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Big Data Analytics Methodology in the Financial Industry

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Abstract

Firms in industry continue to be attracted by the benefits of Big Data Analytics. The benefits of Big Data Analytics projects may not be as evident as frequently indicated in the literature. The authors of the study evaluate factors in a customized methodology that may increase the benefits of Big Data Analytics projects. Evaluating firms in the financial industry, the authors find that business and procedural factors, such as collaboration maturity of the organization and Big Data Analytics governance, are more important than the nuances of technology, such as hardware and product software of technology firms, in beginning to maximize the potential of Big Data Analytics in the firms. The findings of the paper will benefit educators in improving Big Data Analytics curricular programs to be current with the patterns of firms fruitfully initiating Big Data Analytics systems.

Keywords: analytics, big data, big data analytics, financial industry, methodology program.

1. BACKGROUND

Big Data is defined as aggregations of data in applications of bigness and complexity demanding advanced analytic approaches. The approaches to Big Data are described as descriptive analytics, analyzing data from the past; predictive analytics, analyzing data for prediction; and prescriptive analytics, analyzing data for pro-action (Camm, Cochran, Fry, Ohlmann, Anderson, Sweeney, & Williams, 2015). The complexity of Big Data Analytics is described in gigabytes (GB) in a massive miscellany (O'Neil, & Schutt, 2014) of structured, semi-structured and unstructured data, including objects of the Internet of Things (IOT) (Oracle, 2015); and, in the financial industry, Big Data Analytics is described in the volatility of volumetric data (King, 2015). The dimensions of Big Data Analytics are in data base management, data mining, natural language processing, social networking and statistics (Chiang, Goes, & Stohr, 2012) from disparate sources. Big Data Analytics is cited as an enhanced field of innovation (Kiron, Prentice, & Ferguson, 2015) adopted by industry in analyzing ever-increasing information sources.

The Big Data Analytics market is estimated to be $27 billion in 2016, and the market is estimated to be expanding to $50 billion in 2018 (McKendrick, 2015). Most Fortune 1000 firms (75%) are estimated to have a Big Data Analytics initiative in operation, mostly of investments of more than $10 million on projects (Bean, 2015); and most of the Fortune 1000 firms (67%) are estimated to have an edge in their industries from the investments (Mayer-Schonberger, & Cukier, 2013, & Kiron, Prentice, & Ferguson, 2015). Firms, including the financial industry, are indicated to have increasing interest in 2016 in the opportunities from prescriptive analytics (Zoldi, 2016). The majority of firms (70%)

applying real-time analytics systems are indicated to be increasing profitability and solvency from the technology in 2017 (Greengard, 2015). Big Data Analytics for decision-making is cited in the literature to be a disruptive but important transformative trend (Chen, Chiang, & Storey, 2012, & Siegel, 2015) in the 2010s, which is deserving of study.

2. INTRODUCTION

In this study, the authors are evaluating firms in the financial industry as to how they are initiating Big Data Analytics projects in the management of obstacles. To meet the demands for fruitful Big Data Analytics projects, the authors furnish a customized governance methodology of business, procedural and technical factors for decision-making on Big Data Analytics projects in the industry, enhanced from methodology on Big Data Analytics projects in the health sector (Lawler, Joseph, & Howell-Barber, 2016). Governance of Big Data Analytics projects (Kappenberger, McGrattan, & Aven, 2015) is essential in the financial industry, in order to exploit the projects for maximizing return-on-investment (ROI) (Westerman, Bonnet, & McAfee, 2014, & Baesens, 2015) but minimizing the risk of the technology. Maturity of data science initiatives is measurable by a disciplined methodology guiding managers on the impacts, processes and requirements of Big Data Analytics projects (Provost, & Fawcett, 2013). Most organizations are not integrating a governance methodology on Big Data Analytics systems (Davenport, 2014b).

The methodology can be applied by business and information systems departments of financial firms. The emphasis of the methodology is in engaging business professionals in the management of Big Data Analytics without fear of the projects or the technology. This emphasis may be helpful in insuring policies and procedures in the management of Big Data Analytics projects, systems and technologies (Baesens, 2015) in financial firms. The methodology may be helpful in insuring the performance and the stability of the technologies (Fleming, & Barsch, 2015), as in the processing of the volatile volumetric data of the industry. The methodology may be further helpful in maximizing a potential strategy (Goutas, Sutanto, & Aldarbesti, 2016) for Big Data Analytics, as strategies for the technologies are often not evident in firms (Rogers, 2015). Though levels of maturity in meeting Analytics and Big Data Analytics requirements, such as the Cross Industry Standard Process for Data Mining (CRISP-DM), are referenced in the literature (Shearer, 2000, & Ransbotham, Kiron, & Prentice, 2015), the methodology program of this study is inclusive of best-of-class practices found in current Big Data Analytics practitioner sources. The research on Big Data Analytics in the financial industry is largely limited in scholarly sources. The methodology of the authors contributes an organizational program for prudent investment in Big Data Analytics technology in the financial industry.

3. FOCUS

The focus of the authors in this study is in evaluating business, procedural and technical factors in the management of Big Data Analytics projects in the financial industry (Figure 1 in Appendix). The factors originated from an earlier study of Big Data Analytics projects in the health sector by the authors (Lawler, Joseph, & Howell-Barber, 2016) that they now particularize to projects in the financial industry. The factors are defined in Table 1 (in Appendix) and founded in the foremost practitioner sources, given the paucity of scholarly study of Big Data Analytics (Chen, Chiang, & Storey, 2012).
The methodology of this study may be helpful to information systems professors in learning the best practices of Big Data Analytics in the industry.

4. RESEARCH METHODOLOGY

The authors applied a case study of 5 firms in the financial industry, chosen from Big Data Analytics pioneers headquartered in New York State and cited in foremost practitioner publication sources in the August 2015 – February 2016 period. The financial industry is correlated to one of the sectors of the Big Data Analytics curriculum of the Seidenberg School of Computer Science and Information Systems of Pace University, defined by the authors in an earlier study (Molluzzo, & Lawler, 2015). The Big Data Analytics projects in the 5 firms were evaluated by the authors from a checklist definition instrument survey of the business, procedural and technical factors of the customized methodology program in the October 2015 – April 2016 period. The factors were evaluated by the authors on evidence to Big Data Analytics project success, on a 6-point Likert-like rating scale:

- (5) Very High Role to Project Success;
- (4) High Role;
- (3) Intermediate Role
- (2) Low Role
- (1) Very Low Role; and
- (0) No Role to Success.

These evaluations were predicated on in-depth observation of middle-management in the business and information systems organizations; informed perceptions of observation rationale; and research scrutiny of secondary studies, by the authors.

The checklist instrument of the survey was checked in the context of construct, content and face validity and content validity, measured in sample validity. The methodology of the study was dependable in proven reliability with the previous Big Data Analytics study of the authors (Lawler, Joseph, & Howell-Barber, 2016). The data from the evaluations was interpreted in Microsoft EXCEL the Mathworks MATLAB 7.10.0 Statistics Toolbox, and IBM SPSS (McClave, & Sincich, 2012) by the second author in the April – May 2016 period, as detailed in the next section and in the tables in the Appendix of this study.

5. ANALYSIS OF FINANCIAL FIRMS*

Firm 1: Consumer Lending Institution
Firm 1 is a large revenue-sized national organization that began an expanded descriptive / predictive Big Data Analytics initiative, in order to better inform on applicant consumer loans. The goal of the initiative was to integrate increased external demographic data into internal data bases to help loan officers in deciding potential loans at risk. The firm is beginning to benefit from decreased exposure to loans at risk due to increased predictive analytical interpretation of structured data.

The organization empowered its Big Data Analytics project from established features of Analytical Intuition (5.00), Analytical Maturity (5.00) and Analytical Process (5.00) evident in its headquarters. The knowledge to initiate the project was evident with data scientist staff in a Center of Excellence (5.00), partnered in Education and Training (4.00) with the loan officer staff. The management of the project was evident with existing Big Data Analytics Governance (5.00) and Data Governance (5.00) facilitated by Data Services (5.00) by the information systems staff. The project was helped with internally known predictive Software (3.00), instead of investment with Multiple Product Software Vendors (0.00) or new Product Software of the Vendor (2.00). Though Measurements of the Program (2.00) was not a feature initially on the project, the organization was formulating a Big Data Strategy (4.00) with Organizational Strategy (5.00).
Firm 1 is an example of a financial organization benefiting from Big Data Analytics in a controlled methodology, with a foundation for fruitful potential from a Big Data Analytics strategy.

Firm 2: Investment Banking Institution
Firm 2 is a large-sized regional organization that initiated a predictive Big Data Analytics project, in order to inform investment managers of impacts of new customer services. The goal of the project was to integrate increased external and internal data to help the managers learn metrics of profitable services. The firm is benefiting from insights on the services due to interpretation of structured and unstructured data.

This organization empowered its Big Data Analytics project with the existing features of a large-sized organization, such as Analytical Intuition (5.00), Analytical Maturity of Organization (5.00) and Analytical Process (5.00), as found in the prior organization. The Center of Excellence for Big Data Analytics (5.00) was evident as a leader on the project, in partnership with the investment management staff, and was funded by Executive Management Support (5.00) The new processes for interpretation of the results of the services was evident in Change Management (3.00) and Data Architecture (4.00) reviews. Therefore, this organization was focused more on immediate Measurements of Program (4.00) than in the prior organization, in order to insure that the niche project was a success, focusing less on limited Data Ethics and Privacy (3.00) requirements and less on strategic success. This project was helped more by the new Product Software of the Vendor (3.00) that enhanced the Internal Software (2.00), which was limited in interpretation of the new services.

Firm 2 is an example of a financial organization helped by existing methodology that is facilitating a Big Data Analytics project, which may be a model for other projects in a more recognized strategy.

Firm 3: Securities Trading Institution
Firm 3 is a medium-sized national organization that initiated a descriptive / predictive Big Data Analytics project, in order to monitor regulatory thresholds on trades. The intent of the project was to interpolate external data from governmental sources and internal data from securities trades to help managers learn of problematic trades. The firm is benefiting from faster information due to increased interpretation of interpolated semi structured, structured and unstructured data.

The organization enabled its project with features less evident than the functions in the prior organizations. The Analytical Process (3.00), Big Data Analytics Governance (4.00), Internal Standards (3.00), Responsibilities and Roles (3.00) and Risk Management (3.00) were less integrated on the project than in the prior large-sized organizations. The Center of Excellence for Big Data Analytics (3.00) projects was not a bona fide department in this organization, as the project was served by Cloud Methods (4.00), Multiple Product Software Vendors (3.00), and Product Software of the Vendor (3.00), but several information systems and business staff were trained in Education and Training (5.00) on the tools by the vendors. Due to criticality of immediate interpretation of on-line thresholds on trades, the Agility of Infrastructure (5.00), Data Governance (5.00) and Infrastructure of Technology (5.00) were more integrated on to the project than complimentary controls, such as Data Services (3.00), for diverse information not included on the project. Finally, this medium-sized organization was not integrating a Big Data Strategy (2.00) nor an Organizational Strategy (3.00), as the priority was the one project in the period of the study.

Financial Firm 3 is an example of an organization with limited methodological resources for a Big Data Analytics strategy, but which is investing productively in the technology.

Firm 4: Hedge Fund Institution
Firm 4 is a small-sized regional organization that invested in a predictive / prescriptive Big Data Analytics system, in order to inquire into optimal speeds of securities transactions. The objective of the system was to introduce methods for progressively speedy trading. The institution is benefiting from programmatic solutions for structured and unstructured data.

Financial Firm 4 enabled its new system with a culture of functional Analytical Intuition (4.00), Analytical Maturity of Organization (5.00) and Analytical Process (5.00), as found highlighted in the prior organizations 2 and 1. The system was enabled by exceptional Collaboration in Organization (5.00), driven by Executive Management Support (5.00), and was enabled further by extensive research of Best Practices (5.00) of Big Data Analytics systems. The Agility of Infrastructure (5.00) and the Infrastructure of Technology (5.00) were evident in success of the system. This organization was without a Center of Excellence (0.00), as selected Staffing (5.00) were knowledgeable in the Product Software of the Vendor (5.00); and this organization was also limited in Curation of Data (1.00) and even in Data Ethics and Privacy (3.00) and Data Security (3.00), and Internal Standards (2.00) of the system, as the priority was on the intricate processes of the trading. This organization was not planning a Big Data Strategy (0.00), but with the results of the limited productive system was pursuing an Organizational Strategy (3.00).

Financial Firm 4 is an illustration of an organization, as in Firm 3, investing productively but prudently in Big Data Analytics, but without expanded management for a strategy with the technology.

Firm 5: Wealth Management Institution
Firm 5 is a medium-sized regional organization that invested in a predictive / prescriptive Big Data Analytics system, in order to optimize customer portfolios. The objective of the system was to introduce models of products and services for diverse investor portfolios. The institution is benefiting from marketable models of structured and unstructured data that are contributing to increasing return-on-investment.

Firm 5 enabled its new system with evident functions of Analytical Intuition (5.00), Analytical Maturity of Organization (4.00) and Analytical Process (4.00). The firm lacked a full Center of Excellence in Big Data Analytics (3.00), but, as in Firm 3, several information systems staff in Staffing (5.00) were trained in Education and Training (5.00) on new tools by the vendor. The firm was helped by a very high maturity in oversight of Big Data Analytics Governance (5.00), Data Governance (5.00), Internal Standards (5.00), Process Management (5.00) and Responsibilities and Roles (5.00); and the consideration of Data Ethics and Privacy (5.00) and Security (5.00) was notable on this system. The Data Architecture (1.00) function was limited on the system, as the organization was initially leveraging only its internal structured data in the portfolios. Lastly, this organization was interpreting the models of products and services of the productive system into a new Organizational Strategy (5.00) without a similar Big Data Strategy (3.00), as the models involved only structured data at the conclusion of the study.

Firm 5 is an illustration of a financial organization incrementally investing in a Big Data Analytics system, with further potential of the technology to be hopefully pursued strategically.

*Firms are classified as confidential due to competitive imperatives in the sector.

6. SUMMARY ANALYSIS OF FINANCIAL FIRMS

The analysis is highlighting business factors (4.00) [summary in Table 2 and detail in Table 3 of the Appendix], the most highly rated in the study, as important to the Big Data Analytics projects. Analytical Intuition (5.00), Analytical Maturity of Organization (4.60) and Analytical Process (4.40) in decision-making were collectively important in all of the firms in the initiation of projects. The Center of Excellence (3.20), Collaboration in Organization (4.40) and Education and Training (4.00) were collectively important in all of the firms. The Center of Excellence in the large-sized organizations consisted of data scientists in information systems matrixed with the business departments of the organizations. In contrast, the mid-sized and small-sized organizations were without a Center of Excellence, but they were helped by data scientist "scrums" or "data smart" staff in the business departments managing the projects or by the vendors.

Findings in the mid-sized organizations are indicating Staffing (4.60) integrated inter-disciplinary information systems students of local universities.

The analysis of the findings is concurrently indicating procedural factors (3.94) [Tables 2 and 3] of the methodology program as important to the Big Data Analytics projects. Big Data Analytics Governance (4.00) and Data Governance (4.80) were collectively important in the decision management of most of the projects, and committees on governance were key mechanisms in the justification of needs on most of the projects. Data Ethics and Privacy (4.20) and Data Security (4.60) were important on most of the projects, given regulatory requirements
The analysis of the findings of the study is indicating technical factors (2.70) [Tables 2 and 3] as important, but as the most lowly rated in the study, they were less important than procedural and business factors. The Agility of Infrastructure (3.80), Data Services (4.00) and Infrastructure of Technology (3.60) were important on most of the projects. The factors of Internal Software (1.60), Multiple Product Software Vendors (1.20) and Product Software of Vendors (3.20) were generally not as important as other procedural and technical factors on most of the projects, and few of the organizations were fully investing in in advanced prescriptive or advanced architectural technologies, even though most of them were proliferating unstructured data into their structured systems.

Lastly, the firms in the study were focusing less on a Big Data Strategy (2.40) and more on localized Organizational Strategy (4.20), as they were pursuing silo systems essentially tactical; and they were supported with Executive Management Support (5.00).

As to the correlation of factor ratings along pairs of the firms (Table 4) in the study, the correlation of ratings associated with Firms 1 and 2 was significant statistically at the 1% significance level with a value of 0.8440; and the correlations of the ratings with the pairs of Firms 1 and 5, Firms 2 and 5, Firms 3 and 4 and Firms 3 and 5 were significant at the 1% significance level. With respective values of 0.5009, 0.5132, 0.3987 and 0.4001.

(Summary and detailed analysis of the factors in the study are in Tables 2 and 3 of the Appendix, followed by correlations between organizational pairs in Table 4 and by frequency distributions of ratings in Tables 5-8.)

7. IMPLICATIONS

The financial firms of the study are benefiting from an analytical culture that is enabling Big Data Analytics experimentation. The data governance of the projects in especially the large-sized firms is highlighting the foundational maturity of the firms to initiate Big Data Analytics projects. The inherent intuitive maturity of the firms is indicating the potential for profitable Big Data Analytics projects. This maturity is moreover positioning the organizations to pursue non-silo solutions with the technology. The implication is that the analytical maturity of an organization is a clear prerequisite to Big Data Analytics success.

The firms are enabling Big Data Analytics from either a formal center of competency excellence in Big Data Analytics, consisting of data scientists, or from an informal department, consisting of data scientists or data smart quantitative staff aligned with data management information systems staff. Importantly, most of the data scientist and data smart staff are pursuing Big Data Analytics projects in a matrix with the mostly business ownership staff (Harris, & Mehrotra, 2014), a need cited in the literature (Ransbotham, Kiron, & Prentice, 2015). The data scientists are mostly pursuing Big Data Analytics product and service solutions on business and information systems teams (Kiron, Prentice, & Ferguson, 2015), not on isolated scientist teams. The implication is that a multiplicity of skilled staffing is an important prerequisite to Big Data Analytics success.

Lastly, the authors are learning that the financial firms of the study are currently not focusing on a Big Data Analytics strategy, a concern cited in the literature (Davenport, 2014). The firms are focusing on limited silo systems that are benefiting the organizations with impactful results. The foundation of maturity for pursuing further systems in a Big Data Analytics strategy is evident however in the firms, so that the model of data science in the organizations may not be limited to silo systems (Burns, 2015). Most of them have optimal organizational structures. The implication of this finding is that in order to fully leverage the investment, a Big Data Analytics strategy will be eventually a requirement.

8. LIMITATIONS AND OPPORTUNITIES

The findings of the case study are constrained by the limited number of Big Data Analytics organizational participants. The impacts are constrained by the limited maturity of methodological processes and steps of strategy. The findings may not be generalized to the financial sector or other sectors without discretion. Nevertheless, the Big Data Analytics methodology program of this study contributes opportunities for further research. The program may be helpful to practitioners and professors pursuing study of the potential of prudent Big Data Analytics practices and technologies.

9. CONCLUSION

The financial firms of this study are benefiting in decision-making from the factors of the Big Data Analytics methodology program.

The business factors of especially Big Data Analytics maturity of the organizations, centers of competency excellence and collaboration on Big Data Analytics projects managed by business functions, and education and training of data smart staff were collectively important on the study.

The procedural factors of the methodology program of Big Data Analytics governance and data governance were also important on most of the projects on the study.

The technical factors of agility of Big Data infrastructure and the infrastructure of the Big Data Analytics technology were indicated to be important on most of the systems, but the bulk of the technical factors were less important than the procedural and business factors, as the firms were not fully investing in advanced integrated Big Data Analytics systems.

Though the firms of this study were investing in limited Big Data Analytics systems, the foundation if not the momentum for optimizing the potential to be smarter with Big Data Analytics technology strategically was indicated on the study.

The results of this study will be meaningful nevertheless in illustrating best practices in Big Data Analytics, as applied from the methodology program introduced by the authors.

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Editor's Note:

This paper was selected for inclusion in the journal as a EDSIGCon 2016 Meritorious Paper. The acceptance rate is typically 15% for this category of paper based on blind reviews from six or more peers including three or more former best papers authors who did not submit a paper in 2016.

APPENDIX

Figure 1: Conceptual Design of Big Data Analytics Methodology Model of Study

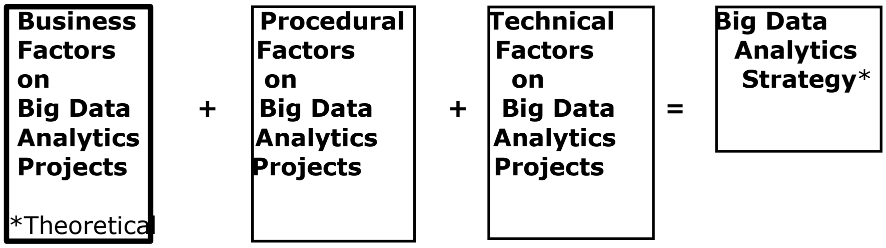

Table 1: Definition of Business, Procedural and Technical Factors of Study

The business factors in the management of Big Data Analytics projects are below:

- Agility and Competitiveness (Phillipps, 2012), Extent to which improved agility and competitiveness contributed to project success;
- Analytical Intuition (Kiron, Prentice, & Ferguson, 2014), Extent to which methods for integrating Big Data Analytics and executive intuition for management contributed to success;
- Analytical Maturity of Organization (Nott 2014, Phillipps, 2012, & Pramanick, 2013), Extent to which maturity of the organization in fundamental Analytics methods contributed to success;
- Analytical Process (McGuire, 2013), Extent to which organizational processes for integrating Big Data Analytics contributed to success;
- Big Data Strategy (Iodine, 2014, McGuire, 2013, & Phillipps, 2012), Extent to which Big Data organizational strategy, having a clearly defined Big Data Analytics subset, contributed to success;
- Budgeting for Big Data Analytics (Columbus, 2014), Extent to which funding for Big Data Analytics contributed to success;
- Center of Excellence (Phillipps, 2012, & Pramanick, 2013), Extent to which growth of Big Data Analytics with Data Analytics best practices, coordinated by a central department of Analytics staff, contributed to success;
- Change Management – Business (Bartik, 2014, Davenport, 2014a, Kiron, Prentice, & Ferguson, 2014, & Nott, 2013), Extent to which changes in business departments of the organization, in order to leverage Big Data Analytics, contributed to success;
- Collaboration in Organization (Columbus, 2014, & Lipsey, 2013), Extent to which cooperation in diverse business and technical departments on Big Data Analytics projects contributed to success;
- Control of Program (Nott, 2013, & Pramanick, 2013), Extent to which control of Big Data Analytics by the business management staff, in close cooperation with the technical staff, contributed to success;
- Data Integration (Columbus, 2014, Lipsey, 2013, Nott, 2013, Phillipps, 2012, & Pramanick, 2013), Extent to which data considered as an asset, common to the organization for accessing and repurposing by diverse business and technical staff, contributed to success;
- Education and Training (Kiron, Prentice, & Ferguson, 2014), Extent to which training of the business and technical staff in Big Data Analytics contributed to success;
- Executive Management Support (Kiron, Prentice, & Ferguson, 2014), Extent to which executive support of Big Data Analytics contributed to success;
- Measurements of Program (Lipsey, 2013, & Phillipps, 2012), Extent to which measurements of performance of the Big Data Analytics projects contributed to success;
- Organizational Strategy (Idoine, 2014, Kiron, Prentice, & Ferguson, 2014, & Nott, 2014), Extent to which integration of Big Data Analytics with organizational strategy contributed to success; and
- Specification of Use Cases (Davenport, 2014a), Extent to which use cases, including functional flows and requirements, contributed to success.

The procedural factors on the projects are below:

- Best Practices (Davenport, 2014, Kiron, Prentice, & Ferguson, 2014, & Pramanick, 2013), Extent to which application of Big Data Analytics best practices from external research contributed to project success;
- Big Data Analytics Governance (Todd, 2010), Extent to which establishment of guidelines for Big Data Analytics initiatives contributed to success;
- Curation of Data (Columbus, 2014, & Nott, 2013), Extent to which curation of Big Data for quality contributed to success;
- Data Ethics and Privacy (Nott, 2013, & Phillipps, 2012), Extent to which initiation of privacy and regulatory requirements contributed to success;
- Data Governance (Nott, 2013, Nott, 2014, & Lipsey, 2013), Extent to which existing data management methods contributed to success;
- Data Security (Columbus, 2014, & Lipsey, 2013), Extent to which initiation of processes for rigorous security of Big Data contributed to success;
- Internal Standards (Bleiberg, 2014), Extent to which governance internal processes contributed to success;
- Process Management (Lipsey, 2013, & Nott, 2013), Extent to which maintenance of processes in Big Data Analytics initiatives contributed to success;
- Program Management and Planning (Bleiberg, 2014, & Davenport, 2014a), Extent to which a centralized management team with iterative planning skills, and with executive management support, contributed to success;
- Responsibilities and Roles (Idoine, 2014, Lipsey, 2013, & McGuire, 2013), Extent to which clearly defined roles of business and technical staff engaged on Big Data Analytics projects contributed to success;
- Risk Management (Weathington, 2014), Extent to which rigorous risk management processes for Big Data contributed to success;
- Selection of Product Software from Vendor(s) (Vance, 2014), Extent to which methodological processes for project selection(s) of software from vendor(s) contributed to success; and
- Staffing (Columbus, 2014, Davenport, 2014, Lipsey, 2013, & Pramanick, 2013), Extent to which business and technical staff on Big Data Analytics projects contributed to success.

The technical factors are below:

- Agility of Infrastructure (Phillipps, 2012), Extent to which infrastructure responsiveness with Big Data contributed to success;
- Change Management – Technology (George, 2014, & Lipsey, 2013), Extent to which infrastructure operational processes for leveraging Big Data Analytics contributed to success;
- Cloud Methods (Pramanick, 2013), Extent to which cloud provider technology contributed to success;
- Data Architecture (Nott, 2014), Extent to which new Big Data organizational processes rules contributed to success;
- Data Services (Lipsey, 2013), Extent to which centralized managed Big Data services contributed to success;
- Entitlement Management (Bartik, 2014), Extent to which management of Big Data access privileges contributed to success;
- Infrastructure of Technology (Columbus, 2014, & Nott, 2013), Extent to which initiation of a scalable technology contributed to success;
- Internal Software (Vance, 2014), Extent to which internal organizational Analytics software contributed to success;
- Multiple Product Software Vendors (Columbus, 2014), Extent to which integration of external Big Data Analytics software from multiple vendors contributed to success;
- Product Software of Vendor (Vance, 2014), Extent to which integration of external Big Data Analytics software from a single vendor contributed to success;
- Usability of Technology (Lipsey, 2013), Extent to which usability of external software and internal organizational software contributed to success; and
- Visualization Tools (Phillipps, 2012), Extent to which Big Data visualization tools contributed to project success.

Table 2: Summary Analytics of Big Data Analytics Factors in Financial Firms of Study

Categorical Factors	Means	Standard Deviations
Business Factors	4.00	1.31
Procedural Factors	3.94	1.51
Technical Factors	2.70	1.62

Legend: (5) Very High in Contribution Role to Big Data Analytics Project Success, (4) High in Contribution Role to Project Success, (3) Intermediate in Contribution Role to Project Success, (2) Low in Contribution Role to Project Success, (1) Very Low in Contribution Role to Project Success, and (0) No Contribution Role to Project Success

Table 3: Detailed Analysis of Big Data Analytics Factors in Financial Firms of Study

Factors of Study	Firm 1 Mean	Firm 2 Means	Firm 3 Means	Firm 4 Means	Firm 5 Means	Summary Means	Standard Deviations
Business Factors							
Agility and Competitiveness	4.00	4.00	5.00	5.00	3.00	4.60	0.55
Analytical Intuition	5.00	5.00	4.00	4.00	5.00	5.00	0.00
Analytical Maturity of Organization	5.00	5.00	4.00	5.00	4.00	4.60	0.55
Analytical Process	5.00	5.00	3.00	5.00	4.00	4.40	0.89
Big Data Strategy	4.00	3.00	2.00	0.00	3.00	2.40	1.52
Budgeting for Big Data Analytics	5.00	5.00	5.00	4.00	5.00	4.80	0.45
Center of Excellence	5.00	5.00	3.00	0.00	3.00	3.20	2.05
Change Management – Business	2.00	3.00	3.00	1.00	3.00	2.40	0.89
Collaboration in Organization	4.00	4.00	4.00	5.00	5.00	4.40	0.55
Control of Program	5.00	5.00	4.00	2.00	5.00	4.20	1.30
Data Integration	5.00	5.00	3.00	5.00	5.00	4.60	0.89
Education and Training	4.00	4.00	5.00	2.00	5.00	4.00	1.22

Executive Management Support	5.00	5.00	5.00	5.00	5.00	5.00	0.00
Measurements of Program	2.00	4.00	4.00	3.00	4.00	3.40	0.89
Organizational Strategy	5.00	5.00	3.00	3.00	5.00	4.20	1.10
Specification of Use Case	5.00	5.00	1.00	1.00	2.00	2.80	2.05
Procedural Factors							
Best Practices	3.00	4.00	3.00	5.00	5.00	4.00	1.00
Big Data Analytics Governance	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Curation of Data	4.00	5.00	5.00	1.00	5.00	4.00	1.73
Data Ethics and Privacy	5.00	3.00	5.00	3.00	5.00	4.20	1.10
Data Governance	5.00	5.00	5.00	4.00	5.00	4.80	0.45
Data Security	5.00	5.00	5.00	3.00	5.00	4.60	0.89
Internal Standards	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Process Management	5.00	5.00	4.00	3.00	5.00	4.40	0.89
Program Management and Planning	5.00	5.00	4.00	1.00	5.00	4.00	1.73
Responsibilities and Roles	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Risk Management	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Selection of Product Software from Vendor(s)	0.00	0.00	0.00	3.00	0.00	0.60	1.34
Staffing	4.00	4.00	5.00	5.00	5.00	4.60	0.55
Technical Factors							
Agility of Infrastructure	3.00	3.00	5.00	5.00	3.00	3.80	1.10
Change Management – Technology	3.00	3.00	3.00	0.00	3.00	2.40	1.34

Cloud Methods	0.00	0.00	4.00	5.00	3.00	2.40	2.30
Data Architecture	3.00	4.00	2.00	0.00	1.00	2.00	1.58
Data Services	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Entitlement Management	4.00	4.00	3.00	1.00	5.00	3.40	1.52
Infrastructure of Technology	3.00	3.00	5.00	5.00	2.00	3.60	1.34
Internal Software	3.00	2.00	1.00	0.00	2.00	1.60	1.14
Multiple Product Software Vendors	0.00	0.00	3.00	2.00	1.00	1.20	1.30
Product Software of Vendor	2.00	3.00	3.00	5.00	3.00	3.20	1.10
Usability of Technology	3.00	3.00	1.00	2.00	4.00	2.60	1.14
Visualization Tools	0.00	0.00	2.00	4.00	5.00	2.20	2.28

For ratings in Table 3 refer to Legend in Table 2.

Table 4: Correlations between Pairs of Big Data Analytics Financial Firms of Study

	Firm 1	**Firm 2**	**Firm 3**	**Firm 4**
Firm 2	0.8440**			
Firm 3	0.2100	0.2120		
Firm 4	0.0032	0.0000	0.3987**	
Firm 5	0.5009**	0.5132**	0.4001**	0.1811

****Correlation is significant at 0.01 level (2-tailed).**
(Kendall tau correlation coefficient)

Table 5: Frequency Distributions of Ratings of Big Data Analytics Financial Firms of Study

- **Business Factors of Study**

Ratings	**Overall**	**Firm 1**	**Firm 2**	**Firm 3**	**Firm 4**	**Firm 5**
0	2.50	0.00	0.00	0.00	12.50	0.00
1	3.75	0.00	0.00	6.25	12.50	0.00
2	7.50	12.50	0.00	6.25	12.50	6.25
3	15.00	0.00	12.50	31.25	12.50	18.75
4	20.00	25.00	25.00	25.00	6.25	18.75
5	51.25	62.50	62.50	31.25	43.75	56.25
Total	100.00	100.00	100.00	100.00	100.00	100.00

Table 6: Frequency Distributions of Ratings of Big Data Analytics Financial Firms
- **Procedural Factors of Study**

Ratings	Overall	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5
0	6.15	7.69	7.69	7.69	0.00	7.69
1	3.08	0.00	0.00	0.00	15.38	0.00
2	6.15	0.00	0.00	0.00	30.77	0.00
3	16.92	7.69	7.69	38.46	30.77	0.00
4	10.77	15.39	15.38	15.38	7.69	0.00
5	56.92	69.23	69.23	38.46	15.38	92.31
Total	100.00	100.00	100.00	100.00	100.00	100.00

Table 7: Frequency Distributions of Ratings of Big Data Analytics Financial Firms of Study
- **Technical Factors of Study**

Ratings	Overall	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5
0	15.00	25.00	25.00	0.00	25.00	0.00
1	8.33	0.00	0.00	16.67	8.33	16.67
2	15.00	8.33	8.33	16.67	25.00	16.67
3	33.33	50.00	41.67	41.67	0.00	33.33
4	10.00	8.33	16.67	8.33	8.33	8.33
5	18.33	8.33	8.33	16.67	33.33	25.00
Total	100.00	100.00	100.00	100.00	100.00	100.00

Table 8: Frequency Distributions of Ratings of Big Data Analytics Financial Firms of Study
- **All Factors of Study**

Ratings	Overall	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5
0	7.31	9.76	9.76	2.44	12.20	2.44
1	4.87	0.00	0.00	7.32	12.20	4.88
2	9.27	7.32	2.44	7.32	21.95	7.32
3	20.98	17.07	19.51	36.59	14.63	17.07
4	14.15	17.07	19.51	17.07	7.32	9.76
5	43.41	48.78	48.78	29.27	31.71	58.54
Total	100.0	100.00	100.00	100.00	100.0	100.00