

# Evaluate Impacts of Big Data on Organizational Performance: Using Intellectual Capital as a Proxy

Thuan L Nguyen

Graduate School, University of North Texas, Denton, Texas, USA

**Abstract** - *Big data analytics has come out as a new important field of study for both researchers and practitioners, demonstrating the significant demand for solutions to business problems in a data-driven knowledge-based economy. Employing the emergent technology successfully is not easy, and assessing the roles of big data in improving firm performance is even much harder. Additionally, empirical studies examining the impacts of the nascent technology on organizational performance remain scarce. The present study aimed to fill the gap. This study suggested using firms' intellectual capital as a proxy for the performance of big data implementation in assessing its influence on business performance. The present study employed the Value Added Intellectual Coefficient method to measure corporate intellectual capital, via its three main components: human capital efficiency, structural capital efficiency, and capital employed efficiency, and then used the structural equation modeling technique to model the data and test the models. The financial fundamental and market data of 100 randomly selected publicly listed firms in the sector of pharmaceutical, biotechnology, and life sciences were collected. The results of the tests showed that only human capital efficiency and capital employed efficiency had a significant positive impact on firm profitability, which highlighted the prominent roles of enterprise employees and financial capital in the impacts of big data technology.*

**Keywords:** Big Data, Big Data Analytics, Organizational Performance, Intellectual Capital, Value Added Intellectual Coefficient (VAIC™).

## 1 Introduction

Although many companies have made big data one of the top priorities of their business strategy, either having invested or planning to invest heavily in the technology, few of them did know how to generate value-added from it [43, 52]. Employing the emergent technology successfully is not easy, and assessing the roles of big data in improving firm performance is even much harder [8, 11, 12, 39, 43, 49]. More importantly, the basic question of whether or not the big data technology has a significant positive impact on the bottom line of firms was not yet answered clearly in academic [8, 39]. Additionally, empirical studies examining the impacts of big data analytics on organizational performance remained scarce [8, 39, 51, 54].

This study aimed to fill the gap, making significant contributions to both academic research and industrial practice. The present study contributed to the literature of multiple related fields: information systems, big data and data science, business intelligence, knowledge management and intellectual capital. The findings of this study contributed to the accumulated empirical evidence that big data can help firms regardless of size improve their business performance and increase profitability because the technology enables companies to serve customers much better and do business much more efficiently [13, 26, 36, 43]. Tan and Wong [48] suggested that if something could not be measured, it could not be managed. As above, it is very difficult to measure the performance of big data in firms, which in turn makes it a daunting task to evaluate the impacts of big data implementation on firm outcomes [8, 11, 12, 39, 43, 49]. To facilitate the assessment of big data effects on organizational performance, this study suggested using firm intellectual capital (IC) as a proxy for big data performance.

The present study tried to answer the following research questions: How does big data performance, represented by the three core efficiency indicators of IC (HCE, SCE, CEE), impact firm performance? The remainder of this study is organized as follows. The next section discusses the theoretical background. The third section is a brief literature review that sheds light on the ultimate goals of implementing big data in firms, then introduces the basic concepts of IC viewed as organizational knowledge and discusses the link between big data performance and IC. Research methodology is presented in the next section, which is followed by the results. The fifth section presents discussion and implications. Finally, the study concludes with the section of implications and conclusions.

## 2 Theoretical Background

There exist various theories that postulate different views of the firm. Although there may be many differences in what these theories state, the central question all of them try to answer is what makes firms different from each other [1, 14, 31]. Why does this firm compete against its competitors much better than another one [2, 4]? How can a firm achieve much better business performance than others in the same industry [27, 28]?

One of the theories of the firm most-mentioned in the literature is the resource-based view (RBV). To the above question, the theory provides an answer that some of organizational resources possessed by a firm – labeled as strategic resources – and how these resources are managed enable it to gain competitive advantage and achieve superior performance [2, 4]. This theory argues that strategic resources help a firm compete better and operate more efficiently because they are valuable, rare, inimitable, and non-substitutable (VRIN) [4, 15].

### 3 Literature Review

#### 3.1 Big Data and Its Ultimate Goals to Create Organizational Knowledge

Big data can help organizations generate more value-added in nearly any aspect of their business. In employing big data technology, firms aim to get analytical insights into huge volumes of data, and then leverage the business intelligence extracted from the data to improve business outcomes [10, 26, 43, 54]. In other words, the ultimate goals of implementing big data in firms are to create more organizational knowledge that can be used to gain and sustain competitive advantage, capture more market share, and improve business performance. Therefore, the measurement of corporate organizational knowledge can reflect the performance of implementing big data in firms.

#### 3.2 Intellectual Capital (IC): Another Name of Organizational Knowledge

It is widely recognized that IC consists of three major components: human capital (HC), structural capital (SC), and relational capital (RC) [32, 40, 47]. Human Capital (HC) represents the collective knowledge, skills, creativity, experience, and even enthusiasm of employees of a firm [19, 46]. Structural Capital (SC) indicates the institutionalized experience and codified knowledge generated by an organization as a whole such as corporate structures, processes, technology models and inventions, patents, copyright, business strategy, and information systems [15, 17]. Relational Capital (RC) represents the value generated through the relationship with customers, suppliers, and other external stakeholders [47].

According to Kianto et al. [24] and Kaya et al. [20], IC is the knowledge within an organization, a.k.a. organizational knowledge. According to these authors, IC and organizational knowledge are the same things if both are viewed from the static perspective of corporate assets [24]. Therefore, IC can be viewed as an organization's stock of knowledge at any time [38]. In other words, firm IC is organizational knowledge that has been acquired and formalized to be used in creating value, gaining competitive advantage, and achieving superior performance [24, 33, 38].

#### 3.3 Intellectual Capital (IC): A Proxy for Big Data Performance

As above, the ultimate goals of implementing big data in firms are to create more organizational knowledge that can be used to gain and sustain competitive advantage, capture more market share, and improve business performance [10, 13, 26]. Besides, corporate IC can be viewed as organizational knowledge that can help companies enhance competitiveness and achieve superior performance [24, 20]. Therefore, IC measurement can be used as a proxy for the performance of big data implementation in firms. In other words, it is reasonable to measure firm IC and then employ its measurement in assessing the impacts of big data on organizational performance, which addresses the research question.

#### 3.4 IC, VAICTM, and Organizational Performance

The concept of IC is believed to be first discussed in detail by the Economist John Kenneth Galbraith in 1969 [20]. Since then, the concept of IC in organizational meaning has been widely known and studied thanks to Thomas Stewart's articles about "brainpower" published by Forbes magazine in 1991 [47].

The IC literature also presents a large variety of methods that can be used to measure IC in firms [38, 47]. Among these approaches, the Value Added Intellectual Coefficient (VAICTM) model is one of the most popular tools to assess IC performance in organizations. Developed by Pulic [37], the VAIC model aims to calculate the set of efficiency indicators (HCE, SCE, and CEE) and the VAIC. The values can be used to represent the measurement of IC in firms [19, 25 29]. The model provides a simple, but effective, approach to measuring IC and then using the measurement to evaluate the influence of IC on firm performance [23]. According to Khanhossini et al. [22], the VAIC model is much better than other methods of measuring IC.

In a broad perspective, the review of the literature supports the accumulated empirical evidence that IC has a significant positive impact on organizational performance [1]. However, the results varied considerably from one industry to another, or from one country to a different one, considering the influence of IC components – HC, SC, RC, or the effect of efficiency elements – HCE, SCE, CEE, on corporate business outcomes.

### 4 Research Methodology

#### 4.1 Value Added Intellectual Coefficient (VAICTM) Model

The VAIC model is based on the concept of value added that is a measurement reflecting the contribution of employees, management, and other resources of a firm to create value [37]. More importantly, value added normally leads to the creation

of wealth in the company [37]. The total value added (VA) can be computed with the following formula:

$$VA = Op. Profit + Emp. Expenses + D + A \quad (1)$$

Where Op. Profit is Operating Profit, Emp. Expenses are normally the total salaries and wages, D is Depreciation, and A is Amortization.

Next, the efficiency indicators (HCE, SCE, and CEE) are computed as follows:

$$HCE = VA / HC \text{ (Human Capital)} \quad (2)$$

Where HC is the employee expenses, normally the total salaries and wages.

$$SCE = SC \text{ (Structural Capital)} / VA \quad (3)$$

$$\text{Where } SC = VA - HC \quad (4)$$

$$CEE = VA / CE \text{ (Capital Employed)} \quad (5)$$

Where  $CE = \text{Property, Plant \& Equipment} + \text{Current Assets} - \text{Current Liabilities}$  (6)

Finally, the VAIC value is the sum of the three efficiency indicators:

$$VAIC = HCE + SCE + CEE \quad (7)$$

Then, the set of efficiency indicators (HCE, SCE, and CEE) or the VAIC value is used straightforwardly as IC measurement in research [1, 29, 41]. VAIC is considered better than other methods for measuring IC because it is simple and transparent [19, 22], and it provides a basis for standard measurement [22]. Additionally, the research data are collected from the annual filing documents reported by firms whose data have been audited by third parties and available on the websites of the companies or governmental agencies that oversee securities markets [19, 22].

### 4.2 Research Variables

In this study, IC – as a proxy for big data performance – was the central predictor that was represented by its three efficiency indicators: HCE, SCE, and CEE [1, 29, 41]. Then, these efficiency indicators were used as the independent variables [1, 29, 41]).

The dependent variables were the three indicators used to measure organizational performance: ROA (return-on-assets) representing profitability, ATO (asset-turnover) indicating productivity, and market value for market performance [18, 50].

### 4.3 Data Collection

The financial fundamental and market data of 100 randomly selected publicly listed firms in the sector of pharmaceutical, biotechnology, and life sciences were collected, using the online service of financial analytics S&P Capital IQ Platform provided by McGraw Hill Financial.

### 4.4 Theoretical Model and Research Hypotheses

Based on the reviewed literature, the following theoretical model is proposed:

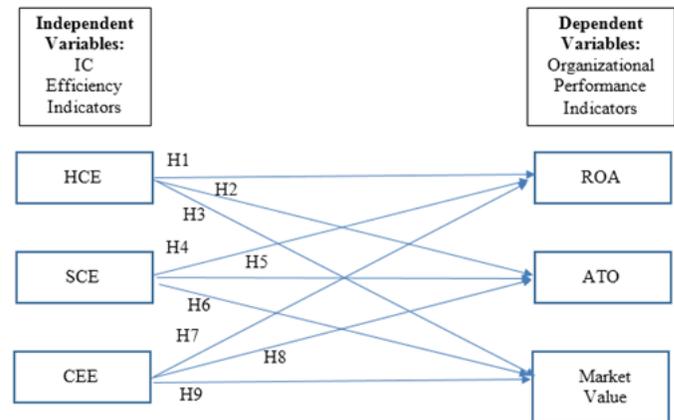


Figure 1. Theoretical Model for Research

Based on the theories of the firm and the reviewed literature, the following hypotheses were proposed:

- H1: HCE has a significant positive impact on ROA.
- H2: HCE has a significant positive impact on ATO.
- H3: HCE has a significant positive impact on market value.
- H4: SCE has a significant positive impact on ROA.
- H5: SCE has a significant positive impact on ATO.
- H6: SCE has a significant positive impact on market value.
- H7: CEE has a significant positive impact on ROA
- H8: CEE has a significant positive impact on ATO
- H9: CEE has a significant positive impact on market value.

### 4.5 Testing the Model

Structural equation modeling (SEM) has been one of the statistical techniques widely chosen by researchers across disciplines [16]. SEM is frequently employed in the IC literature to study the impact of IC on firm performance [9, 22]. A SEM analysis was performed using the AMOS software to test the models in the study. The estimation of the SEM models

was conducted employing maximum likelihood estimation (MLE). MLE is a technique used to reveal the most likely function(s) that can explain, i.e., fit, observed data [30]. MLE has been the most widely used fitting function for structural equation models [6].

### 5 Results

The following fit indices were used for the evaluation of the model fit: Model chi-square ( $\chi^2$ ), goodness-of-fit index (GFI), normed-fit-index (NFI), comparative fit index (CFI), and root mean square error of approximation (RMSEA). The chi-square value ( $\chi^2$ ) assessed the overall model fit [16, 53]. To indicate a good model fit, the chi-square statistic must be insignificant at 0.05 threshold, i.e.  $p > 0.05$  [16].

The results showed that the model fit the data: chi-square = 3.835, degrees of freedom = 2, and probability level = 0.147 ( $> 0.05$ ). Table 1 summarizes the goodness of fit values and thresholds for these fit indices:

Goodness-of-Fit Index	Recommended Values	Values from this study
Comparative Fit Index (CFI)	>0.90	0.992
Goodness-of-Fit Index (GFI)	>0.90	0.987
Normalized Fit Index (NFI)	>0.90	0.984
Root mean square error of approximation (RMSEA)	<0.10	0.096

Table 1. Values of Goodness of Fit Indices: CFI, GFI, NFI, and RMSEA

The findings of the study found that only Hypotheses H1 and H7 are supported. The results are summarized in Table 2 and Table 3:

Hypothesis	Coefficient ( $\beta$ )	Statistical Significance (p)
H1	0.228	***
H2	0.140	0.224
H3	-0.003	0.975
H4	-0.035	0.475
H5	-0.101	0.334

H6	0.044	0.626
H7	0.750	***
H8	-0.038	0.749
H9	0.109	0.525

\* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$

Table 2: Summary of results of testing the first nine hypotheses: H1 – H9

Hypothesis	Hypothesized Path	Supported or Rejected
H1	HCE $\rightarrow$ ROA	Supported
H2	HCE $\rightarrow$ ATO	Rejected
H3	HCE $\rightarrow$ Market Value	Rejected
H4	SCE $\rightarrow$ ROA	Rejected
H5	SCE $\rightarrow$ ATO	Rejected
H6	SCE $\rightarrow$ Market Value	Rejected
H7	CEE $\rightarrow$ ROA	Supported
H8	CEE $\rightarrow$ ATO	Rejected
H9	CEE $\rightarrow$ Market Value	Rejected

Table 3: Summary of results of testing the first nine hypotheses: H1 – H9

Hypothesis H1 proposed that HCE has a significant and positive impact on ROA. The results ( $\beta = 0.646$ ,  $p < 0.001$ ) supported this hypothesis confirming that HCE significantly and positively influences firm profitability. The findings of the present study are consistent with those found in the previous studies conducted by Al-Musali and Ku Ismail [1] and Sarmadi [41]. However, these results are different from those obtained by Joshi et al. [19] and Morariu [29]. In these studies, the authors found that the impact of either HCE or IC on firm profitability was insignificant.

Hypothesis H7 proposed that CEE has a significant and positive impact on ROA. The results ( $\beta = 0.750$ ,  $p < 0.05$ ) supported this hypothesis confirming that CEE significantly and positively influences firm profitability. The findings of the present study are consistent with those obtained by Khahossini et al. [22] and Sarmadi [41]. However, these results are different from those obtained by Morariu [29]. In this study, the author found that the impact of CEE or IC on profitability was insignificant.

## 6 Discussion and Implications

As a nascent field, big data analytics or data science evolve with a warp speed, which has definitely caught the attention of scholars and practitioners in various industries [13, 26] (). The results from a 2015 survey of 437 organizations worldwide administered by the research firm Gartner showed that more than 75% of surveyed firms are investing or having a plan to invest in big data in the next two years.

However, the same survey surprisingly revealed that 43% of the companies that planned to invest and 38% of those that already invested in big data technology were not sure about what would be the results of their investment – whether their investments produces a positive ROI (return on investment) or not (Gartner, 2015). The big issue is that these companies either did not know how to measure or could not effectively evaluate the performance of using big data technology to extract business intelligence that enables them to gain competitive advantage and improve the bottom line [3].

The findings of this study contributed to the accumulated empirical evidence that big data can help firms regardless of size improve their business performance and increase profitability because the technology enables companies to serve customers much better and do business much more efficiently [3, 13, 26, 54]. Most importantly, the present study provided an answer with empirical evidence to the crucial question of whether or not big data or business intelligence, brings out critical business values that has been “left unanswered” [8].

The literature review found that case-based research has been popular in studies on big data analytics, especially about its impacts on organizational performance. With the use of causal modeling approach, this study would help to strengthen the empirical trend in big data research and provide a model for future research on the impact of big data initiatives.

Additionally, the findings of this study will reveal which factor of big data technology – human, technology, or capital employed – may have the most significant influence on firm business outcomes. The results of testing the models indicated that human capital efficiency and capital employed efficiency have a significant positive impact on firm profitability, which highlighted the prominent human role and financial capital in the impacts of big data technology.

## 7 Conclusion

In summary, many hurdles may be found on the path to success of firms' big data implementation [26, 43]. Employing the emergent technology successfully has its own challenges, and managing big data effectively to improve business performance is even much harder [26]. However, companies have clearly recognized that data-driven decisions are those they should make [13, 26, 43]. Many companies of different sizes have considered big data as one of the top priorities that

should get significant time and attention from the top executives (Forbes Insight, 2015). All organizations that have put enough efforts and investments in their big data business strategy and executed it soundly can harvest the results via gaining competitive advantage and improving performance

The primary limitation of the present study is that only publicly listed companies that have reported their annual revenue are included in the research. Another limitation is that only cross-sectional data, for the fiscal year 2014 – 2015, were collected and used for the study. One more limitation is that SEM was employed in analyzing the data and testing the model. Although SEM has been one of the statistical techniques widely chosen by researchers across disciplines [6, 16], this statistical technique has its limitations. In studies with research sample size smaller than 250, the technique may over-reject true models. Future research may include both public listed and privately held companies in the sample. Researchers may use panel data of a larger sample that are collected for three, five years, or longer. Further research may also consider performing a full content analysis on the link between big data performance and IC.

## 8 References

- [1] Al-Musali, M., & Ku Ismail, K. “Intellectual capital and its effect on financial performance of banks: Evidence from Saudi Arabia”; *Procedia - Social and Behavioral Sciences*, Vol. 164, Issue 2014, 201 – 207, 2014.
- [2] Andreeva, T., & Kianto, A. “Does knowledge management really matter? Linking knowledge management practices, competitiveness and economic performance”. *Journal of Knowledge Management*, Vol. 16, Issue 4, 617 – 636, 2012.
- [3] Arora, B., & Rahman, Z. “Using Big Data Analytics for Competitive Advantage”; *International Journal of Innovative Research and Development*, Vol. 5, Issue 2, 248 – 250, 2016.
- [4] Barney, J.B. “Firm resources and sustained competitive advantage”; *Journal of Management*, Vol. 17, Issue 1, 99 – 120, 1991.
- [5] Bean, R. “Why cultural change is necessary for big data adoption?” Retrieved from <https://www.forbes.com/sites/ciocentral/2016/11/08/another-side-of-big-data-big-data-for-social-good-2/#6045b0166288>, 2016.
- [6] Bollen, K. A. “Structural equations with latent variables”. New York, NY: John Wiley & Sons, 1989.
- [7] Bontis, N. “Assessing knowledge assets: a review of the models used to measure intellectual capital”. *International Journal of Management Review*, 3(1), 41 – 60, 2001.

- [8] Chen, X., & Siau, K. "Effect of Business Intelligence and IT Infrastructure Flexibility on Organizational Agility". In Proceedings of the 33rd International Conference on Information Systems, Orlando, Florida, 2012.
- [9] Deep, R., & Narwal, K. P. "Intellectual capital and its association with financial performance: A study of Indian textile sector"; International Journal of Management & Business Research, Vol. 4, Issue 1, 43 – 54, 2014.
- [10] Dhar, V. "Data science and prediction". Communications of the ACM, Issue 56, 64 – 73, 2013.
- [11] Elbashir, M. Z., Collier, P. A., & Davern, M. J. "Measuring the effects of business intelligence systems - The relationship between business process and organizational performance"; International Journal of Accounting Information Systems, 9(2008), 135 – 153, 2008.
- [12] Gartner. "Gartner survey shows more than 75 percent of companies are investing or planning to invest in big data in the next two years". Retrieved from <http://www.gartner.com/newsroom/id/3130817>, 2015.
- [13] George, G., & Lavie, D. "Big data and data science methods for management research"; Academy of Management Journal, Vol. 59, Issue 5, 1493 – 1507, 2016.
- [14] Grant, R. M. "Towards A knowledge-based theory of the firm"; Strategic Management Journal, Vol. 17, Issue Winter Special, 109 – 122, 1996.
- [15] Han, Y., & Li. D. "Effects of intellectual capital on innovative performance: The role of knowledge-based dynamic capability"; Journal of Knowledge Management, Vol. 53, Issue 1, 40 – 56, 2015.
- [16] Hooper, D., Coughlan, J., & Mullen, M. "Structural equation modelling: Guidelines for determining model fit"; Electronic Journal of Business Research Methods, Vol. 6, Issue 1, 53 – 60, 2008.
- [17] Hsu, I. C., & Sabherwal, R. "Relationship between intellectual capital and knowledge management: An empirical investigation"; Decision Sciences, Vol. 43, Issue 3, 489 – 524, 2012.
- [18] Hudgins, M. R. "The Impact of Intellectual Capital on the Performance of U.S. Property-Casualty Insurance Companies"; Business and Economics Journals, Vol. 5, Issue 4, 1 – 6, 2014.
- [19] Joshi, M., Cahill, D., Sidhu, J., & Kansal, M. "Intellectual capital and financial performance: an evaluation of the Australian financial sector"; Journal of Intellectual Capital, Vol. 14, Issue 2, 264 – 285, 2013.
- [20] Kaya, F., Sahin, G., & Gurson, P. "Intellectual capital in organizations"; Problems and Perspectives in Management, Vol. 8, Issue 1, 153 – 160, 2010.
- [21] Khalique, M., Bontis, N., Shaari, J., & Isa, A. "Intellectual capital in small and medium enterprises in Pakistan"; Journal of Intellectual Capital, 16(1), 224 – 238, 2015.
- [22] Khanhossini, D., Nikoonesbati, M., K., Heire, H., & Moazez, E. "Investigating of relationship between intellectual capital and financial performance in MAPNA group companies"; Retrieved from [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2216638](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2216638), 2013.
- [23] Kharal, M., Zia-ur-Rehman, M., Abrar, M., Khan, M., Kharal, M. "Intellectual Capital & Firm Performance: An Empirical Study on the Oil & Gas Sector of Pakistan"; International Journal of Accounting and Financial Reporting, Vol. 4, Issue 1, 238 – 261, 2014.
- [24] Kianto, A., Ritala, P., Spender, J., & Vanhala, M. "The interaction of intellectual capital assets and knowledge management practices in organizational value creation"; Journal of Intellectual capital, Vol. 15, Issue 3, 362 – 375, 2014.
- [25] Kweh, Q., Chan, Y., & Ting, I. "Measuring intellectual capital efficiency in the Malaysian software sector"; Journal of Intellectual Capital, Vol. 14, Issue 2, 310-324, 2013.
- [26] McAfee, A., & Brynjolfsson, E. "Big data: The management revolution"; Harvard Business Review, Issue 90, 61 – 67, 2012.
- [27] Mehri, M., Umar, M.S., Saeidi, P., Hekmat, R.K., & Naslmosavi, S. "Intellectual Capital and Firm Performance of High Intangible Intensive Industries: Malaysia Evidence"; Asian Social Science, Vol. 9, Issue 9, 146 – 154, 2013.
- [28] Mills, A. M., & Smith, T. A. "Knowledge management and organizational performance: a decomposed view"; Journal of Knowledge Management, Col. 15, Issue 1, 156 – 171, 2011.
- [29] Morariu, C. "Intellectual capital performance in the case of Romanian public companies"; Journal of Intellectual Capital, Vol. 15, Issue 3, 392 – 410, 2014.
- [30] Myung, I. J. "Tutorial on maximum likelihood estimation"; Journal of Mathematical Psychology, Vol. 47, Issue 2003, 90 – 100, 2003.
- [31] Nelson, R.R. "How do firms differ and how does it matter?" Strategic Management Journal, Vol. 12, Special Issue, 61 – 74, 1991.

- [32] Nemati, S., Jalilian, H. R., & Akbari, P. "Investigate the relationship between intellectual capital and company performance (Dairy Industry of Kermanshah Province)"; *Scientific Journal of Pure and Applied Sciences*, Vol. 2, Issue 12, 379 – 385, 2013.
- [33] Nguyen, T. L. "Assessing knowledge management values by using intellectual capital to measure organizational performance" (Doctoral dissertation). Nova Southeastern University. Retrieved from NSUWorks, College of Engineering and Computing. (986), 2016.
- [34] Pham, P. "The Impacts of big data that you may not have heard of"; Retrieved from <https://www.forbes.com/sites/peterpham/2015/08/28/the-impacts-of-big-data-that-you-may-not-have-heard-of/#5713d5336429>, 2015.
- [35] Poletto, T., Heuer de Carvalho, V. D., & Costa, A. "The Roles of Big Data in the Decision-Support Process: An Empirical Investigation"; Retrieved from [https://www.researchgate.net/publication/282271513\\_The\\_Roles\\_of\\_Big\\_Data\\_in\\_the\\_Decision-Support\\_Process\\_An\\_Empirical\\_Investigation](https://www.researchgate.net/publication/282271513_The_Roles_of_Big_Data_in_the_Decision-Support_Process_An_Empirical_Investigation), 2015.
- [36] Pulic, A "Measuring the performance of intellectual potential in knowledge economy"; Retrieved from <http://www.vaic-on.net/download/Papers/Measuring%20the%20Performance%20of%20Intellectual%20Potential.pdf>, 1998.
- [37] Ragab, M., & Arisha, A. "Knowledge management and measurement: a critical review"; *Journal of Knowledge Management*, Vol. 17, Issue 6, 873 – 901, 2013.
- [38] Richards, G., Yeoh, W., Chong, A. Y. L., & Popovic, A. "An empirical study of business intelligence impact on corporate performance management"; In *Proceedings of Pacific Asia Conference on Information Systems (PACIS)*, 2014.
- [39] Roos, J., Roos, G., Dragonetti, N., & Edvinsson, L. "Intellectual Capital: Navigating in the New Business Landscape". London: Macmillan Business, 1997.
- [40] Sarmadi, S. "Investigating of relationship between intellectual capital and financial performance of Petrochemical Companies listed in Tehran Stock Exchange"; *Social Science Research Network*. Retrieved from [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2251620](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2251620), 2013.
- [41] Slavkovic, M., & Bbic, V. "Knowledge management, innovativeness, and organizational performance: Evidence from Serbia"; *Economic Annals*, Vol. LVIII, Issue 199, 85 – 107, 2013.
- [42] Stourm, L., and Ebbes, P. "Analytics in the Era of Big Data: Opportunities and Challenges"; Retrieved from <http://www.hec.edu/Knowledge/Point-of-View/Analytics-in-the-Era-of-Big-Data-Opportunities-and-Challenges>, 2017.
- [43] Strawn, G.O. "Scientific research: How many paradigms?" *EDUCAUSE Review*, Vol. 47, Issue 3, 26 – 34, 2012.
- [44] Sudhir, K. "What Is the Impact of Big Data?" Retrieved from <http://insights.som.yale.edu/insights/what-is-the-impact-of-big-data>, 2017.
- [45] Suraj, O., & Bontis, N. "Managing intellectual capital in Nigerian telecommunications companies"; *Journal of Intellectual Capital*, Vol. 13, Issue 2, 262 – 282, 2012.
- [46] Sveiby, K.E. "The New Organizational Wealth: Managing and Measuring Knowledge-Based Assets". New York, NY: Berrett-Koehler, 1997.
- [47] Importance in Performance Measurement"; In *Proceedings of the 11th International Conference on Intellectual Capital, Knowledge Management and Organizational Learning*, Sydney, Australia, 6-7 November 2014.
- [48] Thamir, A. & Poulis, E. "Business intelligence capabilities and implementation strategies"; *International Journal of Global Business*, 8(1), 34 – 45, 2015.
- [49] Vishnu, S., & Gupta, V. "Intellectual capital and performance of pharmaceutical firms in India"; *Journal of Intellectual Capital*, 15(1), 83 – 99, 2014.
- [50] Vuksic, V. B., Bach, M. P., & Popovic, A. "Supporting performance management with business process management and business intelligence: A case analysis of integration and orchestration"; *International Journal of Information Management*, 33(4), 613 – 619, 2013.
- [51] Wedel, M., and Kannan, P. K. "Marketing analytics for data-rich environments"; *Journal of Marketing*, Issue 80, 97 – 121, 2016.
- [52] Wuensch, K. L. "Conducting a path analysis with SPSS/AMOS"; Retrieved from <http://core.ecu.edu/psyc/wuenschk/MV/SEM/Path-SPSS-AMOS.pdf>, 2016.
- [53] Yanqing, D., & Guangming, C. "An analysis of the impact of business analytics on innovation"; In *Proceedings of the 23rd European Conference on Information Systems (ECIS)*, 2015, Munster, Germany, 2015.
- [54] Zikopoulos, P., and Eaton, C. "Understanding big data: Analytics for enterprise class Hadoop and streaming data"; New York, NY: McGraw-Hill, 2011.