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INFORMATION SYSTEMS EDUCATION JOURNAL

A Big Data Analytics Methodology Program in the Health Sector

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Abstract

The benefits of Big Data Analytics are cited frequently in the literature. However, the difficulties of implementing Big Data Analytics can limit the number of organizational projects. In this study, the authors evaluate business, procedural and technical factors in the implementation of Big Data Analytics, applying a methodology program. Focusing on organizations in the health sector, the authors learn that business and procedural factors are collectively more critical than factors of technology in managing Big Data Analytics projects that attempt to contribute discernable impact; and they further learn that managing for practical results than for strategy is more evident on the projects in the sector. The study will benefit educators in improving Big Data Analytics curricula with a methodology program and will benefit practitioners in the sector in initiating systems.

Keywords: analytics, big data, big data analytics, heath sector, methodology program

1. BACKGROUND

Big Data is commonly defined as "bigger and bigger and bigger" (Aiden, & Michel, 2013) agglomerates of data. Big Data is data from disparate external and internal multiple sources (Khawaja, 2014), not mere single sources. Big Data Analytics is defined as methods or practices for dissection of Big Data, in order to derive benefits (Beller, & Barnett, 2009). Because of the disparity and multiplicity of sources of Big Data Analytics, the discipline is challenging for business organizations in attempting to achieve benefits, such that Big Data Analytics may be helped by improved Business Intelligence practices. Business organizations, especially in the health sector, are however initiating Big Data Analytics projects (Mamonov, Misra, & Jain, 2014), as the field is cited as a focus of high priority (CIO, 2014, & DMG Consulting Group, 2015).

The benefits of Big Data Analytics are in the conversion of the applicable data into better information for decision-making (Kontzer, 2015). Managers may gain holistic information contributing to improved customer experiences and new opportunities, in products and services that increase organizational profitability (Goldberg, 2014, & Pellet, 2015). Managers in business organizations may gain meaningfully more improved internal processes that further increase profitability and satisfaction (Overby, 2014). Managers in the health care sector may be helped by methods of Big Data Analytics mining (Eddy, 2015b, & Koh, & Tan, 2014), in optimization of processes and in relationship strategies. Literature (Accenture, 2014) indicates the highest managerial satisfaction from implemented Big Data Analytics projects of sector transformations.

Estimates from consulting firms of the Analytics and Business Intelligence field are $14.4 billion of software installations, of which Big Data Analytics is the fastest in investment by business organizations (Gartner Group, 2014). Field investments by the organizations are increasing at an annual growth of 8.5% that is higher than the growth in investments in other technologies (Kiron, Prentice, & Ferguson, 2014), as the organizations highlight the benefits of Big Data Analytics innovation in their sectors. The health sector is increasing investments in Big Data Analytics at $381 million of its technologies in 2014 (Ghosh, 2014), as organizations in the sector indicate the benefits of clinical, medicinal and operational performance from Big Data Analytics projects, justifying Analytics systems as a high priority in 2015. The information on investments in Big Data Analytics is indicating that organizations are beginning to leverage this technology. Though literature (Forrester Group, 2014) is indicating Big Data Analytics as essentially the highest priority in technology in 2015, the methods followed by organizations for fruitful implementation of this technology are elusive in the research.

2. INTRODUCTION TO STUDY

Big Data Analytics is a challenging endeavor to manage in business organizations (Bell, 2015). The appreciation of data as an asset – capital - in a core culture of analytical data-driven organizations is a concern in the information management of Big Data Analytics projects (Kiron, Prentice, & Ferguson, 2014). The appreciation of collaboration on Big Data across departments of organizations is a concern in the absence of data governance on Analytics projects (Weiss, & Drewry, 2014). The complexity of consolidating diverse external and internal multiple Big Data sources for holistic insight on business opportunities by business staff skilled in Big Data Analytics is a concern on systems (Baldwin, 2014). The difficulties of having skilled Analytics technical staff in integrating new platforms of product resilient software (Gupta, 2014) are problems that may preclude the benefits of Big Data Analytics systems. The mandate of executive management for Big Data Analytics is enabled only if scalable technology managed by skilled Big Data technologists is evident in the organizations (Kiron, Prentice, & Ferguson, 2014). The privacy and security of Big Data systems is a major problem (Barocas, & Nissenbaum, 2014), especially in the health sector (Ghosh, 2015b). Literature (McCafferty, 2014) indicates that most organizations fail to maximize meaningful organizational results from the technology. Big Data Analytics is a daunting initiative to organizations attempting to expand the potential of the technology without the maturity of a methodology or a strategy.

In the study, the authors consider a methodology for business organizations initiating Big Data Analytics projects. Managers may not be cognizant collectively of business, procedural and technical dimensions of data and organizational processes (Jagadish, 2014) that may have to be modified on Big Data Analytics projects (Kiron, Prentice, & Ferguson, 2014), in order to maximize the potential of the technology. Technical staff may be cognizant of existing resources and software technologies for localized Analytics or Business Intelligence projects but not of larger network resources and storage technologies needed on Big Data Analytics systems (Klaus, 2014, Singh, Mathur, & Srujana, 2014, and Stonebraker, 2015). The benefits of a disciplined methodology are in comfortably enabling and guiding business and technical staff in incrementally initiating organizational processes and technologies of Big Data Analytics in a Big Data Analytics strategy. The methodology is not a functional project methodology but a global methodology program recognizing the massive scope of Big Data Analytics.

The Big Data Analytics methodology program of this study is a control plan that may be applied to Big Data Analytics projects by business organizations. The features of the methodology consist of Big Data governance (May, 2014), in order to ensure that information is derived optimally for organizational insight. The methodology contains Big Data infrastructure management (Sonderegger, 2014), in order to ensure that Analytics systems interoperate optimally with resilient and scalable technology. The methodology further includes responsibilities and roles of business staff engaging data scientist and skilled technical staff (Dietrich, 2014), in order to ensure that the focus of the Big Data Analytics projects is on business objectives decided by the business management staff. Inclusion of responsibilities and roles and internal standards in the methodology insures that scientist and technical staff are not isolated from business stakeholder staff. The methodology program is a model for best practices in the evolution of Big Data Analytics projects in organizations, such as in the health sector (Ghosh, 2015a). The research is limited on models of best practices from a methodology program on Big Data Analytics projects (Moore, 2014). In short, the methodology program of the study benefits organizations with best practices that may be a foundation for a fruitful Big Data Analytics strategy.

3. FOCUS OF STUDY

The essence of the study is to evaluate business, procedural and technical factors of a Big Data Analytics methodology program in the implementation of organizational projects. The factors are formulated by the authors from leading practitioner researchers, given limited scholarly sources. The focus of the study is on factor impacts on project success.

The business factors on the implementation 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 Big Data Analytics best practices, coordinated by a central department of Analytics staff contributed to success;
- *Change Management – Business* (Bartik, 2014, Davenport, 2014, 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 technology 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 the 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, and Nott, 2014), Extent to which integration of Big Data Analytics with organizational strategy contributed to success; and*
- *Specification of Use Cases (Davenport, 2014), Extent to which use cases, including functional flows and requirements, contributed to success.*

The procedural factors on the projects are:

- *Best Practices (Davenport, 2014, Kiron, Prentice, & Ferguson, 2014, and 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 Governance (Nott, 2013, Nott, 2014, & Lipsey, 2013), Extent to which existing data management methods 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, 2014), 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;*
- *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:

- *Agility of Infrastructure (Phillipps, 2012), Extent to which infrastructure responsiveness with Big Data contributed to project 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 Ethics and Privacy (Nott, 2013, & Phillipps, 2012), Extent to which initiation of privacy and regulatory requirements contributed to success;*
- *Data Security (Columbus, 2014, & Lipsey, 2013), Extent to which initiation of processes for rigorous security of Big Data 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.*

Literature (IBM, 2014, & Informs, 2014) indicates that most organizations lack a methodology program to evaluate Big Data Analytics maturity, notably in the health sector, which is highly motivated to initiate investment in the technology (Eddy, 2015a). The study will benefit educators (Analytics, 2014) in informing information systems students on organizational practices and will help practitioners (Davis, 2014) in learning an integrated methodology program for strategy and success.

4. RESEARCH METHODOLOGY

The research methodology of the study consisted of a case study of 5 organizations in the health sector, chosen from Big Data Analytics pioneers headquartered in New York City and highlighted in leading practitioner publications in the July – December 2014 period. The health sector was chosen by the authors as the sector correlated to the first sector of study in their concentration curriculum for Big Data Analytics at the Seidenberg School of Computer Science and Information Systems of Pace University (Molluzzo & Lawler, 2015) – energy, entertainment, financial and retailing sectors will be studied in the 2016 – 2019 period.

The projects in the 5 organizations in the health sector were evaluated by the first and third authors from a checklist definition instrument of survey of the 41 aforementioned Big Data Analytics factors of the methodology program, in the January – April 2015 period. The factors were evaluated on evidence of contribution to Big Data Analytics project success, on a 6-point Likert-like rating scale:

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

The evaluations were founded on in-depth observation of mid-management project members in the organizations, averaging 3 – 5 personnel in the organizations; informed perceptions of observation rationale by the third author, a practitioner of 35+ years; and research reviews of secondary studies by the first author.

The checklist instrument of the study was checked in the context of construct, content and face validity and content validity, measured in sample validity, by the second author. The methodology was consistent in creditability and proven reliability with earlier studies by the authors on cloud computing (Lawler, Howell-Barber, & Joseph, 2014) and service-oriented architecture (SOA) technology (Lawler & Howell-Barber, 2008). The data from the evaluations was interpreted in the MATLAB 7.10.0 Statistics Toolbox (McClave & Sincich, 2006) by the second author, in the May – June 2015 period, for the following section and the tables in the Appendix.

5. ANALYSIS OF DATA

Detailed Analysis of Organizations* in Health Sector

Organization 1: Health Insurance Provider
Project: Medical Analytics System

Organization 1 is (in revenue) a large-sized national organization that focused on a medical predictive analytics project, in order to gain a competitive edge in the sector. The goal of the system was to integrate external and internal data of employees of customer organizations that could be helped by interventions in lifestyles to lessen diseases. The system helped the employees in disease management and the member organizations in cost management, in predicting and reducing health risks.

Organization 1 benefited by a *Center of Excellence* (5.00) of Big Data business and technical staff that managed the project with *Cloud Methods* (5.00) and the *Infrastructure* (5.00) of proprietary *Product Software from a Vendor* (5.00). Factors of *Process Management* (4.00) and *Program Management and Planning* (4.00) were evident highly in the *Center of Excellence* (5.00), with data flows of functions and requirements in *Specifications of Use Cases* (5.00). *Data Ethics and Privacy* (4.00) and *Security* (4.00) were evident highly in the process. The *Center of Excellence* (5.00) focused however on incrementally interpolating Big Data on discrete diseases without fully integrating the business departments of Organization 1 in *Control of Program* (1.00) and *Data Governance* (2.00), or in a *Big Data* (1.00) or *Organizational* (2.00) *Strategy*. The project was managed with the factors of *Budgeting* (5.00) and *Executive Support* (3.00), but without *Internal Standards* (0.00) or *Measurements of Program* (1.00).

Organization 1 is an example of an organization gaining leverage with Big Data Analytics, but not optimizing the project for a more fruitful governance and strategy.

Organization 2: Health Monitoring Provider
Project: Medical Monitoring System

Organization 2 is a large-sized national organization that focused on a predictive surveillance system, in order to improve knowledge of health threats and trends. The goal of the system was to integrate external and internal data of events in hospitals that could be helpful and insightful to scientists in investigating and responding sooner to threats. The system helped the scientists in propagating standards in hospital systems, in order to be responsive to trends.

Organization 2 benefited by a higher *Analytical Process* (5.00) than Organization 1, as *Big Data Analytics Governance* (4.00) and *Data Governance* (4.00) were evident on the Organization 2 project. Factors of *Internal Standards* (5.00) and *Measurements of Program* (4.00) were evident highly in the organizational Big Data Analytics project. Organization 2 focused on the external and internal data on the hospitals, through *Internal Software* (3.00) and through predictive *Product Software of Vendor* (2.00), but without historical *Analytical Intuition* (1.00) and without requiring *Cloud Methods* (0.00). *Data Ethics and Privacy* (4.00) and *Security* (5.00) were prudently recognized by the scientists. The project was impressively managed with a *Big Data Strategy* (5.00).

Organization 2 is an example of an organization improving its Big Data Analytics with governance methods and with initiation of strategy with mostly internal technologies.

Organization 3: Health Mail Order Pharmacy Provider
Project: Medical Patient Prescription System

Organization 3 is a mid-sized regional organization that focused on a predictive proactive prescription system, in order to increase knowledge of patient prescriptions. The goal of the system was to integrate external and internal data on patients that could be helpful to the patients and to their physicians in prescribing the taking or non-taking of the prescriptions. The system helped the patients in management of prescriptions and the member physicians in cost and health management, in reducing preventable risks.

Organization 3 distinguished its Big Data Analytics initiative by *Analytical Intuition* (5.00), *Analytical Process* (5.00) and *Analytical Maturity of Organization* (5.00). Procedural factors of *Process Management* (4.00), *Program Management and Planning* (4.00) and *Risk Management* (5.00) were evident highly on the project. The project included a *Center of Excellence* (5.00) of skilled business and technical staff, integrating only its *Internal Software* (5.00) technologies and involving the business departments of the organization in *Collaboration in Organization* (4.00), with *Executive Support* (5.00). *Ethics and Privacy* (4.00) and *Security* (5.00) were recognized in the initiative in Organization 3, as in Organizations 2 and 1. Though the maturity of the organization in analytical processes and technologies was more notable on the project, the maturity was less notable in *Big Data Analytics Governance* (3.00), *Data Governance* (3.00), *Internal Standards* (3.00) and *Measurement of Program* (1.00), and in *Big Data* (2.00) and *Organizational* (3.00) *Strategy*.

Organization 3 is an example of an organization in the health sector increasing its initiative in Big Data projects, but not positioning its processes and technologies for the rigor of a Big Data Analytics strategy.

Organization 4: Hospital Organization Provider
Project: Medical Residential System

Organization 4 is a large-sized national organization that initiated a predictive proactive residential system, in order to integrate Big Data information from localized device monitors of patients. The objective of this system was to integrate this external information into a clinical data repository that could be helpful in a holistic interpretation of patient progress. The system helped hospital physicians and staff, in more meaningful profiling of patients from remote sites.

This organization enabled its Big Data initiative by a *Center of Excellence* (4.00) of internal data scientist staff that managed the project with non-proprietary Analytics *Software from a Vendor* (5.00). Inclusion of *Internal Software* (2.00) and internal non-scientist technical staff not in the *Center of Excellence* (4.00) were limited on the project. The project was limited in *Big Data Analytics Governance* (3.00) and *Data Governance* (3.00), and in *Internal Standards* (3.00) and *Measurement of Program* (1.00) notably, though the project was managed from *Big Data Strategy* (3.00) and *Organizational Strategy* (4.00) of integrating the external information on the monitors of the patients into the internal repository system, with precise *Specification of Use Cases* (5.00). This organization was sensitive to *Privacy* (4.00) and *Security* (4.00), as in Organizations 3, 2 and 1. This project was managed with the concurrence of *Executive Support* (4.00) without reservation.

Organization 4 is an illustration of a provider in the sector initiating a meaningful Big Data Analytics project without re-engineering internal processes.

Organization 5: Hospital Organization Provider
Project: Medical Treatment System

This organization is a small-sized regional organization that initiated a specialized treatment system, in order to interpolate Big Data findings from national studies. The objective of this system was to interpolate this external information with internal information on patients that could be helpful to hospital physicians in offering options of personalized treatments. The system helped the patients and the physicians in scenarios of specialized treatments.

This organizational project was managed by *Center of Excellence* (4.00) data scientist staff with limited organizational technologists. The project was however impressively managed with more *Big Data Analytics Governance* (4.00), *Data Governance* (5.00), *Internal Standards* (5.00), *Process Management* (4.00) and *Program Management and Planning* (4.00) overall, than on the previous projects. The *Product Software of* the *Vendor* (5.00) was the project technology, without *Internal Software* (0.00) technologies. The scientist staff was sensitive to *Privacy* (4.00) and *Security* (5.00), as in the previous projects. The staff was not overtly sensitive to *Big Data Strategy* (2.00) or *Organizational Strategy* (2.00), nor to *Measurement of the Program* (2.00), with senior management in *Executive Support* (5.00) supporting minimal strategic techniques.

This organization is an illustration of a provider in the sector proceeding on a meaningful but specific Big Data Analytics system without further strategic techniques.

*Organizations are not identified in the Analysis due to competitive imperatives in the sector.

Summary Analysis of Organizations in Health Sector

The analysis of the data findings from the organizations in the section is highlighting the business factors (3.09 [summary in Table 1 in the Appendix]) as important to Big Data Analytics success. The *Center of Excellence* in Big Data Analytics (4.20 [detail in Table 2]) having largely scientist staff, the funding through *Budgeting* of the projects (4.00) and the *Management Support* (4.40) were more important in most of the organizations. The factors of *Big Data Strategy* (2.60), *Change Management* (1.40), *Control of Program* (2.00), *Measurements of Program* (1.80), and *Organizational Strategy* (2.60) were less important on most of the projects, as the organizations were focused more on the nuances of the project results, not on re-engineering strategy.

The analysis of the findings is indicating the procedural factors (3.80) were important to success, but more than the business factors (3.09). The procedural factors of *Process Management* (4.00), *Program Management and Planning* (3.40) and *Risk Management* (5.00) were important on most of the projects, but *Big Data Analytics Governance* (3.20), *Data Governance* (3.40) and *Internal Standards* (3.20) were less important on most of the projects to Big Data Analytics success, as the organizations were focused on practical results from systems, not procedural techniques.

The technical factors (3.44) were also important to success, but less than the procedural (3.80) and more than the business (3.09) factors. The technical factors of a single *Product Software of a Vendor* (3.60), interoperating in the *Agility of Infrastructure* (4.60) with the existing organizational *Infrastructure Technology* (4.20) were more important than *Cloud Methods* (1.20), *Internal Software* (2.00) technologies and *Multiple Product Software Vendors* (1.80), as the organizations were focused more on product software technologies of so-called Big Data Analytics vendors. The factors of *Data Ethics and Privacy* (4.00) and *Data Security* (4.60) were important on all of the projects, as the organizations were notably sensitive to Big Data Analytics of health information.

Essentially, the factors of the Big Data Analytics methodology program were found at different ratings to be facilitating the organizational projects in the sector more in results than in strategies.
(Correlations between pairs of the organizations are in Table 3, and frequency of ratings across the factors are in Table 4, of the Appendix.)

6. IMPLICATIONS OF STUDY

The evaluations of the organizations in the study found that a Center of Excellence in Big Data Analytics was critical on the projects in the health sector. The center of data scientists drove the Predictive Analytics projects with their skills. Even though the center might have cooperated more efficiently with the internal organizational staff (Harris, & Mehrotra, 2014), if not integrated more of its skills with this staff, the data scientists enabled insightful integration of the Big Data for management teams. The center, as a dedicated department that was business driven, dissuaded ad hoc Analytics departments (Greengard, 2015) in the organizations. The importance of a distinct department for Big Data Analytics is an immediate implication for the health sector.

The evaluations of the organizations found however that centralized Big Data governance of the projects was not considered as critical in the cultures of these pioneers as an established Center of Excellence. The governance of the projects was not customized for Big Data from the existing governance methods for mundane Data projects. Measurements of optimized performance of the projects were elusive in most of the organizations. The organizations might have further improved methods for ever-increasing needs for resiliency and scalability (CenturyLink, 2014) of the Big Data Analytics systems. The importance of a governance methodology model needed for Big Data Analytics projects is an implication for the health sector.

The evaluations in the study found that privacy and security were considered critical factors for management in the organizations. The organizations had new policies on the privacy of Big Data health information on patients, as security is crucial in the health sector (Shaw, 2014). The importance of privacy and security on Big Data Analytics systems is a further implication of the study.

The organizations were found to be gaining important insight from their Big Data Analytics projects. Still, though these organizations were leveraging the projects, mostly in patient services, for success, they were not maximizing methods or optimizing processes in a Big Data Analytics strategy. They were short of a Big Data Analytics strategy that might be incrementally positioning the potential of Big Data Analytics software technologies (Overby, 2014). This might not be negative in the health sector (Asay, 2014), as other sectors are indicated to be in preliminary stages with these technologies (Batra, 2015, & Major, 2014). The importance of a needed Big Data Analytics strategy, to optimize the potential of Big Data Analytics technologies, is an implication for the health sector.

Finally, the evaluations of the organizations in the study highlighted the need for Big Data Analytics health sector staff (Collett, 2014). Most of the organizational staff, apart from the data scientist staff, were without Big Data Analytics skills. Educational programs in schools of computer science and information systems might be improved with inter-disciplinary skills (Wegryn, 2014), so that graduate and undergraduate students might gradually have initial smarts as specialists in Big Data Analytics. Programs might be improved in internships with organizations (Fitzgerald, 2014), such that they might be initially prepared for projects in the sector. The importance of education and training in Big Data Analytics is the last implication for this sector.

7. LIMITATIONS AND OPPORTUNITIES IN RESEARCH

The findings from this study are from a limited number of organizations incrementally pioneering Big Data Analytics projects in the health sector. The leveraging of Big Data Analytics in the sector is inhibited by a limited maturity in methodology that does not maximize the technologies. The results of this study may not be generalized to the sector or other sectors without caution. The findings from the Big Data Analytics methodology program of this study furnish however a foundation for further research into the implementation of Big Data Analytics projects, as organizations pursue the technologies. This foundation will benefit educators in integrating best practices into information systems curricula and practitioners in the sector in pursuing success.

8. CONCLUSION

The authors conclude that the organizations in the health sector of this study are benefiting from Big Data Analytics projects.

Business factors, from an applied Big Data Analytics methodology program, were important in project success. Centers of Excellence in Big Data Analytics, as distinct entities in the organizations, were instrumental in the success.

Procedural factors of process management, program management and risk management were especially important, more than the business factors. Factors of Big Data governance and Data governance and internal standards were not important on the projects, as the organizations were focused on narrow results from systems, not procedural techniques.

Factors of technology were integral in project success, less pronounced than the procedural but more pronounced than the business factors of the Big Data Analytics methodology program, in the sector. Health information in the Big Data Analytics systems was managed with high privacy and security sensitivity.

The organizations proceeded on the projects short of Big Data Analytics strategies that would have incrementally optimized the power of the technologies. The organizations in the sector were also short of Big Data Analytics skills, but were substantially supported by the data scientist specialist staff in the Centers of Excellence, in the period of this study.

The results of this study will be helpful to instructors in schools of computer science and information systems and to practitioners in the health sector, and other organizational sectors, interested in searching for Big Data Analytics success techniques if not transformation.

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APPENDIX

Table 1: Summary Analysis of Big Data Analytics Factors in Organizations in Health Sector

Categorical Factors of Methodology	Means	Standard Deviations
Business Factors	3.09	1.37
Procedural Factors	3.80	1.06
Technical Factors	3.44	1.68

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

Table 2: Detailed Analysis of Big Data Analytics Factors in Organizations in Health Sector Organizations

Business Factors	Org 1 Means	Org 2 Means	Org 3 Means	Org 4 Means	Org 5 Means	Summary Means	Standard Deviations
Agility and Competitiveness	5.00	2.00	4.00	5.00	3.00	3.40	1.52
Analytical Intuition	1.00	1.00	5.00	3.00	3.00	2.60	1.67
Analytical Maturity of Organization	5.00	3.00	5.00	4.00	4.00	4.20	0.84
Analytical Process	3.00	5.00	5.00	3.00	4.00	4.00	1.00
Big Data Strategy	1.00	5.00	2.00	3.00	2.00	2.60	1.52
Budgeting for Big Data Analytics	5.00	3.00	4.00	4.00	4.00	4.00	0.71
Center of Excellence	5.00	3.00	5.00	4.00	4.00	4.20	0.84
Change Management	0.00	1.00	2.00	2.00	2.00	1.40	0.89
Collaboration in Organization	3.00	1.00	4.00	3.00	3.00	2.80	1.10
Control of Program	1.00	2.00	2.00	2.00	3.00	2.00	0.71
Data Integration	2.00	3.00	3.00	2.00	5.00	3.00	1.22
Education and Training	1.00	4.00	3.00	3.00	3.00	2.80	1.10
Executive Management Support	3.00	5.00	5.00	4.00	5.00	4.40	0.89
Measurements of Program	1.00	4.00	1.00	1.00	2.00	1.80	1.30
Organizational Strategy	2.00	2.00	3.00	4.00	2.00	2.60	0.89
Specification of Use Cases	5.00	4.00	2.00	5.00	2.00	3.60	1.52

Procedural Factors	Org 1 Means	Org 2 Means	Org 3 Means	Org 4 Means	Org 5 Means	Summary Means	Standard Deviations
Best Practices	4.00	4.00	3.00	3.00	5.00	3.80	0.84
Big Data Analytics Governance	2.00	4.00	3.00	3.00	4.00	3.20	0.84
Curation of Data	4.00	5.00	4.00	4.00	5.00	4.40	0.55
Data Governance	2.00	4.00	3.00	3.00	5.00	3.40	1.14
Internal Standards	0.00	5.00	3.00	3.00	5.00	3.20	2.05
Process Management	4.00	4.00	4.00	4.00	4.00	4.00	0.00
Program Management and Planning	4.00	2.00	4.00	3.00	4.00	3.40	0.89
Responsibilities and Roles	5.00	2.00	4.00	3.00	5.00	3.80	1.30
Risk Management	5.00	5.00	5.00	5.00	5.00	5.00	0.00
Selection of Product Software from Vendor(s)	5.00	3.00	3.00	3.00	4.00	3.60	0.89
Staffing	5.00	3.00	4.00	3.00	5.00	4.00	1.00

Technical Factors	Org 1 Means	Org 2 Means	Org 3 Means	Org 4 Means	Org 5 Means	Summary Means	Standard Deviations
Agility of Infrastructure	5.00	4.00	4.00	5.00	5.00	4.60	0.55
Change Management	4.00	4.00	4.00	4.00	5.00	4.20	0.45
Cloud Methods	5.00	0.00	0.00	1.00	0.00	1.20	2.17
Data Architecture	1.00	4.00	2.00	4.00	2.00	2.60	1.34
Data Ethics and Privacy	4.00	4.00	4.00	4.00	4.00	4.00	0.00
Data Security	4.00	5.00	5.00	4.00	5.00	4.60	0.55
Data Services	0.00	3.00	1.00	2.00	5.00	2.20	1.92
Entitlement Management	5.00	5.00	4.00	4.00	5.00	4.60	0.55
Infrastructure of Technology	5.00	3.00	3.00	5.00	5.00	4.20	1.10
Internal Software	0.00	3.00	5.00	2.00	0.00	2.00	2.12
Multiple Product Software Vendors	0.00	2.00	3.00	4.00	0.00	1.80	1.79
Product Software of Vendor	5.00	2.00	1.00	5.00	5.00	3.60	1.95
Usability of Technology	3.00	4.00	5.00	4.00	5.00	4.20	0.84
Visualization Tools	5.00	4.00	4.00	4.00	5.00	4.40	0.55

Legend: Refer to Legend in Table 1.

Table 3: Correlations between Pairs of Big Data Analytics Organizations in Health Sector Study

	Organization 1	**Organization 2**	**Organization 3**	**Organization 4**
Organization 2	-0.0122			
Organization 3	0.1905	0.2307		
Organization 4	(0.4956)*	0.2104	0.2371	
Organization 5	(0.3257)**	(0.3535)*	(0.2753)**	0.2471

*Correlation is significant at the 0.01 level (2-tailed).
**Correlation is significant at the 0.05 level (2-tailed).
[Kendall Tau Correlation Coefficient]

Table 4: Frequency of Ratings across Big Data Analytics Factors in Health Sector Study

	Organization 1	**Organization 2**	**Organization 3**	**Organization 4**	**Organization 5**
Ratings					
0	12.2	2.4	2.4	0.0	7.3
1 – Very Low	14.6	7.3	7.3	4.9	0.0
2 – Low	9.8	17.1	14.6	12.2	14.6
3 – Intermediate	9.8	22.0	24.4	31.7	12.2
4 – High	17.1	31.7	29.3	36.6	22.0
5 – Very High	36.6	19.5	22.0	14.6	43.9
in Significance					

Legend: Refer to Legend in Table 1