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ORIGINAL ARTICLE

Business analytics and firm performance: role of structured financial statement data

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ABSTRACT
Although business analytics has received its fair share of attention, extant research has paid insufficient attention to establishing and communicating a general understanding of the relationship between analytics and performance. In order to reduce the identified knowledge gap, this study proposes a comprehensive, theoretical framework to explain the key types of business analytics, their relationships, and how business analytics use impacts operational and financial performance. This study proposes a combination of critical systems, "holistic thinking/big picture/decision-making," approaches to moderate key relationships to impact performance. Additionally, this study presents a case illustration of a real-world contract manufacturer, employing the proposed framework, to demonstrate the innovative use of integrated business analytics to turnaround an organization, and position it to survive, thrive, innovate, and grow. Findings indicate that firms, "overwhelmed by" and "struggling to use" data to improve business results, have a viable cost-effective framework to advance business analytics capability, in their organizations.

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Big data; business analytics; holistic thinking; financial performance; operational performance

1. Introduction

In every industry, all over the world, leaders face a complex array of financial and administrative challenges, they never dreamed of, or prepared for. Their organizations can't survive and thrive, over time, without becoming fiscally responsible, accountable, and transparent. To do so, leaders of these organizations need to manage massive amounts of data, and find better ways to obtain value from that data, in order to successfully compete in the marketplace. Leaders need to collect and analyze data, and transform data into information, information into knowledge, knowledge into insight, and insight into action that leads to improved performance. Questions on how to best achieve this, continue to persist, and effective answers remain elusive to many.

Managers and leaders, of increasingly complex global enterprises, are searching for ways to implement cost-effective business analytics solutions to help them survive, and thrive, in this turbulent business world. Various tools are available, but other barriers or challenges exist that prevent most organizations from adopting business analytics software and hardware technology. Some of these hurdles include issues associated with talent, culture, ROI, data, technology adoption and use, as well as security and privacy issues. One problem is that firms cannot wait, forever, until a significant number of employees are sufficiently trained in business analytics capability, in order to start to apply all of the right technology to help their firms compete.

Recent research has suggested that "organizations are overwhelmed by data, and struggle to understand how to use it to achieve business results" (Evans, 2012). A survey, conducted jointly by *MIT Sloan Management Review*, and the IBM Institute for Business Value, reported that six out of 10 respondents "agreed that their organization has more data than it can use effectively" (LaValle, Lesser, Schockley, Hopkins, & Kruschwitz, 2010). The MIT-IBM study incorporated a large scale study. It included more than 3,000 business executives, managers, and analysts from organizations, in 30 industries, located in 108 countries around the world, thereby giving an indication of the pervasiveness of "data overload." Furthermore, LaValle et al. (2010) report that almost four of 10 respondents indicate that "lack of understanding of how to use analytics to improve the business" is the leading obstacle to widespread analytics adoption.

Successful analytics depend on the quality and quantity of data, and require that data be effectively and efficiently managed. Data can be categorized as structured (e.g. CRM, ERP, Legacy, and 3rd Party, etc.) and unstructured (e.g. Weblogs, Social Media, Mobile Data, Images & Videos, and Survey & other, etc.) (Verhoef, 2016). These data types may fall under one of the seven, "V" dimensions (Vuorela, 2018), such as: **1) Volume**-scale of data (Berman, 2013; Sahay, 2016; Sakr &

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Elgammal, 2016); **2) Velocity**- analysis of streaming data (Berman, 2013; Demirkan et al., 2015; Sahay, 2016; Sakr & Elgammal, 2016); **3) Variety/variability**- different forms of data (Berman, 2013; Demirkan et al., 2015; Sahay, 2016; Sakr & Elgammal, 2016); **4) Veracity**- uncertainty of data (Demirkan et al., 2015; Sahay, 2016); **5) Validity**- data reflects primary sources of collection (Sahay, 2016); **6) Volatility**- data is available over time (Sahay, 2016); and **7) Value**- relative importance of data to the decision making process (Demirkan et al., 2015), the use worthiness of data to help address problems (Sahay, 2016), and the potential of data to be utilized for development (United Nations Global Pulse, 2013).

Recent studies identify challenges posed by data, and indicate that "contemporary forms of data are tending to get larger and larger" (Kraak, 2017). LaValle et al. (2010) report that there is "too much data to efficiently process, or easily handle" (e.g. volume), that the "speed at which the data flows in and out makes it difficult to effectively analyze" (e.g. velocity), and that the "array, kind, and type of data sources are too abundant to integrate and assimilate" (e.g. variety). Moreover, these studies point to the "inability to comprehend how to use analytics to improve business outcomes," as a key reason for low rates of analytics adoption. Thus, for this reason, and others to which the author has alluded, lead to the research problems identified in the following section.

1.1. Research problems

The obstacles and challenges, cited by organizations in previous research studies, is the motivation for formulating this study's research problems. These problems state, that "organizations are overwhelmed by data," "struggle to understand how to use data to achieve business results," and "most organizations simply don't understand how to use analytics to improve their businesses" (Evans, 2012). Therefore, the identified challenges and stated research problems, concerning data and business analytics, point up pertinent research questions, in the ensuing section.

1.2. Research questions

In addition to the prerequisite foundational research question, "what is business analytics," another important question is "what can leaders do today, to advance business analytics capability, in their firms." In the researcher's quest to inform on business analytics, several ancillary relationship questions are raised. These include: 1) "what is the relationship between business analytics and performance;" 2) "what is the relationship between business analytics and decision making;" 3) "what is the relationship between business analytics and management strategy;" and 4) "how can insight from business analytics use be infused into all organization processes." Given the importance of these research questions, and the prevalence of the stated research problems, the author of this manuscript was inspired to review recent literature, covered in the next section, to understand the constructs associated with business analytics, and their relationships.

1.3. Purpose and motivation

Extant research gives a lot of attention to business analytics, and to various trends associated with it. Recent articles on data analytics, and affiliated streams of data analytics-related research, cover a myriad of topics, including the following subset, to name a few: major "types of data analytics" (CI&T, 2014; Ingram Micro Advisor, 2017); "analytics methods, models, and decisions" (Evans, 2013); "the year when analytics means business" (Elliott, 2012); "business analytics as the "next new frontier" (Evans, 2012); "data is dead…without what-if models" (Haas, Maglio, Selinger, & Tan, 2011); "big data analytics" (Russom, 2011); "information and analytics at work" (Hopkins, LaValle, Balboni, Kruschwitz, & Shockley, 2010); "big data, analytics, and the path from insights to value" (LaValle et al., 2010); "the analytics movement" (Liberatore & Luo, 2010); and "competing on analytics" (Davenport, 2007). Although merely a tiny subset of today's data analytics scholarly universe, these articles and research studies lend support to the notion that data, and data analytics are interesting and hot topics among today's business practitioners and academics, and create excitement for their potential, to help "business people make better decisions" (Elliott, 2012).

Even with all the enthusiasm and diversity of topics, there is one research stream of business analytics, however, that is sorely lacking. That research stream establishes, communicates, and informs on a general understanding of the conceptual relationship between business analytics and performance. The absence of such research makes it difficult for scholars to study the pertinent constructs, sub-constructs, and their relationships to determine causal associations that will impact performance. The absence of such research also limits the ability of practitioners to quickly and easily develop effective business analytics systems that enable organizations to get full value from the massive amounts of information, they already have within their organizations. Therefore, based on this perceived research gap, this research paper seeks to help bridge the research divide, and propose a comprehensive theoretical framework that informs on the relationship between business analytics and performance.

1.4. Contributions

This manuscript offers a number of contributions, five of which deserves special mention and are itemized below:

- Proposes a comprehensive theoretical framework positing the linear relationship of the 5 major business analytics types and operational and financial performance, that is moderated by holistic thinking/decision making, using a "big picture perspective" (Figure 1);
- Proposes a simplified flow chart, of a business analytics process, for data acquisition, data management, and data-driven decision-making (Figure 2);
- Develops a standard business analytics approach to solve real-world problems using structured operational and financial statement data, already existing in firms;
- Provides a cost-effective solution that can be applied to small, mid-sized, and large firms;
- Presents a case illustration of a real-world contract manufacturer, employing the proposed comprehensive, theoretical framework, to demonstrate the innovative use of integrated, business analytics to turnaround an organization, and position it to survive, thrive, innovate, and grow (Appendix – Table A1); and
- Presents 72 months, or 6 years, of actual performance results, depicted in a Visualization Dashboard (Figure 3), of a real-world case illustration, using the five major types of business analytics.

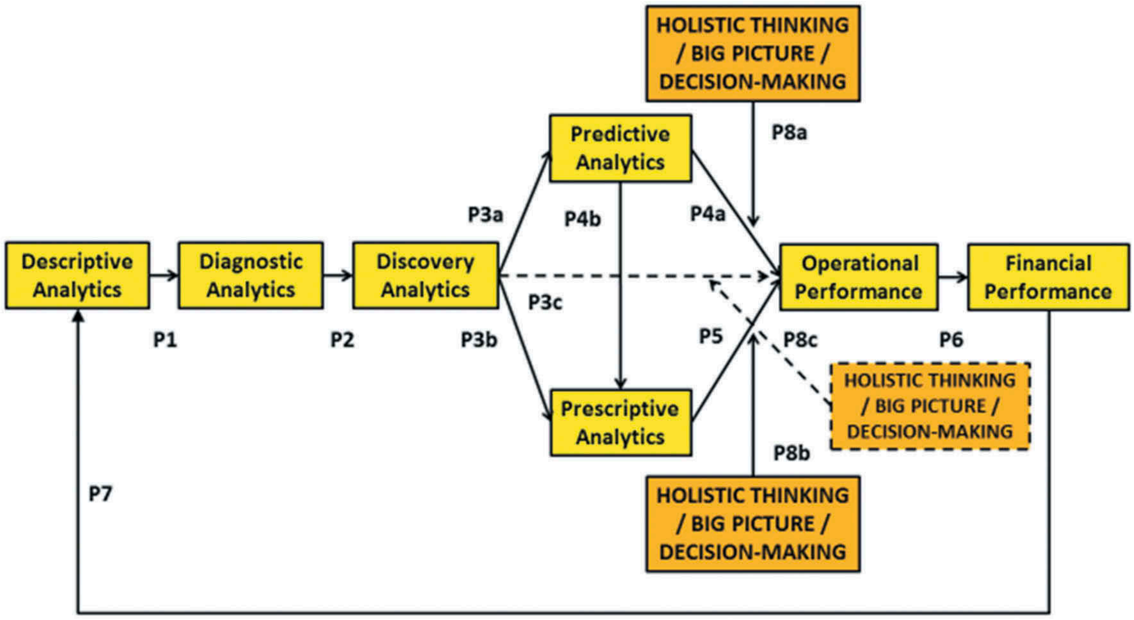

Figure 1. Buisiness analytics and performance.

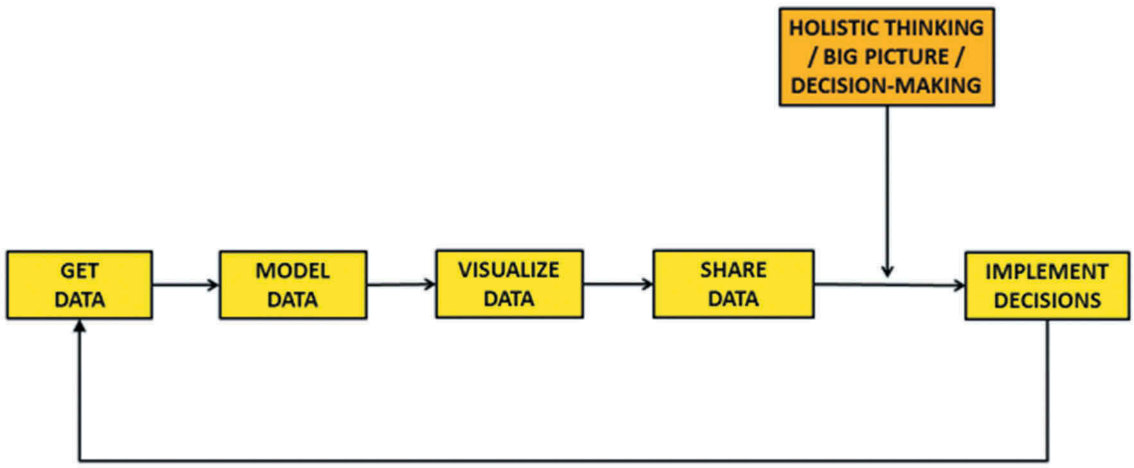

Figure 2. Business analytics process.

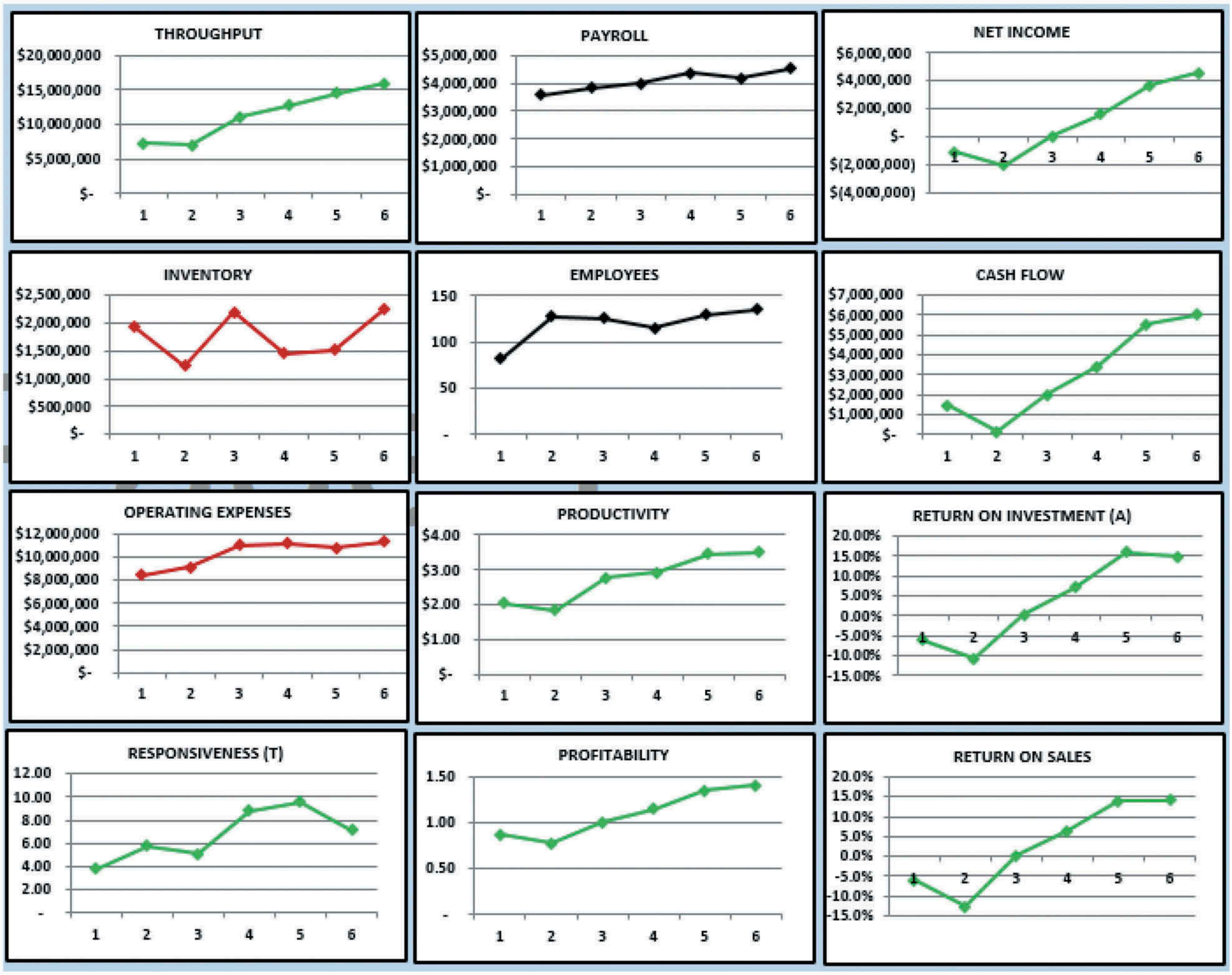

Figure 3. Performance results (Dashboard visualization).

2. Literature review

Business analytics has been defined as “a process of transforming data into actions through analysis and insights in the context of organizational decision-making and problem-solving” (Liberatore & Luo, 2010). Evans (2012) defines business analytics as “the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their business operations, and make better, fact-based decisions.”

Business Analytics, to others, is a research stream that emphasizes developing novel insights, systems perspectives, and holistic understandings of a firm’s business ecosystem (Ram & Delen, 2018). It is a special branch of analytics that applies its tools, techniques, and principles to develop solutions to difficult business problems (Delen & Ram, 2018). The business analytics research stream seeks to inform on practices to help individuals make sensible, timely, and correct decisions, in order to survive, thrive, innovate, and grow. Accordingly, business analytics concentrates on the full spectrum of *descriptive, diagnostic, discovery, predictive*, and *prescriptive analytics*, to encourage data driven decisions and create improved, intermediate outcomes and financial performance.

2.1. Taxonomy for business analytics

- ***Descriptive analytics*** is a process for “finding patterns and relationships in historical, and existing data” (Haas et al., 2011; Ingram Micro Advisor, 2017). According to recent research, conducted by CI&T, about 90% of the companies, use this very basic analytics technique, on occasion, and only 35% of companies surveyed, say they use this technique on a consistent basis (CI&T United States, 2014). Research conducted by PwC (2016) found that U.S. Automotive senior executives employ the descriptive analytics technique 24% – 60% of the time, depending on their company’s stage of development.

- ***Diagnostic analytics***, enables one to quickly examine and understand what happened in the past, or based on incoming data (Ingram Micro Advisor, 2017), what is currently happening, now, and attempts to explain the reasons for its occurrence. According to CI&T, less than 10% of companies surveyed, say they use "diagnostic analytics," on occasion, and less than 5% say they use it on a consistent basis. Research conducted by PricewaterhouseCoopers (PwC) (2016) found that U.S. Automotive senior executives employ the diagnostic analytics technique 21% – 32% of the time, depending on their company's stage of development.

- ***Discovery*** *(or "exploratory")* ***analytics*** generally involves a "deeper dive" into the data to understand patterns, trends, and relationships, in order to derive results that can be used as a basis to make better decisions. It examines "what happened in the past," then diagnoses "why it happened" and determines the root cause, in order to understand and discern the bigger picture of "what is happening" and "why it is happening" (Delen & Zolbanin, 2018). Compared to diagnostic analytics, discovery analytics gives a "more" illuminating and "discerning view of the present."
- ***Predictive analytics*** is concerned with "forecasting, or predicting future probabilities, and trends, and allows what-if analyses." (Haas et al., 2011). With respect to prediction, CI&T (2014) reports that less than 1% of companies surveyed, say they have tried "predictive analytics." Research conducted by PricewaterhouseCoopers (PwC) (2016) found that U.S. Automotive senior executives employ the predictive analytics technique 14% – 38% of the time, depending on their company's stage of development.
- ***Prescriptive analytics*** divulges "what actions should be taken to maximize good outcomes, and minimize bad outcomes," during a giving period of time. Essentially, prescriptive analytics is concerned with "deterministic and stochastic optimization to support better decision making" (Haas et al., 2011). This is a very valuable, analytics type, although quite difficult for most to implement. According to Gartner (2012), "13 percent of organizations are using predictive [analytics], but only 3 percent are using "prescriptive analytics." Research conducted by PricewaterhouseCoopers (PwC) (2016) found that U.S. Automotive senior executives employ the prescriptive analytics technique 2% – 16% of the time, depending on their company's stage of development.

Table 1 illustrates constructs, definitions, and characteristics of the constructs, contained in this research, along with the percentage of companies adopting a particular analytics type, identified in the CI&T United States (2014) research study. Table 2 illustrates the results of a survey, conducted by PricewaterhouseCoopers (PwC)

Table 1. Construct definitions and characteristics.

Item No.	Construct	Question Answered	Temporal View	Line of Sight	Data Analysis Process	Analytics Adoption (%)
1	Descriptive Analytics	What Happened?	View of the Past	Hindsight	Financial Statement Reports	35%
2	Diagnostic Analytics	Why Did It Happen?	View of the Present	Nearsighted	Financial Statement Analysis	5%
3	Discovery Analytics	What Is Happening? Why Is It Happening?	Discerning View of the Present	Insight	Financial Statement Analysis Deep Dive	5%
4	Holistic Thinking/ Decision-Making	What is the Global Impact on the Enterprise?	Strategic View of Enterprise	Global	Synchronous Management	NA
5	Predictive Analytics	What Will Happen, If …	View of the Future	Foresight	Financial Statement Sensitivity Analysis (What If)	1% – 13%
6	Prescriptive Analytics	What Should Happen To Maximize Good, and Minimize Bad Outcomes?	Clearer View of the Future	Farsighted	Optimization Outcomes (Maximize Good) (Minimize Bad)	3%
7	Operational Performance	What is the Global Impact on T, I, OE, T/I, T/OE	Operational Excellence View	Global	Responsiveness (T/I) Productivity (T/PR) Profitability (T/OE)	NA
8	Financial Performance	What Is The Global Impact on NI, CF, ROI	Financial Excellence View	Global	Balance Sheet Income Statement Cash Flow Statement	NA

Table 2. Types of data analytics adopted.

(In U.S. Automotive Industry)			
(2,106 Senior Executives – C-suite Leaders, Business Unit Heads and SVPs)			
Type of Analytics	Rarely Data-Driven (6%)	Somewhat Data-Driven (48%)	Highly Data-Driven (46%)
Descriptive	60%	29%	24%
Diagnostic	23%	32%	21%
Predictive	14%	28%	38%
Prescriptive	2%	10%	16%

Source: PricewaterhouseCoopers (PwC) (2016). "PwC's Global Data and Analytics Survey: Big Decisions," https://www.pwc.com/us/en/services/consulting/analytics/big-decision-survey.html (Accessed last, November 26 2018, 2:15 AM).

(2016), of over 2,100 Senior Executives in the U.S. Automotive industry, regarding which analytics type they rely on most. The companies in the PwC study were classified as "Rarely data-driven" (6%), "Somewhat data-driven" (48%), and "Highly data-driven" (46%). The key takeaways from the PwC study, regarding the respondent's choice of analytics, are that the "highly data-driven" decision-makers: 1) "look backwards, when needed"; 2) "use predictive and prescriptive analytics to model the future"; and 3) "take a more holistic approach" to decision-making (PwC, 2016).

2.2. Business analytics challenges

Review of literature indicates, that although business analytics is receiving a lot of hype, and gaining popularity, many opportunities still exist to capitalize on the merits of implementing robust business analytics solutions. Some of the barriers to business analytics adaptation, according to Delen and Ram (2018) and Sharda, Delen, and Turban (2017), include: 1) lack of talented individuals with sufficient analytics training; 2) slow cultural change from gut and intuition decision-making to evidence-based management (i.e., evidence-based/data-driven decision-making); 3) inability of implementers to demonstrate satisfactory ROIs in their project plans; 4) lack of a cogent strategy for converting structured data, unstructured data, and "Big Data" into actionable insight; 5) slow technology adoption due to cost, training, and technology-challenged personnel issues; and 6) risk aversion profiles to perceived risks associated with security and privacy issues.

However, as firms overcome their barriers to adaptation of analytics technology, and as organizations learn to harness and master the five data analytics types, they will be able to: 1) demystify the data that flows in and out of their organization, by adding context to the data; 2) uncover hidden patterns and trends to tell a more complete story; 3) gain insight, for better decision-making; 4) more accurately forecast future business outcomes; and 5) integrate the knowledge, experience, and intelligence, gained, to make decisions that optimizes value to the organization. More specifically, once descriptive, diagnostic, discovery, and predictive capabilities have been consistently, firmly, and effectively established, one becomes very close to implementing prescriptive analytics, through optimizing performance, by maximizing good outcomes (like revenues and profits), and minimizing bad outcomes (like costs, expenses, and losses).

From a casual review of literature, it is safe to say data visualization, in the form of charts, scorecards, and dashboards, etc., enhances analysis and communication of results for each of the five types of business analytics. "Visualizing data, and results of analyses, provide a way of easily communicating data at all levels of a business, and can reveal surprising patterns and relationships" (Evans, 2012).

3. Theoretical foundation

3.1. Holistic thinking

Implementing descriptive, diagnostic, and discovery analytics is relatively simple, compared to predictive and prescriptive analytics. Each type offers value, in terms of information, but in order to successfully implement predictive and prescriptive analytics, one needs to add "cognition" or big-picture thinking, to achieve optimal results. Cognition is defined as "the act or process of knowing or perceiving" (Merriam-Webster, 2017). It is the knowledge product of an analysis process, acquired through learning algorithms, such as Systems Theory, Systems Thinking Theory, or Holistic Thinking Theory, etc.

Analytical thinking is the opposite of holistic thinking. Analytical (analysis) thinking, according to Hitchins (1992, p. 14), is like reductionism, in that it "reduces the parts to smaller components," and contains the following steps: 1) "taking apart the thing to be understood;" 2) "understanding how the parts worked;" and 3) "assembling an understanding of the parts into an understanding of the whole" (Hitchins, 1992, p. 14). Holistic thinking, on the other hand, according to References.com (2017), refers to "a big picture mentality" in which someone "recognizes the interconnectedness of various elements that form larger systems, patterns, and objects" (References. com, 2017).

Holistic thinking, the preferred theoretical base for this paper, enables one to perceive phenomena from numerous perspectives (inputs), and permits one to also view various possible outcomes (outputs), as opposed to viewing things from a single perspective with a single outcome. It involves "understanding a system by sensing its large-scale patterns and reacting to them," whereas analyzing refers to "understanding a system by thinking about its parts and how they work together to produce larger-scale effects" (CreateAdvantage, 2017). Holistic thinking is the investigation of an intricate whole, and with respect to business organizations, it considers the organization's "purpose, values, function in its environment, process, and structure" (CreateAdvantage, 2017).

Holistic thinking, essentially, views the entire system in order to achieve global optimization, instead of looking at part of a system to attain local optimization. It also incorporates a number of perspectives, that can be used "when studying an organization either to gain an understanding of it, or in response to an undesirable situation such as falling sales, or some uncertainty about launching a new product" (Kasser, 2013, pp. 158–159). But the two most relevant perspectives, pertaining to this paper, are the "Big Picture" perspective and the "Operational" perspective.

3.2. Big picture perspective and operational perspective

"Big Picture" perspective encourages one to take an enterprise view of the firm when implementing decisions. It enables one to gather, store, and analyze information about the organization's mission, values, strategy, products, customers, and suppliers, etc. From this perspective one attempts to achieve global (versus local) optimization, when implementing decisions.

The "Operational perspective" enables one to gather, store, and analyze information about the ways the organization interacts with its customers (including how sales take place) and its suppliers (including how raw material is ordered and received). Together these perspectives enable organizations to implement holistic thinking practices that incorporate not only thinking about a system as a whole, but also by doing the "thinking in a systemic and systematic manner" (Kasser, 2013, p. 145). Table 3 lists the nine Holistic Thinking Perspectives (HTPs).

4. Theoretical framework

4.1. Theoretical model

This section introduces the proposed comprehensive theoretical framework that was developed to examine and explain the relationship between business analytics and performance. The framework posits mediating relationships among 5 business analytics constructs and 2 performance constructs. It also includes 3 moderating constructs. The analytics constructs are identified as *descriptive analytics, diagnostic analytics, discovery analytics, predictive analytics*, and *prescriptive analytics*. The performance constructs are *operational performance* and *financial performance*. The moderating construct is *holistic thinking/big picture/decision-making*. The framework is comprised of nine mediating relationships, and three moderating relationships. Figure 1 depicts the relationship of Business Analytics and Performance framework.

4.2. Construct identification and definitions

The business analytics constructs are positioned from left to right, in hierarchical order, according to the sophistication of the construct's technique. The business analytics constructs are not necessarily mutually exclusive, in that a firm can only implement one at a time. To the contrary, these tools overlap, and can be used concurrently in different areas of the firm. Practically speaking, firms general employ the least sophisticated technique, first, and continues to

Table 3. Holistic thinking perspectives (HTP).

Item No.	Perspective	Definition
1	Big Picture Perspective (E)	The place to store information about the mission, strategy and goal of the business, the industry, products, competitors, partners, country, etc.
2	Operational Perspective (E)	The place to store information about the way the business interacts with customers and suppliers. For example, scenarios describing how sales take place and how raw material is ordered and received.
3	Functional Perspective (I)	The place to store information about what the business does and how it does it. Some of this information is often in the form of processes. For example in purchasing, a low inventory triggers a purchase request which initiates a purchasing process.
4	Structural Perspective (I)	The place to store information about how the business is organized. This information tends to show up in hierarchical organization charts.
5	Generic Perspective (P)	The place to store information about how the business compares with similar organizations.
6	Continuum Perspective (P)	The place to store information about alternatives to customers, suppliers and potential markets etc.
7	Temporal Perspective (P)	The place to store information about the past, present and future of the business.
8	Quantitative Perspective (D)	The place to store numeric and other quantitative information associated with the business. For example, number of employees, sales, profits, and other financial information.
9	Scientific Perspective (S)	The place to store the hypothesis for (the reason), or cause of, the symptoms that generated the study or recommendations for further action.

(D) Descriptive Perspective; (E) External Perspective; (I) Internal Perspective; (P) Progressive Perspective; (S) Scientific Perspective.
Source: Information extracted, adopted, and adapted from **Holistic Thinking: Creating innovative solutions to complex problems**, Dr. Joseph E. Kasser, Published by The Right Requirement. 50 Crane Way, Cranfield, Bedfordshire, MK43 0HH, England. Visit the web site at http://therightrequirement.com, SETE2013 restricted version.

incorporate more sophisticated analytics techniques, as the firm's experience with business analytics develops.

Most organizations start with descriptive analytics, which is the most frequently used and most well understood type of analytics. Descriptive analytics helps one to understand what happened in the organization. This technique classifies, describes, combines, and categorizes data to transform it into valuable information for the purposes of understanding and evaluating organizational performance (Evans, 2012).

The next construct, in the analytics-performance link, is diagnostic analytics. This technique provides an opportunity to analyze why something occurred in a previous period of time, or in the present, and uses charts, scorecards, and dashboards to analyze trends. Once analyzed, one can see if the trends are going in the right direction. If the trends are not going in the right direction, corrective actions can be taken to put the organization back on the right track.

The third construct, in the analytics-performance link, is discovery analytics. This technique provides an opportunity to analyze "what is happening" and "why something is happening." Its objective is to explore large volumes of data (with plenty of detail) and relationships, through deep-dives to determine, ascertain, or discern new facts or relationships, previously unknown to the organization. Coupled with data visualization tools, discovery analytics offers the potential to easily uncover trends and patterns, to understand relationships and gain insight in order to explain phenomena and solve problems.

The fourth and fifth constructs, in the analytics-performance link, are predictive analytics and prescriptive analytics. These two techniques capitalize on the data, information, knowledge, and insight gleaned from the first three analytics constructs. They use these benefits to foretell and predict future outcomes, and try to maximize good outcomes, and minimize bad outcomes.

The sixth construct, in the analytics-performance link, is operational performance. Operational performance is the intermediate outcome construct that indicates how well the organization is performing in operational areas, such as on-time delivery (OTD), premium freight (PF), customer complaints (CC), rejects I, and defective parts per million opportunities (DPPMO). Other operational performance areas, associated with structured financial statement data, which happens to be the focus of this paper, is throughput (T), inventory (I), operating expense (OE), responsiveness (T/I), profitability (T/OE), and productivity (T/Payroll).

Throughput (T) is defined as the money generated through sales. It is calculated as sales minus the purchased material cost. Inventory (I) is defined as the amount of money tied up in materials that the company intends to sell. Inventory is calculated as the sum of the purchased material value of Raw Material, In-process and Finished Goods Inventories. Operating expense (OE) is defined as the actual money spent to convert Inventory into Throughput. In evaluating performance, the authors Srikanth and Robertson (1995, pp. 76–80, 86) indicate that the ratios "T/I" (Responsiveness) and "T/OE" (Profitability) are more useful than the numerical values of T, I, and OE, alone, because the ratios force the organization to consider all the measures simultaneously (Srikanth and Robertson, 1995, pp. 76–80, 86).

The seventh construct, in the analytics-performance link, is financial performance. Financial performance is the final outcome construct that indicates how well the organization is performing, in terms of making money. Making money, in financial performance measures, is indicated through increasing levels of sales (S), net income (NI), return on investment (ROI), and cash flows (CF).

The eighth construct, in the analytics-performance link, is holistic thinking/big picture/decision-making. Holistic thinking/big picture/decision-making is the moderating construct that impacts the relationships between the discovery analytics-predictive analytics link, the discovery-prescriptive analytics link, and the discovery-operational performance link.

4.3. Business analytics-performance links

The proposed *comprehensive* theoretical framework suggests that Descriptive analytics influences Diagnostic analytics, which influences Discovery analytics, which in turn influences, both, Predictive analytics and Prescriptive analytics, as well as Operational Performance. The framework also depicts the relationship where Predictive analytics influences, both, Prescriptive analytics and Operational Performance. In addition, the framework depicts the relationships where Prescriptive analytics influences Operational Performance, and Operational Performance influences Financial Performance, which in turn, closes the cycle and influences Descriptive analytics.

4.4. Proposition development

With respect to business analytics research, the correlation between business analytics and performance has important implications for organizations, whether they are seeking profitability, growth, efficiency, or product and competitive differentiation. Much of the findings, of the research on the link between business analytics and performance, are the result of respondents self-reporting, and although correlation between evidence-based/data-driven decision-making management and performance may be inferred, there are a few bright stars that show objective results that indicate causation.

One researcher says "the business case for analytics is strong," and that "various research studies have discovered strong relationships between a company's performance (in terms of profitability, revenue, and shareholder return,) and its use of analytics" (Evans, 2012). Other researchers say that "top performing organizations are three times more likely to be sophisticated in their use of analytics than their competitors," and "are more likely to state that their use of analytics differentiates them from competitors" (Davenport & Harris, 2007; Hopkins et al., 2010).

Moreover, the claims are clear, and existing research indicates that business analytics is beneficial to performance in many areas, although it is not easy to find published direct business analytics – financial performance links. Still, other authors indicate that their research "clearly connects performance and the competitive value of analytics" (LaValle et al., 2010). They also say that those "organizations that know where they are in terms of analytics adoption are better prepared to turn challenges into opportunities" (LaValle et al., 2010).

Relying on logic, and over 30 years of real-world manufacturing experience in implementing business analytics (formally known as data analytics), the current researcher has documented evidence of a number of firms that have turned around, survived, thrived, innovated, and expanded by implementing the proposed comprehensive theoretical framework, described in this paper. The evidence demonstrates, over and over, that properly progressing through the basic techniques (e.g. descriptive analytics and diagnostics analytics), and employing the more sophisticated techniques (e.g. predictive analytics and prescriptive analytics), numerous firms have been rewarded with improved operational and financial performance (Whitelock, 2019).

With this backdrop, a set of propositions were designed and developed, specifically for the proposed comprehensive theoretical framework, described in this paper. Table 4 describes the set of propositions for the Business Analytics and Performance framework.

Table 4. Propositions.

Item No.	Description
P1	As the use of Descriptive Analytics increases, the use of Diagnostic Analytics will increase
P2	As the use of Diagnostic Analytics increases, the use of Discovery Analytics will increase
P3a	As the use of Discovery Analytics increases, the use of Predictive Analytics will increase
P3b	As the use of Discovery Analytics increases, the use of Prescriptive Analytics will increase
P3c	As the use of Discovery Analytics increases, Operational Performance will improve
P4a	As the use of Predictive Analytics increases, Operational Performance will improve
P4b	As the use of Predictive Analytics increases, the use of Prescriptive Analytics will increase
P5	As the use of Prescriptive Analytics increases, Operational Performance will improve
P6	As Operational Performance improves, Financial Performance will improve
P7	As Financial Performance improves, the use of Descriptive Analytics will increase
P8a	Holistic Thinking/Big Picture/Decision-Making moderates the effectiveness of decisions made concerning Operational Performance
P8b	Holistic Thinking/Big Picture/Decision-Making moderates the effectiveness of decisions made concerning Operational Performance
P8c	Holistic Thinking/Big Picture/Decision-Making moderates the effectiveness of decisions made concerning Operational Performance

5. Findings

The current study, as demonstrated in the case illustration, clearly connects the competitive value of business analytics and performance. In the case illustration, a tier one contract supplier, to original equipment manufacturers, was losing money for several consecutive years, prior to the arrival of a new general manager. The new general manager, who was well-versed in evidenced-based management techniques, implemented a business analysis process, described in Figure 2 that standardized the steps for managing data. This process included the activities of obtaining, modeling, visualizing, and sharing data, before implementing data-driven decisions. This process was carried out with the help of descriptive, diagnostic, discovery, predictive, and prescriptive analytics, and enabled the firm to gain insight from structured operational and financial statement data, already captured within its enterprise system.

The data-driven, decisions, that were implemented, had a measurable impact on the performance of the enterprise. The empirical, performance results are seen in the trends of the metrics located in the Executive Balanced Scorecards and Dashboards that were created and implemented to drive and sustain the firm's strategic, operational, and financial goals and objectives. Figure 3 shows the actual results, in a Balanced Dashboard, for the turnaround of the firm in the case illustration.

The case illustration describes the strategic and tactical activities that turned around a mid-sized company with annual sales of $70 million. The company, operating multiple plants, in multiple cities, and losing as much as $4 million per year, was transformed to one that generated $25 million of Net Income and $40 million in EBITDA, over a six year period. In the process, the number of employees was reduced by 26%, operating expenses was reduced by 20%, inventory was reduced by 30%, throughput per hour worked was improved by 50%, and inventory turns were improved by 45%, while increasing sales by 25%. The main objective was to reduce the company's break-even point by several million dollars, to reposition it for survival and growth, while increasing On-Time Delivery to 80%, in the first year, which was accomplished. Appendix –

Table A1 documents the problem, challenge, and turnaround of the firm featured in the case illustration.

6. Implications for research, practice, and limitations

6.1. Implications for research

With respect to scholars, this conceptual paper has several theoretical implications for business analytics/performance research. **First**, since the proposed model, is among the first, to propose a comprehensive theoretical framework to explain the relationships among use of business analytics and performance, and also among the first analytics research papers to propose a way, through moderation, to evaluate the impact of using holistic thinking/decision-making on the operational and financial performances of organizations, this paper provides a kind of road map to help researchers empirically test performances of organizations, using their longitudinal, structured financial statement data.

Second, the proposed model, offers a comprehensive, theoretical framework to examine the relationship between analytics and performance using, a variety of performance options, including: 1) internal, *structured operational* performance data (e.g. TIOE, T/I, and T/OE, etc.); 2) external, *structured operational* performance data (e.g. customer/supplier-related data, rejects, complaints (C), defective parts per million opportunities (DPPMO), premium freight (PF), and on-time delivery (OTD), etc.; and 3) internal, *structured financial* performance data (e.g. Sales, NI, ROI, and CF, etc.).

6.2. Implications for practice

Organizations cite various obstacles and challenges, to Business analytics adoption, such as, being "overwhelmed by data," struggling to "understand how to use data to achieve business results," and not understanding "how to use analytics to improve their businesses" (Evans, 2012). With respect to practitioners, this conceptual paper has several practical implications for managers and consultants, who are engaged in implementing analytics/performance practices in organizations. **First**, the overarching implication to practitioners is that this conceptual paper offers a proposed theoretical framework that is unique, insightful, thought-provoking, and important, and addresses the compelling management issues of "business analytics" adoption. **Second**, the proposed theoretical framework, described herein, is simple, intuitive, easy to implement, uses familiar, structured financial statement data, and provides holistic thinking/decision-making practices to achieve global (versus local) optimization results. **Third**, the proposed theoretical framework, is an integrated, virtual closed-loop system, that provides a systemic and systematic approach to improved decision-making. **Fourth**, the proposed model offers opportunities for corrective action and continuous improvement, through use of data description, diagnosis, discovery, prediction, and optimization, for improved operational and financial results.

6.3. Limitations

This paper is conceptual in nature, and suggests propositions, based on extant literature, prior practical knowledge, and extensive executive, turnaround experience. Although, this conceptual paper offers a case illustration, using structured financial statement data, of a real life turnaround, to demonstrate a strong fit to the business analytics/performance model, the proposed model still merits other empirical verification for generalizability, across organizational types, industries, and periods, using other structured financial statement data sets. Therefore, it is suggested that further research is needed to empirically investigate the propositions associated with the proposed business analytics/performance framework, using other types of data sets. Additionally, scholars and practitioners would also benefit from more empirical evidence that sheds light on the effectiveness and rewards of organizations adopting their own approaches to driving operational and financial performances, through use of various business analytics types.

7. Conclusion

This conceptual paper proposed a comprehensive, theoretical framework to examine the relationship between business analytics and performance (Figure 1). It provided a simplified flow chart, of a business analytics process, for data acquisition, data management, and data-driven decision-making (Figure 2). It also developed a standard business analytics approach to solve real-world problems, using structured operational and financial statement data, already existing in firms. The framework is also a cost-effective solution that can be applied to small, mid-sized, and large firms, thereby, providing firms, that are "overwhelmed by data," and "struggling to use data to achieve improved business results," with a viable option to advance business analytics capability, in their organizations. Furthermore, this research also provided a real-world, case illustration (Appendix – Table A1), employing the five major business analytics, and 72 months, or 6 years, of actual performance results, displayed in a dashboard visualization (Figure 3).

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Appendix

Table A1. Illustrative case example.

Tier One Automotive uses Holistic Thinking/Decision-Making to transform its Operating Model
A leading plastics, metal fabricator, and assembler, located in OH, was struggling to respond to challenging market dynamics, particularly in the contract manufacturer's slice of the Truck, Bus, and Automotive components market segment. Tier One Automotive (TOA) employed approximately 300 workers, at three plant locations, generated annual sales in excess of $38 million, and was regularly losing as much as $4 million per year. The near- and medium-term forecasts looked even worse, with likely contractions in unit sales volume, and potentially, even in revenues. The company's operations were challenged, saddled by unprofitable profit margins, and were underperforming in cost, quality, service and delivery. A cultural change, and a comprehensive transformation effort was needed, in order to survive.
On January 2 2001, a new outside General Manager (GM) was hired and installed, replacing the previous one. The new General Manager's role was to be a Steward and Leader, and create shareholder value for the company's operations. Specifically, the GM was to lead, coach, build stakeholder value and serve as a visionary, a strategist, a change agent, a statesmen, a diplomat and a spokesperson, while satisfying customer requirements for price, quality, delivery, service and technology.
After gathering, compiling, and organizing significant amounts of historical, and existing, operational and financial data, over a 30 day period, a detailed organization analysis was conducted, using "**descriptive analytics**." That exercise enabled the GM to uncover certain hidden patterns, relationships, and trends, to determine "**what happened**," over the past 5 years, to contribute to the organization's annual unprofitable performances. That exercise, in essence, provided a "**view of the past**," offered a line of sight that can be termed, "**hindsight**," and also describes "**what was currently happening in the present**," during that time period.
The GM also used "**diagnostic analytics**" techniques, and organized the compiled data into data visualization tools, in the form of charts, scorecards, and dashboards. These techniques and formats, not only enhanced the analysis and communication of results, but they also helped the GM to quickly understand "**why some things happened**," over the past 5 years, to contribute to the organization's annual unprofitable performances. The techniques of "**diagnostic analytics**," provided an illuminating "**view of the present**," and offers a line of sight that can be termed, "**insight**."
So in March 2001, after employing a deep-dive into 5 years of structured financial statement data, using "**discovery analytics**" coupled with **data visualization** to unmask trends and relationships, previously unknown, to the organization, the GM garnered a more "**discerning view of the present**," as to "**what is happening**" and "**why things are happening**."
In response to this new information, the GM created a "**Sense of Urgency**," developed aggressive plans for improvement, and implemented an organization change. It organized its management team, and with them systematically evaluated the strategic, financial and operational viability of each of the company's business units. Then the GM created and implemented a plan of attack.
To fund the journey, the company looked at several cost-reduction initiatives, including plant consolidations, and logistics. Previously, the company had worked with a large number of suppliers and logistics providers, causing it to miss out on scale efficiencies.
The plant layout, manufacturing flow, and operating practices were studied, and more effective practices were developed, saving the company hundreds of thousands of dollars, annually. Administrative overhead was reduced, and strict World-Class manufacturing practices were instituted to control manufacturing costs, while simultaneously improving cost, quality, delivery, and service.
Those were just a few of the many tactical changes that were implemented to stop the hemorrhaging, make the company healthy, and return it to profitable growth. One of the most important strategic changes for the company, however, was the adoption of the Transformation Management System, which featured Lean Manufacturing, elements of the Toyota Production System, and Synchronous Manufacturing, as a philosophy, and as a strategic weapon.
Synchronous Manufacturing is a management philosophy in which every action of the organization, at all levels is focused on the common, global company goal, to Make Money, by increasing Net Income, Cash Flow, and Return on Investment. Its intent is to increase "Throughput", reduce "Inventory", and reduce "Operating Expenses", simultaneously, while satisfying the customers' requirements for cost, quality, service, delivery, and technology.
Using the Synchronous approach every business decision was made from a Holistic perspective, in that the decision was evaluated on the perceived simultaneous global impact of Throughput, Inventory and Operating Expenses, **for the entire enterprise**. While satisfying customer requirements, if the prospective decision tended to drive Throughput "up", Inventory "down", and Operating Expenses "down", all at the same time, then the decision was implemented. If the perceived results were contrary, then the decision was **not** implemented.
Using "**descriptive**," "**diagnostic**," and "**discovery**" analytics, coupled with data visualization, the GM was able to demystify the historical, and current, data, by adding context to the data. The GM was also able to uncover hidden patterns and trends to tell a more complete story, of what went on in the organization. Additionally, the GM was able to gain "**insight**," for better decision-making, and ultimately, with the application of cognitive, "**holistic thinking/decision-making**," it was able to use "**predictive analytics**" (or a "**view of the future**") to more accurately "**forecast**" and "**predict**" future business outcomes. "**Holistic thinking/decision-making**," embodies "**a big picture mentality**" in that decisions are made from the perspective of impacting the entire enterprise, rather than just a plant or division. Thus, once descriptive, diagnostic, and predictive capabilities had been consistently, firmly, and effectively established, by the TOA organization, the management team's decision-making evolved to become a close approximation of implementing "**prescriptive analytics**," (or a "**clearer view of the future**") through optimizing performance, by maximizing good outcomes (like revenues and profits), and minimizing bad outcomes (like costs, expenses, and losses).
Immediate Results
The results, in three months, of implementing Lean/Synchronous Manufacturing were dramatic. Since implementing Synchronous Manufacturing, the company in the first half of 2001, reduced the number of employees by 26%, reduced operating expenses by 20%, reduced inventory by 30%, improved throughput per hour worked by 50% and improved inventory turns by 45%, while increasing sales by 25%. The objective was to reduce the company's break-even point by several million dollars, while increasing On-Time Delivery to 80%, in the first year.
Long Term Results
The company's financial statements now showed that it carries little inventory relative to sales, and its inventory now turns rapidly. As a result, the company was able to increase production with fewer employees, and with modest investment in new equipment. Also, during the six-year period (January 2001 – December 2006) of the implementation of the Transformation Management System, the following results were achieved:
• Turned around a mid-sized $70 million annual sales company, operating in multiple plants and in multiple cities, that was losing as much as $4 million per year to one that generated $25 million of Net Income and $40 million in EBITDA, over a six year period.
• Transitioned one division from ISO/QS 9000 to ISO/TS 16949:2002 Without Design, and another from ISO/QS 9001 to ISO/TS 16949:2002 With Design, in less than 90 Days each, while incurring Zero dollars of operating expense, other than the usual and customary certification and registration audit fees.
• Created and implemented Executive Balanced Scorecards and Balanced Dashboards to drive and sustain achievement of Strategic, Financial and Operational goals and objectives.
The Transformation Management System® is a World Class business performance management model that focuses first on identifying waste, and then on eliminating it. It is a competitive secret weapon, that gives the organization a unique, distinct, sustainable, competitive, advantage by providing its business leaders with a practical, holistic, strategic, financial and operational solution to help the organization "Make Money, Now and In The Future," by delivering products, goods, services, information, and money that satisfy customer requirements for Price, Quality, Delivery, Service, and Technology.
The benefits of implementing the Transformation Management System are increased Net Income, Cash Flow, Return on Investment, Inventory Turns, and On-Time Delivery, and reduced Customer Complaints, Rejects, and PPM. These accomplishments result in "Making Money," for the organization, while improving Customer Satisfaction. Figure 2 – **Business Analytics Process** depicts the data management process. Figure 3 – **Performance Results (Dashboard Visualization)** describes 72 consecutive months, or 6 years, of real-world results, created from structured financial statement data, of a firm that turned around, survived, thrived, innovated, and expanded using Business Analytics.