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Big Data Analytics Talent Quality

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Abstract

Competing in today's business world depends on big data analytics (BDA). Organizations are increasingly realizing the importance of BDA and investing accordingly in infrastructure and BDA talent quality, both critical as firms look to gain a competitive advantage. This study examines significant group differences between several selected variables (i.e., gender, age, BDA usage length, and management level) and BDA talent quality. Findings are discussed and recommendations are made for building and enhancing BDA talent quality in organizations

Keywords: Big data analytics, talent quality, competencies

Introduction

Organizations are increasingly investing in big data analytics (BDA) to gain a competitive edge (Constantiou & Kallinikos, 2015). Big data, according to Kamioka & Tapainen (2014), is large-scale data that includes data storage, management, analysis, and visualization of very large and complex datasets. BDA is defined by Ghasemaghaei et al (2015) as tools and processes related to very large datasets that generate meaningful insights to organizations for gaining competitive advantage. BDA is defined by other scholars as a means to analyze and interpret all types of digital information (Loebbecke & Picot, 2015); as the application of multiple analytic methods that address the diversity of big data producing actionable descriptive, predictive, and prescriptive results (Lamba & Dubey, 2015); and as the statistical modeling of large, diverse, and dynamic datasets (Müller et al., 2016).

BDA talent quality, i.e.; the ability of the analytics personnel to be able to execute tasks related to technology management, technical issues, business processes, and relational matters that influence a firm's performance become a vital issue for gaining competitive advantage (Koohang & Nord, 2021; Kiron et al., 2014).

Davenport & Harris (2006) defined BDA capabilities as a unique competency in setting up the organization for gaining competitive advantage. Xu & Kim (2014) looked at the BDA capability as business intelligence capabilities from the viewpoint of infrastructures, skills, execution, and relationships. Kung et al. (2015) viewed BDA capabilities as a firm's ability to acquire, store, process, and analyze large-scale data or big data to improve firm performance. Koohang & Nord (2021) referred to BDA Talent quality as technical competencies, technology management competencies, business competencies, and relational competencies demonstrated by the analytics personnel within a firm.

The goal of this paper is to examine mean differences between/among the levels of some selected variables and BDA talent quality (technical competencies, technology management competencies, business competencies, and relational competencies). This paper is organized as follows. First, a review of the literature is presented following the purpose of the study and the research question. Second, the research methodology is described. Third, the results are presented. Fourth, the findings and their implications are discussed.

Literature review

Human capital is fundamental to support companies and organizations' operations. Companies and organizations attempt to hire personnel that are efficient, bring value, and make important contributions to the organization (Maurer, 2015; Bates, 2018). Human capital is defined as "people's wisdom, knowledge, ideas, skills, and health" (Chen, Hsu, Hung, & Wu, 2016, p. 86). In the hiring process, employers look for the employees' talents and experience, focusing on hiring talent quality. However, most of the time employees are not assessed for quality in their job performance and companies struggle while spending time and resources (McGuire, 2018; Lermusi, n.d).

Organizations provide training to employees, which is considered an investment rather than a waste (Chen et. al., 2016). Training is defined as "the process of using a learning plan to help employees improve their work performance by verifying, evaluating, and assisting their personal development" (Chen et. al., 2016, p.85). Quality is accomplished when employees reach and/or exceed expectations in their work performance (Röger, Rütten, Ziemainz, & Hill, 2010). Efforts are made to improve employees' talent quality since human capital is a key factor and a valuable asset possessed by organizations (Chen et. al., 2016; Waheed & Zaim, 2015). Also, the organizations' success depends on the professional abilities of its employees (Meenakom & Wajeetongratana, 2018).

Competencies and experience are vital factors in terms of talent quality (Chen 2014). As argued by Keller and Meaney (2017), complex jobs are now being taken by personnel with more sophisticated technical skills that can identify and analyze the organization's data. As mentioned by Wamba, Akter, and Bourmont (2017, p. 2), big data analytics is now being used by companies as a "… process to manage, process and analyze the five Vs (volume, variety, velocity, veracity, and value)" to be competitive. Companies use big data and data analytics to recognize trends and needs before making decisions.

According to Nocker & Sena (2019), data analytics "refers to the methodologies that allow one to analyze big data stored by businesses" (p. 4). Personnel in charge of data analytics should be able to inform stakeholders about the organization's functioning and development. Data analytics personnel, or talent analytics, are professionals who can "help answer key questions" and also are able to identify sources of risks (Nocker & Sena, 2019, p. 2). According to George et al. (2016), big data refer to a large and wide-ranging volume of data that can be collected and managed. According to Davenport (2013, pp. 66-67) big data "… came to be distinguished from small data because it was not generated purely by a firm's internal transaction systems. It was externally sourced as well, coming from the internet, sensors of various types, public data initiatives such as the human genome project, and captures of audio and video recordings."

Big data analytics (BDA) is defined as the "…complex process of examining big data to uncover information -- such as hidden patterns, correlations, market trends, and customer preferences -- that can help organizations make informed business decisions." (TechTarget, n.d.) According to Gantz and Reinsel (2012), BDA centers on three major characteristics - the data itself, the analytics applied to the data, and the presentation of results. All these characteristics create business value for organizations.

Big data analytics (BDA) has surfaced as a holistic method to managing, processing, and analyzing the five data-related dimensions, i.e., volume, variety, velocity, veracity, and value that generates actionable ideas for delivering sustained value, measuring performance, and establishing competitive advantages (Fosso et al., 2015).

Loebbecke & Picot (2015, p. 2) defined BDA as "… a means to analyze and interpret any kind of digital information. Technical and analytical advancements in big data analytics, which – in large part – determine the functional scope of today's digital products and services, are crucial for the development of sophisticated artificial intelligence, cognitive computing capabilities, and business intelligence."

Hagstrom (2012, p. 2) referred to BDA as a "… new paradigm of knowledge assets" while Manyika et al. (2011) indicated that BDA is the future for innovation that leads to competition and productivity. Other scholars believe that BDA enhances data-driven decision making and innovation (Kiron, 2013; Yiu, 2012; Hagel, 2015); helps companies manage risks, reduces costs, improves supply chain visibility (Verbraken et al. 2012); gain competitive advantage (Tan et al. 2015); and improve overall firm performance (Kiron, 2013).

In general, BDA is looked at as technology and technique (Kwon et al., 2014) and application of multiple analytic approaches to descriptive, predictive, and prescriptive results (Lamba & Dubey, 2015) to improve organizational performance. Kiron et al. (2014) stated that the adoption of analytics within organizations is growing exponentially and organizations are confronting the issue of quality to sustain gaining competitive advantage. Quality, according to Srinivasan and Kurey (2014, p.23), has "… never mattered more. New technologies have empowered customers to seek out and compare an endless array of products from around the globe." Kiron, et al. (2014) stated that quality in BDA is critical to all businesses that capitalize on value.

Kim et al. (2012) defined talent quality as the ability of data scientist personnel to have competencies in technology management, technical, business, and relational. Kiron et al. (2014) stated that the talent capabilities such as analytical talent, technical knowledge, and business knowledge of personnel positively affect the effective dissemination of knowledge, consequently, contributing to a firm's performance. Similarly, other scholars agree that talent competencies positively influence a firm's core business and operational functions (Davenport et al., 2012); corporate strategy, and IT infrastructure and process (McAfee and Brynjolfsson, 2012, Wixom et al., 2013, Wamba et al., 2015, Ransbotham et al., 2015); building an effective model-based decision and control (Ransbotham et al., 2015); building advanced analytics models for predicting and optimizing outcomes (Barton and Court, 2012); planning and coordinating between analytical producers and managers (Ransbotham et al., 2015).

The success of BDA largely depends on the talent quality of data scientists. Davenport (2013) stated that the talent quality of data scientist personnel influences all the business processes related to BDA and in turn leads the organization to gain a competitive advantage.

The purpose of this study is to examine whether there are significant differences between/among the independent variables (gender, age, BDA usage length, and management level) and the dependent variable (BDA talent quality). Consistent with its purpose, the following research question (RQ) is asked. Is there a significant difference between/among the levels of each independent variable and the dependent variable?

For the present study, we chose and adapted the BDA talent quality definition from a study conducted by Koohang and Nord (2021). Accordingly, BDA talent quality is defined as technical competencies, technology management competencies, business competencies, and relational competencies demonstrated by a firm's analytics personnel as they play a key role in influencing an organization's performance (Koohang & Nord, 2021). These competencies specifically point to analytics personnel 1) being skilled in various aspects of big data analytics i.e., expert systems, artificial intelligence, data warehousing, mining, marts, programming, data management, project life cycle, etc.; 2) showing superior ability to manage existing and new technologies related to BDA; 3) being capable of interpreting business problems to develop appropriate solutions related to BDA; and 4) being skilled to work closely with internal and external customers to maintain productive user/client relationships in an organization that uses BDA.

We chose gender, age, BDA usage length, and management level to determine if any of these independent variables are significant contributors to the perception of BDA talent quality. Previous studies have addressed the importance of BDA to businesses in gaining a competitive advantage, but few have conducted research to look at contributing factors regarding talent quality perception.

Methodology

Instrument

The instrument used for this study is based on a study conducted by Kim et al. (2012) and further adapted by Koohang and Nord (2021). It is a Likert-type instrument consisting of four items that explain the BDA talent quality – technical competencies, technology management competencies, business competencies, and relational competencies. The items of the instrument were slightly modified for the present study and they are as follows.

1. Our analytics personnel are skilled in various aspects of big data analytics (i.e., expert systems, artificial intelligence, data warehousing, mining, marts, programming, data management, project life cycle, etc.)
2. Our analytics personnel show superior ability to manage existing and new technologies.
3. Our analytics personnel are capable of interpreting business problems to develop appropriate solutions.
4. Our analytics personnel work closely with internal and external customers to maintain productive user/client relationships.

The instrument used a seven-point scale for scoring strategy, i.e., 7 = Completely Agree, 6 = Mostly Agree, 5 = Somewhat Agree, 4 = Neither Agree nor Disagree, 3 = Somewhat Disagree, 2 = Mostly Disagree, and 1 = Completely Disagree.

Subjects & Procedure

The subjects (N = 164) were intermediate, middle management, senior management employees from organizations that used BDA in various regions in the USA. The survey instrument was administered electronically to approximately 300 employees. We received 167 completed surveys. Of the 167, 3 were eliminated (See the result section regarding outlier test). Subjects were from various types of organizations, i.e., Manufacturing = 4%, Banking/Financial Services = 9%, Insurance = 6%, Tech/Computer Software = 13%, Health Care/Medical = 16%, Retail = 11%, Government/Military = 7%, Services = 14%, and Other = 21%. The company size where the subject came from was 1- 50 = 21%, 51- 500 = 31%, 501- 2,000 = 18%, 2001- 10,000 = 13%, and Over 10,000 = 17%. The top 10 BDA software used by the organizations were Tableau, SAS, Python, Splunk, R, Qlikview, Apache Spark, RapidMiner, Apache Storm, and KNIME. Subjects were 18 years and older and they were assured confidentiality and anonymity.

Data Analysis

We used univariate Analysis of Variances (ANOVA) to answer the research question. The univariate ANOVA procedure is used when there are multiple independent variables with one dependent variable. According to Mertler & Vannatta (2010), five requirements must be fulfilled before conducting the univariate ANOVA. They are

1) The dependent variable must be continuous.
2) Each independent variable must be comprised of two or more levels.
3) There must be no relationship between the observations in each group or between the groups.
4) The outliers must be identified and eliminated.
5) Data must be tested for homogeneity of variances using Levene's test which determines the equality of variances of the data. A non-significant value from Levene's test indicates homogeneity of variance.

When the above requirements are met, the univariate ANOVA is conducted where the F value is calculated for each independent variable to determine the significance of the groups on the dependent variable. For any significant findings, post hoc analysis is conducted for groups of more than two levels. Descriptive analyses are performed to show the means and standard deviation of the dependent variable with each independent variable.

Results

Our data showed that the following conditions were fulfilled, i.e., the dependent variable (Talent quality) was continuous and all four independent variables (Gender, Age, BDA Usage Length, and Management level) were comprised of two or more levels. Next, an outlier test was conducted to identify and eliminate outliers. Three cases from the original data (N = 167) were eliminated because of unusual or extreme multivariate outliers. This yielded a final number of subjects (N = 164) to be entered into the analysis.

Figure 1 shows the descriptive analysis of the BDA talent quality (technical competencies, technology management competencies, business competencies, and relational competencies). As can be seen, the values for all BDA talent quality were above the statistical average.

Figure 1: Descriptive Analysis for Talent Quality Competencies

Subsequently, the data were tested for homogeneity of variances using Levene's test which determines the equality of variances of the data. Results showed a non-significant value ($p = .449$) from Levene's test indicating homogeneity of variance. In other words, Levene's test examined the null hypothesis that the error variance of the dependent variable is equal across groups (See Table 1).

Table 1. Levene's Test of Equality of Error Variances

F	df1	df2	Sig.
1.026	65	98	.449

Design: Intercept + Gender + Age + BDA Usage Length + Management Level
Dependent Variable: Talent quality

Univariate ANOVA

Table 2 shows the results of the univariate ANOVA for the dependent variable of Talent quality and the independent variables of Gender, Age, BDA Usage Length, and Management level.

Non-significant Variables

Gender and age: As can be seen from Table 3, there were no significant differences found for the independent variables of gender and age. Male and female subjects believed that talent quality equally exists among the analytics personnel in their organizations. Moreover, subjects in all age categories also equally believed that BDA talent quality exists among the analytics personnel in their organizations. Tables 3 & 4 show means and standard deviations for gender and age.

Table 2. Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	26.286[a]	9	2.921	2.008	.042
Intercept	3141.759	1	3141.759	2160.530	.000
Gender	.056	1	.056	.038	.845
Age	2.800	3	.933	.642	.589
BDA Usage Length	13.780	3	4.593	3.159	**.026**
Management Level	9.621	2	4.810	3.308	**.039**
Error	223.941	154	1.454		
Total	4731.188	164			
Corrected Total	250.227	163			

Dependent variable: Talent quality

Table 3: Means and Standard Deviations for Gender

	N	Mean	Std. Deviation	Std. Error
Female	81	5.2222	1.31992	.14666
Male	83	5.2319	1.16267	.12762
Prefer not to say	0	0	0	0
Total	164	5.2271	1.23901	.09675

Table 4: Means and Standard Deviations for Age

	N	Mean	Std. Deviation	Std. Error
20 - 35	50	5.3500	1.02145	.14446
36 - 45	44	5.0625	1.41640	.21353
46 - 55	42	5.1250	1.30694	.20166
Over 55	28	5.4196	1.20772	.22824
Total	164	5.2271	1.23901	.09675

Significant Variables

BDA Usage Length: As can be seen from Table 2, there was a significant difference found for the independent variable of BDA usage length. Subjects with longer experience with BDA usage in their organizations scored significantly higher (4 – 5 years and more than 5 years) than those with shorter experience with BDA usage in their organizations (less than 1 year and 1 – 3 years). The longer the experience with BDA usage, the more the subjects believed that BDA talent quality exists among the analytics personnel in their organizations. Table 5 shows the means and standard deviations for BDA usage length. The results of the Post hoc analysis are shown in Table 6.

Table 5: Means and Standard Deviations for BDA Usage Length

	N	Mean	Std. Deviation	Std. Error
Less than 1 year	16	4.3438	1.78856	.44714
1 - 3 years	42	5.2440	1.07279	.16554
4 - 5 years	68	5.3493	1.08942	.13211
More than 5 years	38	5.3618	1.28754	.20887
Total	164	5.2271	1.23901	.09675

Table 6: Multiple Comparisons for BDA Usage Length

(I) Usage	(J) Usage	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1	2	-.9003	.35427	.096	-1.9017	.1011
	3	-1.0055*	.33507	.032	-1.9526	-.0584
	4	-1.0181*	.35938	.049	-2.0339	-.0023
2	1	.9003	.35427	.096	-.1011	1.9017
	3	-.1052	.23666	.978	-.7742	.5637
	4	-.1178	.26998	.979	-.8809	.6454
3	1	1.0055*	.33507	.032	.0584	1.9526
	2	.1052	.23666	.978	-.5637	.7742
	4	-.0126	.24424	1.000	-.7030	.6778
4	1	1.0181*	.35938	.049	.0023	2.0339
	2	.1178	.26998	.979	-.6454	.8809
	3	.0126	.24424	1.000	-.6778	.7030

* The mean difference is significant at the .05 level | 1 = Less than 1 year, 2 = 1 - 3 years, 3 = 4 - 7 years, and 4 = More than 10 years

Management Level: As can be seen in Table 2, there was a significant difference found for the independent variable of management level. Senior management significantly scored higher than other levels of management (middle and intermediate). In other words, the belief in the existence of talent quality among the analytics personnel was significantly higher among senior management. Table 7 shows the means and standard deviations for the management level. The results of the Post hoc analysis are shown in Table 8.

Table 7: Means and Standard Deviations for Management Level

	N	Mean	Std. Deviation	Std. Error
Senior management	41	5.6098	1.27359	.19890
Middle management	64	5.0508	1.33792	.16724
Intermediate	59	5.1525	1.05252	.13703
Total	164	5.2271	1.23901	.09675

Table 8: Multiple Comparisons for Management Level

(I) Level	(J) Level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1	2	.5590*	.24122	.022	.0824	1.0355
	3	.4572	.24518	.064	-.0271	.9416
2	1	-.5590*	.24122	.022	-1.0355	-.0824
	3	-.1018	.21764	.641	-.5317	.3282
3	1	-.4572	.24518	.064	-.9416	.0271
	2	.1018	.21764	.641	-.3282	.5317

* The mean difference is significant at the 0.05 level | 1 = Senior management, 2 = Middle management, and 3 = Intermediate

Discussion

This study was conducted to find out whether there are significant mean differences between the independent variables (gender, age, BDA usage length, and management level) and the dependent variable of BDA Talent quality. BDA talent quality was defined as the competencies that the analytic personnel within an organization possess and demonstrate to advance a firm's performance. These competencies are technical, technology management, business, and relational.

The findings showed that males and females believed that BDA talent quality (technical competencies, technology management competencies, business competencies, and relational competencies) equally exists among the analytics personnel in their organizations. Furthermore, subjects in all age categories also believed that BDA talent quality technical competencies, technology management competencies, business competencies, and relational competencies) equally exists among the analytics personnel in their organizations.

There were, however, significant differences between the independent variables (BDA usage length and management levels) and the dependent variable of BDA talent quality. Subjects with more experience with BDA usage had significantly more favorable belief that BDA talent quality (technical competencies, technology management competencies, business competencies, and relational competencies) exists among the analytics personnel in their organizations. Moreover, senior management had a significantly more favorable belief that BDA talent quality (technical competencies, technology management competencies, business competencies, and relational competencies) exists among the analytics personnel in their organizations.

Although results revealed that BDA talent quality was perceived equally among respondents regardless of their gender or age, this finding is important in that it is an indication that these variables do not influence the perception of talent quality.

Organizations with more experience with BDA usage had a significantly higher belief that BDA talent quality competencies exist among the analytics personnel in their organizations. This finding suggests that experience with BDA usage may play a role in analytics personnel influencing the success of the firm's performance. Building and enhancing BDA talent quality competencies among analytics personnel within organizations requires a significant effort of creating a culture that includes continuous training and education. The training and education must focus on providing the necessary tools and resources to analytics personnel with sound strategies to successfully gain and improve the competencies that influence a firm's performance.

Management should implement specific training for the analytics personnel for the specific competencies (technical competencies, technology management competencies, business competencies, and relational competencies) as a strategic plan for continued success in BDA. Various competencies relating to managing existing and new technologies, awareness of BDA technical aspects, evaluating business challenges and solutions, and building and maintaining internal and external relationships with customers and clients allow organizations to further enhance the skills and abilities of the analytics personnel.

Conclusions

Big data analytics (BDA) talent quality (technical competencies, technology management competencies, business competencies, and relational competencies) as perceived by the respondents of this study resulted in values above the statistical average. Although there were significant differences between the independent variables (BDA usage length and management levels) and the dependent variable of BDA talent quality, senior management had a significantly more favorable understanding (more than middle and intermediate management) of the existence of BDA talent quality among the analytics personnel in their organizations. This finding is unique because of the nature of the senior level managers' responsibilities, i.e., articulating the organizational vision, formulating strategies, establishing goals and objectives. It is the responsibility of middle-level managers to execute organizational plans while intermediate-level managers execute tasks and deliverables. Looking at the responsibilities of the three levels of management, the following questions merit future exploration and discussion: Does the information regarding BDA Talent quality competencies flow effectively among the three levels of management so each level of management understands what they have to accomplish to address competencies? Do all management levels effectively communicate (upward and downward) with each other to address any issues with the BDA Talent quality competencies of the analytics personnel?

Each organization should assess its BDA talent quality and implement programs based on the results and recommendations of this study. Just as corporate communication and leadership skills emerge from employees with vast experience and knowledge, analytics personnel could incorporate mentorship to instill the lessons learned in the past into the present. As steel sharpens steel, the core competencies of the more experienced employees would sharpen the skills and competencies of existing employees and future recruits. This could create a culture that continuously encourages competencies impacting BDA with a strong foundation of skillsets and talents that grow and transform the organization.

The limitations of this study that may constrain the generalizability of the results are 1) the use of a sample of convenience and 2) the use of a traditional survey statements method. Future studies may choose a random sample and a scenario-based approach that may yield different results. Future studies should also examine other BDA qualities, i.e., BDA information quality, BDA Technology quality, BDA security quality, and BDA privacy quality.

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