analysis of historical data.

3.2.2. *Predictive analytics*

Predictive analytics is the next step taken with the knowledge acquisition from descriptive analytics (Bertsimas and Kallus, 2014) and answers the question of what could happen (IBM, 2013). It is characterized by predictive and probability models, forecasts, statistical analysis and scoring models. Predictive models use historical data accumulated over time to make calculations of probable future events. Most businesses use predominantly descriptive analytics and are just beginning to use predictive analytics (IBM, 2013).

3.2.3. *Prescriptive analytics*

Prescriptive analytics (Bertsimas and Kallus, 2014; Holsapple et al., 2014; IBM, 2013; Ayata, 2012) answers the question of what should be done given the descriptive and predictive analytics results. Prescriptive analytics may be described as an optimization approach. Prescriptive analytics go beyond descriptive and predictive by recommending one or more solutions and showing the likely outcome of each.

The techniques for predictive and prescriptive analytics may appear similar, but their orientation and ability to prescribe depends on the type and amount of data available for analysis. The more varied the data types, the more likely the solution may be prescriptive. Prescriptive techniques may utilize quantitative and qualitative data from internal and external sources. The main difference between prescriptive and predictive analytics is not one of required data types, but one of orientation – that is, is this an optimization query or a trend-based analysis? What are the questions critical to management? Analytics based on quantitative financial data alone are utilizing only a fraction of all available data, since most data is qualitative (Basu, 2013). Based on business rules, constraints, and thresholds, in a prescriptive orientation, mathematical simulation models or operational optimization models are built that identify uncertainties and offer solutions to mitigate the accompanying risks or adverse forecasts.

More importantly, prescriptive analytics can take in all types of new data to re-prescribe and then refine prescriptions based on a feedback loop. Prescriptive analytics can automatically improve prediction accuracy and best decision choice scenarios. Business analytics undertaken by management accountants where big data is available may result in a prescriptive analytics approach where a set of techniques computationally identifies several alternative actions to be taken by management, given their complex objectives and limitations, with the goal of reducing business risk. For example, external social media could be used to project the optimal marketing budget and reduce the risk of directing resources in the wrong market segment. Social media and other new or refreshed exogenous data could also be used to re-estimate and re-run models, based on changes in the business environment, economic conditions, government policies, and unexpected events.

The techniques of business analytics can be considered as either qualitative or quantitative, or as deterministic or statistical, or

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Table 1
The orientation and techniques of business analytics in the managerial accounting domain, where:

D, PD, PS = descriptive, predictive, prescriptive.

E, C = exploratory, confirmatory.

S, SS, U = structured, semi-structured, unstructured.

QN, QL = quantitative, qualitative.

D, S = deterministic, statistical.

(Adapted from Appelbaum et al., 2016).

Orientation	Techniques		Technique type			
Descriptive (D) Predictive (PD) Prescriptive (PS)			Exploratory (E) Confirmatory (C)	Structured (S) Semi-structured (SS) Unstructured (U)	Quantitative (QN) Qualitative (QL)	Deterministic (D) Statistical (S)
D	Basic accounting analysis	Ratio Analysis	C	S	QN	D
D	Unsupervised	Clustering Models	E	S	QN	S
D		Text Mining Models	E	SS, U	QL	S
D		Visualizations	E	SS, U	QL, QN	S
D		Process Mining: Process Discovery Models	E	S, SS	QN	S
PD	Supervised	Process Mining: Process Optimizations	C	S, SS	QN	S
PD		Support Vector Machines (SVM)	C	S	QN	S
PD, PS		Artificial Neural Networks (ANN)	C	S	QN	S
PD, PS		Genetic Algorithms	C	S	QN	S
PD, PS		Expert Systems/Decision Aids	C	S, SS, U	QN, QL	S
PD		Bagging and Boosting Models	C	S	QN	S
PD		C4.5 statistical Classifiers	C	S	QN	S
PD		Bayesian Theory/Bayesian Belief Networks (BBN)	C	S	QN	S
PD		Dempster-Shafer Theory Models	C	S	QN	S
PD		Probability Theory Models	C	S	QN	S
PD. PS	Regression	Log Regression	C	S	QN	S
PD, PS		Linear Regression	C	S	QN	S
PD, PS		Time Series Regression	C	S	QN	S
PD, PS		Auto Regressive Integrated Moving Average (ARIMA)	C	S	QN	S
PD, PS		Univariate and Multivariate Regression Analysis	C	S	QN	S
PD	Other statistics	Multi-criteria Decision Aid	C	S	QN	S
PD		Benford's Law	C	S	QN	S
D		Descriptive Statistics	E	S	QN	S
PD		Structural Models	C	S	QN	S
PD		Analytical Hierarchy Processes (AHP)	C	S	QN	S
D		Spearman Rank Correlation Measurements	E	S	QN	S
PD		Hypothesis Evaluations	C	S	QN	S
PD, PS		Monte Carlo Study/Simulation	C	S	QN	S

based on unstructured, semi-structured, or structured data (Table 1). The most traditionally used accounting techniques are those that are quantitative, statistical, and based on structured data. While in the past most advanced business analytics techniques came from statistical data analysis, more recently research has begun incorporating techniques that originate in machine learning, artificial intelligence (AI), deep learning, text mining, and data mining (Oracle, 2015; Schneider et al., 2015; Warren et al., 2015). Some of these techniques do not make any statistical assumptions about underlying data, and consequently generate models that are not statistical in nature. The techniques of business analytics are classified as follows in Table 1.

Visualizations, in the forms of dashboards and menus, are already quite common in business use (Dilla et al., 2010). These are

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ubiquitous with the Balanced Scorecard (BSC) (Kaplan and Norton, 1996) method and in most BI applications. Furthermore, business management in general prefers the results of analysis to be presented in an easily understood format (Kohavi et al., 2004; Davenport, 2014), so typically reports are in the format of pie charts, heat maps, geo-maps, and other charts to facilitate quick understanding (Davenport, 2014). Management generally has little desire to wade through complex analysis and reports. Even though the enterprise system is expected to facilitate complex predictions and optimizations, management accountants are expected to be able to communicate these findings clearly with easily understood visualization tools.

3.3. Enterprise systems with big data and business analytics

As discussed earlier, enterprise systems applications are software packages that are generally based on relational databases, which impact and facilitate business events such as order capturing, to accounting, and to warehouse management (Edwards, 2001). All levels and sources of information are entered in the system once, at the time of occurrence, and the enterprise-wide scope of the system allows this new data to be instantly available anywhere internally. Enterprise systems resulted from the need by business management to plan, manage, and account for resources and activities in a real-time, relevant, and insightful manner (Edwards, 2001). Previously disconnected legacy systems have been replaced by, or more commonly connected to, integrated enterprise systems in many businesses to provide improved support for more impactful insights and subsequent decisions and actions. Furthermore, the cloud, big data, business analytics, and a competitive business environment are challenging the functions and scope of enterprise systems and driving businesses to realize new "actionable insights" and better outcomes from these new capacities and capabilities (Oracle, 2015).

The integration of these various external big data streams along with the increasing volume of internal data in the enterprise environment could create challenges. It could become unmanageable unless the enterprise system is re-engineered to accommodate the new complexities presented by different data streams and advanced business analytics.

In a big data context, business analytics is faced with several challenges: complex data extracts, data fluctuations, data duplications, data security weaknesses, and the potential for multiple analytical tools and languages (such as SAS, SAP, R, SQL, Python, SPSS and Tableau,). Furthermore, traditional analytical and machine learning methodology may pose problems in a big data enterprise system context. For example, typical data analysis begins by extracting a representative sample or "training set" of the data to a separate "sandbox" environment where tools such as SAS, R, Python, or SPSS may be applied. A descriptive, predictive, or prescriptive model or solution is then developed or built and which is determined to be applicable and beneficial. However, this model and all its associated data preparation and transformation steps will need to be somehow transposed into SQL (most enterprise systems) and recreated for "mass analysis" internal to the system. This conversion can be a time consuming and error prone process.

Enterprise system providers are beginning to offer this functionality so that businesses may take full advantage of the actionable benefits that big data analytics can provide (Oracle, 2015). These systems also prepare the data for analysis. Data is cleaned, normalized, and formatted prior to extraction. These enterprise systems allow management accountants to access more information exogenous and endogenous to the firm and provide informed predictions, all while working with big data internally. R and other open source applications such as Python are accessible directly within the enterprise system (Oracle, 2015). Accountants can build automated analytical applications within the system once the tasks have been defined (Oracle, 2015). With these new capacities of modern enterprise systems, and the possibilities presented by big data and business analytics, management accountants can do more than simply monitoring and tracking key indicators of historical financial reports.

4. Integration of data analytics in ERP systems for management accounting

This section proposes the Managerial Accounting Data Analytics (MADA) framework that integrates data analytics in enterprise systems for management accounting purposes based on the balanced scorecard (BSC) concept.

4.1. Balanced scorecard theory

BSC was first developed by Kaplan and Norton (1992) to supplement traditional financial measures. The proponents argue that traditional financial measures are lag indicators that report on the outcomes from past actions and that BSC supplements this information with measures on the drivers, the lead indicators, of future financial performance. The BSC framework measures corporate performance from four perspectives: financial (how do we look to shareholders?), customer (how do customers see us?), internal business processes (what must we excel at?), and learning and growth (can we continue to improve and create value?). Specifically, Kaplan and Norton (2001) interpret BSC as a framework for organizing strategic objectives and illustrate four perspectives as follows: "Financial—the strategy for growth, profitability, and risk viewed from the perspective of the shareholder; Customer—the strategy for creating value and differentiation from the perspective of the customer; Internal Business Processes—the strategic priorities for various business processes that create customer and shareholder satisfaction; and Learning and Growth—the priorities to create a climate that supports organizational change, innovation, and growth" (Kaplan and Norton, 2001, p.90). Empirical studies have found a positive relationship between implementation of BSC and long-term financial performance (Davis and Albright, 2004, p.149; Yancy, 2014, p.67–68).

BSC provides an opportunity to integrate data analytics methods into ERP systems for the purpose of measuring corporate performance. Specifically, various types of data analytics can be supported by data warehouses that combine external big data with the enterprise data that includes such large volume data streams such as RFID feeds. Management accountants then can benefit from

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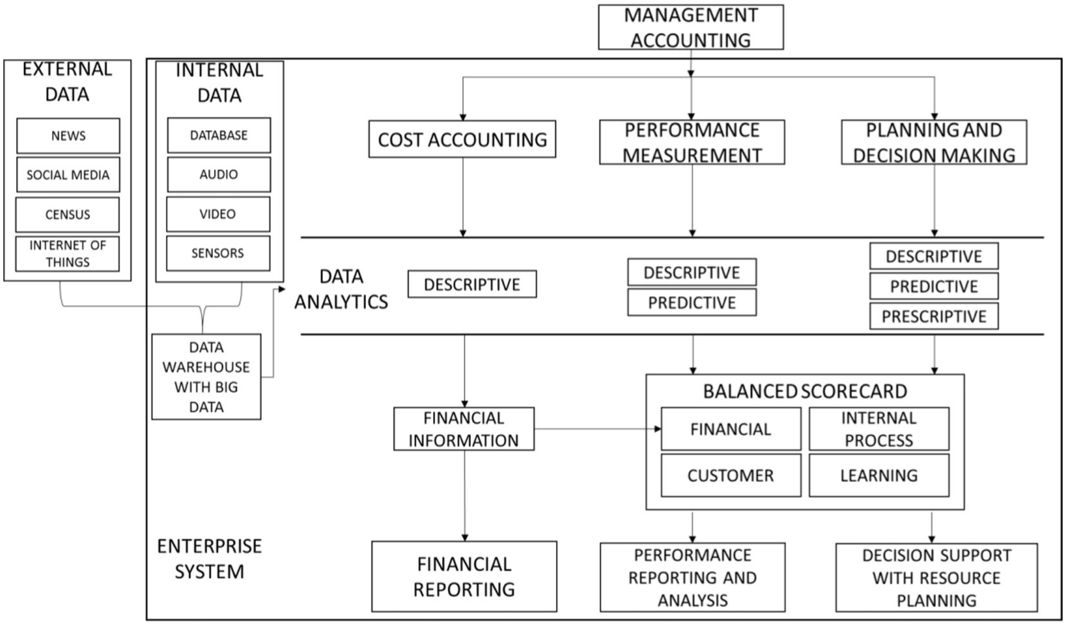

Fig. 1. The Managerial Accounting Data Analytics (MADA) framework, motivated from Cokins, 2013, pg. 27.

data analytics by measuring the corporate performance or providing management with other useful information.

4.2. Managerial Accounting Data Analytics (MADA) framework

Fig. 1 exhibits the framework for implementing data analytics in managerial accounting based on balanced scorecard theory. According to Cokins (2013), management accounting can be classified into cost accounting, cost reporting and analysis, and decision support with cost planning. Thus, in this framework, management accounting is classified into cost accounting, performance measurement, and planning and decision making. In cost accounting, management accountants focus on using internal data to generate financial reports of the organization. Performance measurement focuses on the insights, inferences, and analysis of the processes or events that have taken place to measure corporate performance. Data used in performance measurement includes mostly internal data. However, external data, such as industry benchmark information, can be used for performance evaluation. Planning and decision making involves using the result of both cost accounting and performance measurement to provide accurate, timely, and relevant information in combination with other external information to assist management. External data are heavily used in combination with internal data to provide relevant information for decision making.

Data analytics can be implemented to assist management accountants in all three aspects of management accounting. For financial reporting purposes, the most applicable type of data analytics is descriptive analytics which helps to summarize and describe the financial situation of a business. In the field of performance measurement, management accountants can utilize predictive analytics, which can employ machine learning algorithms with inputs from descriptive analytics, to provide prediction of future organization performance. With the results from both cost accounting and performance measurement, prescriptive analytics are incorporated into planning and decision making to provide information regarding the optimized solution for decision makers. Serving as the data source of data analytics, big data is comprised of both internal and external data. Internal data represents data gathered inside the entity (i.e., the company's database). This type of data is generally structured and familiar to management accountants. On the other hand, external data represents data collected from sources outside the company, such as news, social media, or Internet of Things (IoT). Usually, external data are unstructured data that can only provide information after being processed by analytics tools. Data types listed in both internal and external boxes represent only examples, not the inclusive list of the entire internal and external data types.

In this framework, the BSC methodology is implemented under performance measurement and planning and decision making aspects of management accounting for the purpose of incorporating data analytics in the related process. For each perspective of the BSC (financial, customer, internal process, and learning and growth), different types of data analytics are applied to provide a comprehensive measurement of each perspective.

4.2.1. Financial perspective

The ultimate goal of profit-seeking corporations is to increase shareholder value. Kaplan and Norton (2001) point out that companies increase economic value through revenue growth and productivity. Revenue growth generally includes two components: new initiatives (new markets, new products, and new customers); and increase sales of products or services on existing customers by deepening the relationship with them. The financial perspective of BSC measures the financial situation of a company. Cash flow,

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sales grow rate, market shares, or return on equity (ROE) are examples of measures that reflect the financial perspective of the company (Kaplan and Norton, 1992).

Descriptive data analytics provides management accountants the overall view of the current financial performance of the company. For example, ratio analysis that compares ROE and return on investment (ROI) with historical data gives management accountants the information on the growth of the company. On the other hand, comparing such ratios with industry benchmark data describes whether the company maintains competitive advantage. Interactive visualization tools allow managerial accountants to present financial information much more effectively.

Predictive analytics use accumulated historical data to estimate possible future events. In the financial perspective, predictive analytics are commonly applied for predicting future financial performance. The algorithms for prediction can be classified as either supervised or unsupervised. Examples of supervised algorithms include support vector machines (SVM), artificial neural networks (ANN), genetic algorithms, bagging and boosting models, C4.5 statistical classifiers and Bayesian Belief Networks (BBN).[2] Such supervised algorithms develop the model based on datasets with output. In contrast, unsupervised algorithms do not require datasets with output. Specifically, they classify or cluster the data into different classes, and thus reveal the potential relationships between the data. In general, unsupervised learning is not appropriate for financial predictive analysis because most of the predictions are based on historical value. Other statistics, such as structural models or analytical hierarchy processes (AHP) (Hogan, 2000), are also available as business analytics techniques for management accountants to provide estimation of future financial performance of a company.

With the results of descriptive and predictive analytics, management accountants can utilize prescriptive business analytics to recommend the optimal solutions and their likely outcomes. While prescriptive analytics share the similar techniques and algorithms as predictive analytics, prescriptive analytics essentially compare the result of such algorithms and aim to find the optimized solution. For example, to reduce cost and at the same time maintain the product quality in a reasonable area for generating revenue, manufacturing companies face the challenge of selecting the raw material vendors with a reasonable price and appropriate quality. Incorporating the results generated from analyzing internal data together with data from vendors using SVM, ANN, or C4.5 classifiers, prescriptive analytics help management accountants to choose the vendor that will help the company to reduce cost and increase revenue. For example, data from news articles and social media can also be used in the selection of a vendor. Besides cost reduction, with prescriptive analytics management accountants are also able to provide valuable information on other issues in the financial perspective, such as exploring new markets, new products, and new customers.

4.2.2. Customer perspective

The customer perspective of BSC answers the question of “How do customers see us?” In the original BSC framework, Kaplan and Norton (1992) describe the customers' concerns from four categories: time, quality, performance and service, and cost. Time refers to the time required for the company to meet customers' needs. Quality measures the customers' perceived defect level of products or service. The combination of performance and service measures how the company's products or services contribute to creating value for the customers. Finally, cost measures the price to the company of reaching certain level of previous measures. The customer perspective stands as the primary goal of most non-for-profit organizations and government departments. Non-profit and government organizations generally have financial donors or other funding. The primary goal for them is to satisfy their customers and achieve progress in designated missions. It is the mission, rather than the financial/shareholder objectives, that drives the organization's strategy (Kaplan and Norton, 2001).

Descriptive business analytics provide a comprehensive view of the current situation of customer measures from the BSC. For instance, a ratio analysis that integrates product defect rate, goods returned rate, and warranty claim rate can be used to measure the customer's satisfaction level about the latest product of a manufacturing company. Data analytics also enables management accountants to incorporate customer ratings from websites and reviews or complaints from the product forum. Techniques such as text mining allow users to extract opinions from online text content (e.g., twitter feeds) and generate useful information. While most business analytics require structured data sources, text mining and visualization allow management accountants to extract decision-related information from unstructured data such as social media data.

With predictive business analytics, management accountants are able to provide reasonable estimates of each of the four aspects of the customer's perspective of a company's products or services. Specifically, time, quality, performance and service, and cost can be estimated using internal historical data or external website or social media data through predictive analytics algorithms (e.g., SVM, ANN, genetic algorithms, BBN, log regression, time series regression, structural models, analytical hierarchy processes and Monte Carlo study/simulation). For example, management accountants could use a business analytic tool that trains the ANN model with internal data to predict the time period between the point that the company receives the customer's order and the point that the product or service is delivered. This would help coordinate the cooperation among different company departments and to assist managers adjust company strategies accordingly. Tuarob and Tucker (2013) utilize text mining techniques to analyze social media data (e.g. twitter feeds) to predict information related to product features, product competition and market adoption.

Prescriptive business analytics provides the optimal solution between corporate cost and the first three factors – time, quality, and performance and service – of the customer perspective. The corporation usually emphasizes ongoing improvement with customer satisfaction, which entails faster response to customers' requests, higher product quality, and better performance and service, all while facing budget constraints. Management's strategy of capital and labor input to improve customer satisfaction and loyalty can be

[2] Illustrative references for application of techniques: SVM (Hua et al., 2007); ANN (Zhang et al., 1999); genetic algorithm (Duman and Ozcelik, 2011); C4.5 (Foster and Stine, 2004); BBN (Kirkos et al., 2007).

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a set of complex decisions. By incorporating various types of descriptive and predictive analytics, management accountants can provide decision-related information to management to answer questions like “Does our measurement method of customer satisfaction reveal the truth?”; “Which customer performance enhancement will lead to the highest return in revenue?”; and “Who will be our potential customers?”. The availability of efficient analysis techniques (e.g. text mining) and real time social media data (e.g. twitter data) enables management accountants to perform analysis on-the-fly and to assist management with forming appropriate customer perspective related strategy. As Kaplan (2009) points out, to differentiate from their competitors, companies need to express objectives for the value proposition they offered to the customers. The value proposition includes price, quality, availability, ease and speed of purchase, functionality, relationship, and service. Rather than considering each component individually, management accountants can employ prescriptive analytics techniques, such as artificial neural networks and linear regression, to analyze how such components affect the customer measurement simultaneously.

4.2.3. Internal process perspective

The internal process perspective of BSC measures the business process by factors that affect cycle time, quality, employee skills, and productivity (Kaplan and Norton, 1992). To apply the measurement effectively, management accountants must decompose the overall cycle time, quality, employee skills, and productivity from department and workstation levels to local levels, which provides lower level employees a clear target for actions, decisions, and improvements. Information systems provide an important communicating role between management accountants and the corporate workforce. A well functioned responsive information system provides management accountants valuable “in time information” which can be presented to the managers for decision making.

The current condition of internal processes can be summarized with descriptive analytics. The clustering technique in descriptive analytics could be utilized to identify highly efficient employees by combining measurement of employee skills, productivities, and other characteristics of the employees. On the other hand, text mining can be used to identify employees that go astray against the company. For example, Holton (2009) uses text mining to identify disgruntled employees from email text. In addition to traditional measurement of the overall cycle time, quality, employee skills, and productivity proposed by Kaplan and Norton (1992), process mining provides management accountants an overview and understanding of the flows of process within the entity. For example, using event logs provided by ERP systems, process mining can be used to extract workflow processes (Van der Aalst et al., 2004), which can be integrated with visualization techniques to provide a comprehensive illustration of the work processes that are taking place within the organization.

Predictive analytics play an important role in measuring and managing internal processes. Based on historical data, management accountants can utilize predictive analytics tools to build models to predict future values of the related areas of the four main measurements and thus providing the benchmark for monitoring. If management accountants identify that the actual performance is significantly worse than the predicted result, then they would need to decide whether this deficiency is either caused by poor performance (e.g. deficiency in internal control) or by an inappropriate model selection. The prediction model sometimes deteriorates if not properly maintained. For instance, as the business operation becomes more complex, factors that have significant impact on internal process may not be included in the original prediction model. Thus, predictive analytics tools should be continuously monitored and modified to ensure the usefulness of prediction results. An example of implementing predictive analytics in the internal process perspective is to apply process mining to optimize enterprise transactions. Management accountants can use process mining to understand the flows of transactions and predict process efficiency in various situations. Based on such information, management can modify routine processes to achieve organizational efficiency. In addition, making predictions of possible future events helps management accountants to reduce the possibility of contingencies. Specifically, management accountants can provide the predictive report to all levels of employees of the company so that each individual employee will have a broader understanding of the current and expected internal process of the company.

Prescriptive analytics aim to provide optimization of internal processes based on the analysis results from descriptive and predictive analytics. For example, for a company that emphasizes productivity, management accountants can use prescriptive analytics to find the optimal solution among employee skills, transaction processing complexity, and production quality. Traditionally, complicated decisions are made based on experience and simple descriptive statistics. With prescriptive analytics tools, management accountants can provide decision makers more specific decision related information that are extracted through statistics and models. For the internal process perspective in BSC, techniques such as goal programming (Lin, 1979) or Pareto optimization (Cushing, 1977) can be used in prescriptive analytics to transform the complicate decision making process to optimization models that include information provided by descriptive and predictive algorithms from other different perspectives.

4.2.4. Learning and growth perspective

To answer the question of “Can we continue to improve and create value”, the learning and growth perspective measures the company's ability to innovate, improve, and learn that ties directly to the company's value (Kaplan and Norton, 1992). Specifically, it measures the company's ability to launch new products, create more value for customers, and continually improve operating efficiencies. Such measurements align human resources and information technology with the strategic requirements from the company's critical internal business processes, differentiated value propositions, and customer relationships (Kaplan and Norton, 2001). Examples of learning and growth perspective measurements include, for example, market share of new products and employees training expenses.

Learning and innovation are critical in almost every company. The conditions of learning and innovation can be interpreted both as developing new products or services and adopting new technologies. Descriptive analytics can be used as tools that demonstrate

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how much emphasis companies put on innovation and how the employees are learning to work with new challenges. For instance, the ratio of research and development expense to the total expense can be used to describe how much the company is focusing on developing new products or services. On the other hand, visualization and text mining methods can be used to evaluate the progress of learning. Chand et al. (2005) indicates in a case study that the implementation of ERP systems requires 4–5 weeks of training with the users. Thus, descriptive business analytics tools that exhibit the progress of learning of new systems enable the management accountants to monitor the progress of adopting new technologies.

Predictive analytics is an essential part of measuring the learning and growth perspective. As both innovation and learning focus on the future benefits, it is imperative to know the possible outcome of current investments in innovation and employee training. Predictive algorithms such as SVM, ANN, time series regression and probability theory models can all be trained to predict results. In addition, expert systems and decision aids help management accountants to understand specific situations and to provide stimulated estimation accordingly.

Prescriptive business analytic tools help management accountants to integrate descriptive and predictive analytics in the learning and growth perspective and find the optimized strategy or direction. Machine learning algorithms included in prescriptive analytics techniques are used to train models for the purpose of taking an innovation perspective into consideration with other factors such as customer satisfaction and revenue of sales, and identifying the optimized strategy to improve the design of a new version of smart phones. Management accountants also can use prescriptive analytics to decide which new technology to incorporate to increase productivity and work efficiency. Choices of ERP vendors such as Oracle and SAP can be decided through analyzing news and customer reviews from websites or social media.

Table 2: Implementation of Data Analytics Techniques in BSC Perspectives provides a summary of applications of data analytics techniques in managerial accounting from the BSC perspective. Three types of data analytics techniques, descriptive, predictive, and

Table 2
Implementation of data analytics techniques in BSC perspectives.

	Financial	Customer	Internal process	Learning and growth
Descriptive				
Clustering Models		✓	✓	✓
Descriptive Statistics	✓	✓	✓	✓
Process Mining: Process Discovery Models			✓	
Ratio Analysis	✓	✓		✓
Spearman Rank Correlation Measurement	✓	✓	✓	✓
Text Mining Models		✓	✓	✓
Visualization	✓	✓	✓	✓
Predictive				
Analytical Hierarchy Processes (AHP)		✓		
Artificial Neural Networks (ANN)	✓	✓	✓	✓
Auto Regressive Integrated moving Average (ARIMA)	✓	✓	✓	✓
Bagging and Boosting models	✓	✓	✓	✓
Bayesian Theory/Bayesian Belief Networks (BBN)	✓	✓	✓	✓
Benford's Law	✓	✓	✓	✓
C4.5 Statistical Classifiers	✓	✓	✓	✓
Dempster-Shafer Theory Models	✓	✓	✓	✓
Expert Systems/Decision Aids			✓	✓
Genetic Algorithms	✓	✓	✓	✓
Hypothesis Evaluations	✓	✓	✓	✓
Linear Regression	✓	✓	✓	✓
Log Regression	✓	✓	✓	✓
Monte Carlo Study/Simulation	✓	✓	✓	✓
Multi-criteria Decision Aid	✓	✓	✓	✓
Probability Theory Models	✓	✓	✓	✓
Process Mining: Process Optimizations			✓	
Structural Models	✓	✓	✓	✓
Support Vector Machines (SVM)	✓	✓	✓	✓
Time Series Regression	✓	✓	✓	✓
Univariate and Multivariate Regression Analysis	✓	✓	✓	✓
Prescriptive				
Artificial Neural Networks (ANN)	✓	✓	✓	✓
Auto Regressive Integrated Moving Average (ARIMA)	✓	✓	✓	✓
Expert Systems/Decision Aids	✓	✓	✓	✓
Genetic Algorithms	✓	✓	✓	✓
Linear Regression	✓	✓	✓	✓
Log Regression	✓	✓	✓	✓
Monte Carlo Study/Simulation	✓	✓	✓	✓
Time Series Regression	✓	✓	✓	✓
Univariate and Multivariate Regression Analysis	✓	✓	✓	✓

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prescriptive, are implemented into the four perspectives of BSC framework. The check mark indicates whether the technique is considered applicable for the specific BSC perspective. For example, the "ratio analysis" technique under the descriptive category is appropriate for applications in financial, customer, and learning and growth perspectives. While the selection of the appropriate techniques is an important factor for successful implementation of data analytics in managerial accounting, other factors, such as consideration of business intelligence context, data integrity, and privacy, are also critical determinants of effective applications.

5. Critical success factors for MADA implementation

5.1. Business intelligence (BI) context

Management accounting tasks as described in the MADA framework could be regarded as an essential component of Business Intelligence (BI). A successful application of MADA could largely rely on its seamless integration within the overall BI system and its ability to contribute meaningful insights. BI has been largely described as "as set of techniques and tools for the acquisition and transformation of raw data into meaningful and useful information for business analysis purposes" (Rud, 2009). Business Intelligence as such may be considered as the management support system for gathering, storing, accessing, and analyzing data for decision making (Chaudhuri et al., 2011). It would be difficult to find a business with extensive data sources and enterprise system capacities that is not leveraging these assets to realize a competitive advantage (Davenport, 2006).

Research results indicate that investment by businesses in BI infrastructure and functionality is associated with increased competitive advantage (Peters et al., 2016). Davenport (2006) discusses how BI forces businesses to evolve to fact-based decision making from that of intuitive decision making. Watson and Wixom (2007) relate the benefits of BI systems to date, which include time savings, improved information and business processes, and improved strategic decisions. Management accounting tasks in the modern business enterprise fall neatly as an essential component of BI functionality. Since BI software is a "collection of decision support technologies for the enterprise aimed at enabling…executives, managers, and analysts to make better and faster decisions" (Chaudhuri et al., 2011, p. 88), the management accountant's task of providing analyses and forecasts to management requires usage of BI components. Hence, the management accountant would also be expected to leverage big data and the capacity of BI systems to support the use of advanced analytics. Successful implementation of the MADA framework depends on its success as a component of a holistic enterprise-wide BI system (Fig. 2).

The past few decades have seen explosive growth in the use of BI by enterprises, particularly regarding the value and success factors involved with such BI integration (Fink et al., 2017). Several papers (Yeoh and Popovič, 2016; Yeoh and Koronis, 2010) formalize critical success factors (CSFs) for the implementation of BI (DeLone and McLean 1992, 2003). DeLone and McLean (1992, 2003) propose that the measurement of any IS success be based on the research objectives and IS context. As such, Yeoh and Koronis (2010) apply the domain of BI to the IS success and BI literature to develop a BI Critical Success Factors (CSF) framework (Table 3).

The two most dominant CSFs for management accountants would be: one, a business driven, scalable, and flexible technical framework; and two, sustainable data quality and integrity. Both CSFs are the focus of this paper. However, the success of any

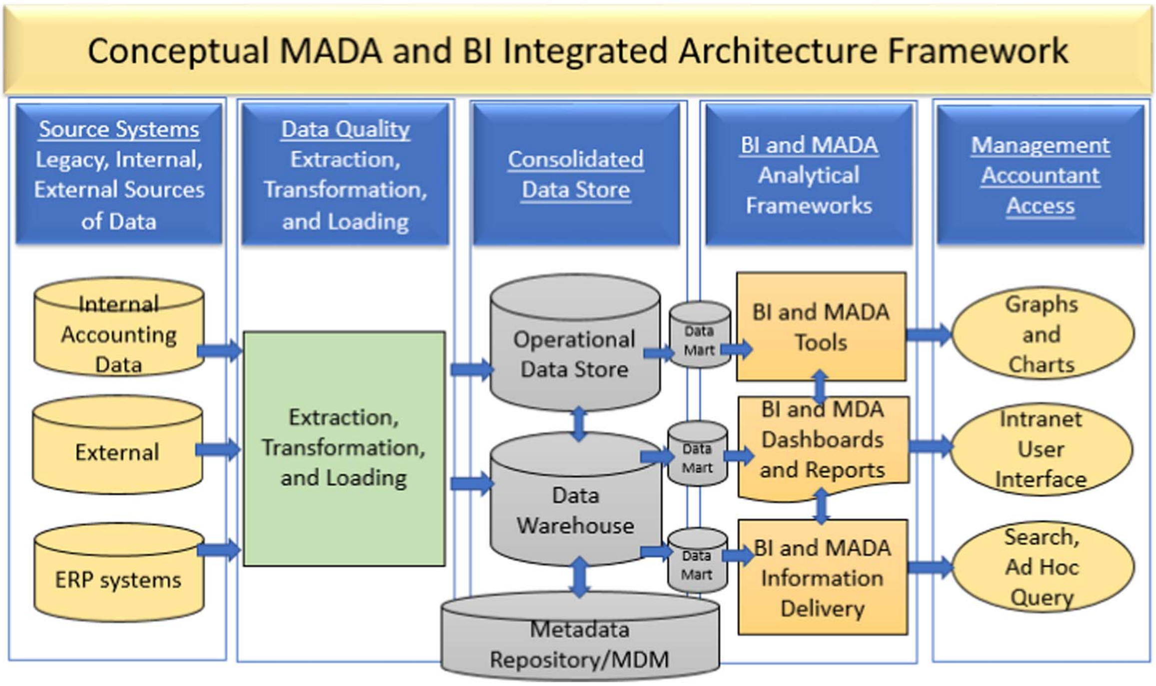

Fig. 2. Ideal enterprise system structure that supports management accountants in a BI system motivated from Chaudhuri et al., 2011, p. 90.

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Table 3
Three main dimensions of CSFs for BI (Yeoh and Koronis, 2010; Yeoh and Popovič, 2016).

Dimension	Critical success factors (CSF)
Organization	Committed management support and sponsorship
	A clear vision and well-established business case
Process	Business-Centric championship and balanced project team composition
	Business-driven and iterative development approach
	User-oriented change management
Technology	Business-driven, scalable and flexible technical framework
	Sustainable data quality and integrity

projects undertaken by the management accountant could be impacted by the other CSFs as well. The CSF framework of Table 3 is expanded here to describe the CSFs for Managerial Accounting in the BI domain (Table 4).

5.2. CSF: business-driven, scalable, and flexible technical framework

Data delivers limited value to management accountants unless they can access it and use it to provide analysis and projections for management (Watson and Wixom, 2007). Data is often regarded as a highly valuable asset of an organization (Chugh and Grandhi, 2013). This value can be realized as a competitive advantage for the organization if the appropriate BI tools, expanded data sources and appropriate systems are in place (Chugh and Grandhi, 2013). Major software vendors such as SAP, Oracle, IBM, and Microsoft have developed ETL and BI tools and applications, all which should contain the functions listed in Table 5 to assist the management accountant:

The steps of Data Consolidation and Data Quality are not specified in the MADA framework as conceptualized in Fig. 1 but are usually part of most corporate enterprise systems. Like other analytical functions in the enterprise, MADA relies on the system processes and functions to provide quality data. Conceptually, MADA could be integrated in an enterprise BI system similar to that portrayed in Fig. 2.

The MADA framework is envisioned to be integrated at the same level in the system as the other BI applications (Fig. 2). The source systems are where all the business events and transactions take place, either inside or outside to the system. In MADA (Fig. 1), this is depicted in the upper left hand quadrant as external and internal big data. But this data is varied and messy, so it needs to be extracted, transformed, and loaded (ETL) before it can be stored or analyzed. This ETL process creates consolidation, consistency, convenience, and referential integrity of the data. This allows the third process of data storage in the enterprise system to occur, where data can be integrated with meta tags. Data Marts serve to facilitate the data for a particular MADA or BI analysis. The Data Marts contain a semantic layer (fourth layer) which allows for MADA and business analytics to occur. The last layer allows for multiple ways for management accountants to consume the information provided by MADA at the previous layer.

5.3. CSF: sustainable data quality and integrity and big data

Data quality and integrity are recognized as essential components of a business analytics system (Cosic et al., 2012; Chae and Olson, 2013). Data quality is also an essential element of any enterprise system (Xu et al., 2002; Chae and Olson, 2013; Kwon et al., 2014) and its architecture. However, as data volumes increase, the more the complexity of data management increases. As the type of data format varieties increase, so does the flexibility demands of managing it (Kwon et al., 2014). The greater the data velocity speed, the more capacity is required of the system. The more varied the data veracity becomes, the greater the demands for system assurance and controls. With the Four V's of big data, the risk of poor quality information to businesses increases (Watts et al., 2009; Wu et al., 2014).

The impact of poor quality data has been identified in numerous academic studies (Wu et al., 2014; Yeoh and Koronis, 2010; Watson and Wixom, 2007) and these concerns are magnified with big data. Poor quality data that was not identified as such, but was

Table 4
The CSFs for managerial accounting in the BI domain.
(Adapted from Yeoh and Popovič, 2016).

Dimension	Critical success factors (CSF)
Organization	Committed management support and sponsorship for more advanced analytics and the necessary infrastructure to support these initiatives
	A clear vision and well-established understanding of the business case and domain of the business and industry.
Process	Business-Centric championship and balanced project team composition with support from IT staff
	Business-driven and iterative development approach with frequent feedback of incremental results
	User-oriented change management where scope and functions of management accounting processes evolve to the new enterprise paradigm
Technology	Business-driven, scalable, and flexible technical framework that is capable of handling big data and many varied analytics and data mining techniques
	Sustainable data quality and integrity of big data that is enforced with a master data approach and with which the management accountant is familiar

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Table 5
BI functionalities to support the management accountant.
(Adapted from Chugh and Grandhi, 2013, page 4).

Categories	Function
Data consolidation	➢ Integration of internal and external data ➢ Simplified extraction, transformation, and loading of data ➢ Deletion of unwanted and unrelated data
Data quality	➢ Sanitize and prepare data to improve overall accuracy
Reporting	➢ User defined and standard reports generated at any level ➢ Personalized reports for any level of management
Forecasting and modelling	➢ Supports analytics used in predictive and prescriptive analytics which use historical and real-time data, qualitative or quantitative
Tracking of real-time data	➢ Monitor current progress with defined project objectives/KPIs ➢ Prioritize scarce system resources
Data visualization	➢ Interactive reports and graphics, possibly with real time updates ➢ Scorecards and dashboards
Data analysis	➢ What-if analysis ➢ Sensitivity/optimization analysis ➢ Goal seeking/goal supporting analysis ➢ Descriptive analysis
Mobility	➢ Portability to multiple devices and formats
Rapid insight	➢ Drill down features that enable many layers of analysis ➢ Dashboards that are interactive and that can monitor trends and outcomes
Report delivery & Share-ability	➢ Deliver reports in common formats such as Microsoft Office ➢ Email reports in different formats
Ready to use applications	➢ Pre-built meta-data with mappings defined considering performance & security needs ➢ Pre-built reports, dashboards to support management
Language support	➢ Multiple language support

used instead to generate market predictions, forecasts, and other analyses, could have substantial negative economic impact on a business (Haug and Stentoft Arlbjørn, 2011). These negative effects on profits may be felt in the marketplace, in the operations, in the business performance, and in the business culture.

Available software applications analyze the datasets for internal and external validity, accuracy, timeliness, completeness, and consistency. The most basic challenge of big data applications with analytics is the exploration of the big data and the subsequent extraction of useful information for the analytical application. Typically, big data is heterogeneous and of varied formats and requires preparation before analysis. Also, the data extraction process needs to very efficient and as close to real time or continuous as possible because storage of big data could be infeasible (Wu et al., 2014).

Two secondary concerns include 1) data sharing and privacy/security; and 2) domain and application specific knowledge. The first is more challenging then the second, as management accountants usually possess a thorough understanding of the enterprise's business orientations and culture. The concerns of data privacy and security that result from the sharing and integration of many different data types from varying origins is the greater challenge. Data privacy may be an issue with any reports involving employee and customer information. Information acquisition, sharing, and integration are the goals when the management accountant is combining different big data sources. If some of this data involves personal or sensitive information, disclosure of a person's actions/locations over time could be compromised even with data security and privacy measures. Two typical approaches for privacy maintenance are data access restriction and data anonymization (Cormode and Srivastava, 2009), controls which should be enforced system-wide. Data security is an enterprise wide concern, with controls and procedures established by the IT department and the management accountant needs to ensure that the controls and procedures are followed.

6. Conclusion and future work

The role of managerial accounting is evolving from the traditional emphasis on financially oriented decision analysis and budgetary control to a more strategic approach that emphasizes the identification, measurement, and management of the key financial and operational drivers of shareholder value (Ittner and Larcker, 2001). With the developments in enterprise systems that provide management accountants access to more data and data types, larger data storage, and better computational power, enterprise systems that incorporate this additional data now can utilize data analytics techniques to answer the questions including: what has happened (descriptive analytics), what will happen (predictive analytics), and what is an optimized solution (prescriptive analytics). However, research shows that the nature and scope of managerial accounting has not developed to take advantage of such techniques (Sangster et al., 2009). This situation is not unique to managerial accounting – according to Gartner (2016), the number one issue for businesses that have invested in big data is determining exactly how to get value or information from this data.

This paper first examines the impact of enterprise systems, big data, and data analytics on managerial accounting. Second, the managerial accounting data analytics (MADA) framework is proposed for management accountants to utilize data analytics in the

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environment of enterprise systems. The MADA framework implements data analytics techniques based on the balanced scorecard (BSC) theory. Descriptive, predictive, and prescriptive analytics are applied to measure corporate performance from four aspects: financial, customer, internal process, and learning and growth. Data analytics are also a key component in the feedback and learning process when company designs a strategic management system based on BSC theory. Finally, attributes for successful implementation of the MADA framework are discussed. Data analytics and managerial accounting tasks as described in the framework could be regarded as essential components of Business Intelligence (BI). The analytical technique(s) selected by the accountant should not only be appropriate, but the data or big data selected for analysis should possess high quality attributes such as relevance, timeliness, and accuracy, to ensure the usefulness of the information generated through the analytics.

One major challenge facing the MADA framework is how it could be tested. Ideally, with MADA serving as methodological guideline, the framework could be applied as a case study within a company's actual enterprise system. With such a case study, researchers could then determine whether the proposed benefits can be achieved and how these should be measured. Furthermore, a greater understanding of the enterprise and corporate system changes that would be required for a successful MADA implementation can be acquired. However, gaining access to such a case study situation usually presents major challenges for researchers – typically, companies are reluctant to allow outsiders access to internal enterprise systems and data.

Due in part to the utilization of enterprise systems by business, the methodology of continuous monitoring (Alles et al., 2006; Vasarhelyi et al., 2004), facilitated by the progressive decrease of computation and storage costs, is emerging. In this progressive scenario, the fact that the incremental cost of repeating analytic procedures is low allows a more frequent (not exactly continuous) application of analytic procedures and consequently better managed/monitored processes. Research is needed to develop a framework for the timing, frequency, management, and measurement needed for this manner of analytic application.

Another challenge facing the MADA framework is obtaining greater clarification and detailed analysis of when, where, and under what circumstances certain analytics should be undertaken. That is, given a broad understanding of the techniques categorized in Table 2, the context of a certain industry, the scope of the managerial accounting task required, and the type of available data, what would be the best technique(s) from the framework to apply and how would these approaches measure against current managerial accounting practices? Such a comparison should be examined not only in the context of prediction accuracy but also of feasibility. For example, perhaps theoretically an artificial intelligence application might provide the greatest prediction accuracy for a cost analysis of delivery routes for a firm; but practically, a predictive regression model may be more feasible even though the accuracy level might be somewhat lower. Fortunately, comparing the performance and feasibility of such individual MADA applications to that of current managerial accounting practices is a less prohibitive task for researchers than that of a case study.

A third challenge facing MADA integration would be that of the analytical skills and knowledge acquisition required by management accountants to successfully apply it. Many currently practicing management accountants may not possess extensive knowledge of analytics and big data. Would training or course work be provided by commercial ERP providers if MADA is offered commercially? Or, would companies support or encourage training in analytics by funding their accountants to take online/on-campus courses offered by universities? And for future accountants, would university programs offer more possibilities for analytics and big data courses? These are challenges facing the field of accounting and auditing in general, as businesses migrate towards the use of more technology, analytics, and big data.

This paper presents the MADA framework, which implements data analytics techniques based on BSC theory in an enterprise system environment. Currently, the scope and processes for managerial accounting tasks are challenged by the enormous potential that these expanded enterprise systems, big data, and analytics present. Integrating MADA in such an environment could provide huge possibilities for management accountants to overcome these complexities and subsequently evolve to a new expanded level. This paper presents the theoretical framework that discusses the important elements and proposed design of MADA. Ideally, the MADA framework and its proposals should be researched empirically before it would be applied as a case study in the managerial accounting domain.

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