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ASSESSING THE EFFECTS OF BIG DATA ANALYTICS AND AI ON TALENT ACQUISITION AND RETENTION

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Article Info

Abstract

This has led businesses to pay more attention to the process of collecting, storing and analyzing big data, which they believe will lead to better decision-making performance for everyone in the organization. Business owners are using this big data to improve organizational performance. How is the HR sector changing to leverage technology in this era of big data? Many elements of the HR department, such as attitude, behavior, etc., are inherently difficult to assess. The purpose of this article is to relate BDA to innovation and management skills that need to be considered, such as intelligence, drive, thinking and ethics. This study uses quantitative analysis and relates it to human resources to identify the full spectrum of management skills. Self-developed survey rotation, SPSS analysis shows the impact of BDA on management skills.

Keywords: *Big data Analytics, Talent Management and Artificial Intelligence*

Introduction

Making good talent management decisions is difficult because decision makers often have little or no evidence to determine who is best at any given time. Stressed decision makers recognize that they must rely on their intuition and knowledge enough to determine the best response. This is not always the case with knowledge and the ability to use it appropriately (McAfee & Brynjolfsson, 2010). (2012). Talent management decisions are not only difficult, they can also be costly if not done correctly. When companies invest in the wrong people or projects, they create teams that are doomed to failure and management skills are destroyed. The organization's work then comes to a near standstill. We present case studies that show how data-driven assessment skills (DAS) can help top executives make better management decisions. After all, information is increasingly being used to change decisions in other workplaces (Malthouse, Haenlein, Skiera, Wege, & Zhang, 2013; Payne & Frow, 2005); our example shows how good information can help executives maintain and improve company performance by improving the quality of people management choices. What has happened to change management skills knowledge? Over the past few years, we have made significant progress in understanding, measuring, and classifying personality traits and skills. Since these behaviors are not changed much by training, coaching, or motivation, it is important to recognize and understand them when hiring, training, or motivating people. Even if a person has the right attitude and training, they will not be successful if they do not have the ability to know and the right work attitude. If a team does not have the combination of these qualities and skills to get the job done, their performance will suffer. So how does reliable, accurate, and relevant information affect management decision-making? Here are three examples of how companies across industries have discovered a way to collect, analyze, and interpret data that results in effective talent management and thus improves the organization's performance.

2.Literature Review

In recent years, the use of big data (i.e., large-scale and non-standard products generated by organizations' normal activities) has become popular (Mayer-Schönberger and Cukier 2013). The reasons for this interest are well known: the cost of storing data (in any form) has decreased, and data-generating technologies (such as sensors and wearable devices) have increased. At the same time, procedures for managing and processing data collected by companies are included in software standards, allowing physicians to easily extract insightful information from the data and use it to improve organizational performance (McAfee and Brynjolfsson 2012; Brands 2014). Responding to practitioner interest, studies have begun to focus on the use of big data in business and its impact on performance (Davenport et al. 2010; Rifkin 2014). Research in this area has progressed along two main lines: the first has sought to identify how organizations can use their big data to improve performance; the second has sought to identify ways in which organizations can use their big data to improve performance (Davenport et al. 2010). We now have evidence that, due to the increasing ability to use big data, companies are now willing to adopt new "data-driven" decision-making models in many areas of business (Kiron 2013; Beath et al. 2013). 2012). (e.g., Akter et al., 2016; Erevelles et al., 2016; Wamba et al., 2017). Second, studies have measured the impact of informed decision-making models on firm performance: a comprehensive study by McAfee and Brynjolfsson (2012) found that companies that use big data to guide planning and decision-making are more effective at doing business than not using big data at all. These companies are, on average, 5% more active than their peers in the same industry) in the HR function? Talent analytics2 (as a subfield of business analytics) has emerged as a process for identifying trends in business data for managing employees, driving change (Guenole et al. 2017), and ultimately creating value (Marler and Boudreau 2017; Boudreau and Jessusasan 2011; 2012; Boudreau and Ramstad 2007). Intelligence related to creativity refers to the ideas and skills that influence the formation of the concept of motivation, defined as a person's interest in a task. Amabile believes that motivation is important because it can make a difference in what a person can achieve (defined as having ideas about the resources and skills related to talent) and what the person will actually do. In other words, motivation is important in relation to the full and proper use of talent and creative skills in order to perform well. Amabile emphasizes the importance of the environment in this concept. The social environment has received special attention because of its ability to influence one of the three factors that stimulate creativity, especially motivation. In summary, Amabile's (1993) approach makes a positive contribution by emphasizing the influence of contextual factors (e.g., organizational environment) in relation to human characteristics that are important for creativity. We will return to this model when we discuss safety management characteristics later in this chapter.

1. THEORETICAL FRAMEWORK

The large data generated by sensors, wearable devices, and social media platforms is called big data. Big data can take many forms, including structured and unstructured data, but it is worth noting that unstructured data (i.e. data with uncertainty) is the largest source of data (Dedic and Stanier 2016). The 3Vs (Akter et al. 2016) refer to volume, velocity, and variety and are often used to describe big data. The amount of information generated by various sources, such as social media, marketing, and the Internet of Things, is called data volume. The second V represents the speed and value of the product, while the third V represents variety. Variability and complexity have brought out the importance of big data (McAfee and Brynjolfsson (2012) and Kwon and Sim (2013)). The frequency of data (e.g. daily, hourly or instantaneous) is called variability, while complexity refers to the variety of data sources that make them difficult due to different data schemas supported in writing. In many companies, databases are often used to store complex information. The repositories are usually cloud-based and are ideal for creating reports and viewing information. Employee records, holidays, working hours, rotations, attendance sheets and other records. The concept of a "data lake" has become quite popular in the context of big data management. Data lakes allow companies to store multiple types of data at low cost, as they do not require data processing to fit a predefined data model. Data lakes are great for discovering new insights rather than being used for analysis. A data lake is a data warehouse in addition to a data store, which usually uses a predefined data model and therefore allows for reporting and complex analysis (which usually requires a data schema).

3.Conceptual Architecture

With the acceptance of the concept of big data in the business world, the term “analytics” has also become popular. Although this term is sometimes used interchangeably with big data, the two terms are actually quite different. Analytics refers to the process that allows companies to analyze large amounts of data. Different types of business analytics can be categorized, and INFORMS says that analytics useful to organizations fall into three categories: descriptive analytics, predictive analytics, and strategic medical imaging. Descriptive analytics looks for patterns in data and uses data analysis to describe and explain it (Joseph and Johnson 2013). (Lehman et al. 2016). Forecasting is a collection of techniques that can be used to predict future events based on past data. Forecasting relies heavily on machine learning and predictive models (Joseph and Johnson 2013; Gandomi and Haider 2015; Rehman et al. 2016). Finally, it uses analysis, optimization, simulation, and heuristic techniques to simulate different scenarios and their impact on business outcomes (Evans and Lindner 2012). People have always been intrigued by information about their employees. Although the term “intellectual analytics” is new, companies have long sought to collect data from their employees to improve their overall performance. Although the wisdom of human observation can be traced to the concept of “management science” (Kaufman 2014), interest in evidence-based management (i.e., determined based on the use of evidence from multiple sources) is leading to the adoption of people analytics (Barends et al. 2014). What is particularly new is that companies can now combine (through tagging) multiple data streams (internal and external) and use them to answer important questions about the recruitment, retention and management of people (CIPD 2013; Org Vue 2019). Technical analysis can also be used to analyse the return on investment in specific areas and the cost of compensation plans, providing key insights to help senior managers develop ideas (Guenole et al., 2017). One of the key benefits of cognitive analysis in this context is that it eliminates the ‘gut feelings’ that can influence the best choices (Levenson 2015; Guenole et al., 2017). However, there is still a misunderstanding among HR professionals about what intelligence analytics actually means, as it is often confused with other HR-based metrics. Fink and Sturman (2017) argue that metrics and key performance indicators (KPIs) are important in assessing the effectiveness of current processes. In other words, they can evaluate the current activities of the HR department (Fink and Sturman 2017). This is not the case with cognitive analytics, where the ultimate goal is to predetermine the choices that can be used to make good decisions (Levenson 2015). An example may help clarify the difference. Organizations may develop policies to improve racial diversity among their employees. In this case, cognitive analysis can help identify potential sources of diversity and analyze their future impact on change. This is very different from measurement methods and KPIs that simply record the current period (e.g. whether the number of employees of which nationality has increased) without analyzing the impact for future work.

2. HYPOTHESES

The following null hypotheses were developed based on the conceptual framework and associated theories of Big Data Analytics and innovation:

H01: Given the influence of artificial intelligence, there is no major link between Big Data Analytics and personnel management.

3. RESEARCH METHODOLOGY

The research adopted a quantitative analysis model and investigated the influence of "5V" (independent variable) on management skills through a self-administered 5-level Likert scale survey (dependent variable). The survey selected 50 well-known companies from various industries in Henan Province, China, with sufficient operating and working capital to cover the installation and control costs of big data analytics. The survey was administered to the study participants (managers) using paper and pencil. In order to ensure the fairness of data collection, the study emphasized the ethics of informed consent and confidentiality of participants.

Table 1: Composition of Sample

S/No.	Categories	N	Impact
1	Board of Directors	200	**Talent Management**
2	Executives	121	**Talent Management**
Total		**321**	

Using the Slovenian standard for participant size from the (known) population size resulted in a study with 139 participants (see Table 2). Participants are randomly selected when determining the sample size of Chinese manufacturing companies. Participants were informed about the purpose of the study and given instructions regarding the survey. Participants were sent 5 Likert-scale questions ranging from strongly disagree to strongly agree (5 to 1).

Table 2:Impact Ratings of questionnaire

S/No.	Scale	Categories
1	**1 to 1.49**	**Strongly Disagree**
2	**1.50 to 2.49**	**Disagree**
3	2.50 to 3.49	**Neutral**
4	3.50 to 4.49	**Agree**
5	**4.49 to 5.0**	**Strongly Agree**

3.1 Reliability Analysis

Before all the data were collected from (384) participants, a reliability test was conducted to validate the survey. The survey was sent to 20 people in the sample for pre-testing, and the "Cronbach's Alpha" scores of five groups of the survey exceeded the standard. The desired rate is 70% or 70%. Table 4 shows the Cronbach's Alpha value for BDA, Technical Management, and Artificial Intelligence, which means that all the confidence results are higher than necessary and the survey design is worth doing more.

Table 3: Reliability Analysis Test

S/No.	Variables	No.	Cronbach' sAlpha	%
1	Volume	20	.89	**89**

2	Velocity	20	.95	**95**
3	Variety	20	.95	**95**
4	Veracity	20	.78	**78**
5	Value	20	.88	**88**
6	**Overall**	**20**	**.85**	**85**

3.2 Hypotheses Testing

Null hypotheses were testes for *t*-values and *p*-values, in order to nullify the null hypotheses and accept study hypotheses. Table 3 gives details of hypotheses and t-values for all statistics. Values of construct > 1.98 in all cases so study hypotheses is accepted.

Table 4: Hypotheses Testing (Independent Sample Test)

S/No.	Factors	numbers	t-test statistic	P Value
1	Volume	2 1	32.41	**.023**
2	Velocity	2 1	22.39	**.023**
3	Variety	2 1	22.26	**.023**
4	Veracity	2 1	11.99	**.023**
5	**Value**	**2 1**	**22.34**	**.023**

Artificial intelligence and big data analytics have an impact on talent management in China's labor economy, but the degree of impact varies from high to low. Table 6 also shows the kurtosis test values used for hypothesis testing to provide the results of t-value statistics and p-value statistics.

Table 5: Kurtosis (Normality Test) for Hypotheses Testing

S/No.	Factors	Z value	Error	Value	Range
1	Volume	23.56	.21	.633	> **+1.96**
2	Velocity	16.89	.21	.901	> **+1.96**
3	Variety	13.78	.21	.038	> **+1.96**
1	Veracity	12.43	.21	.281	> **+1.96**
2	**Value**	**16.78**	**.21**	**.521**	> **+1.96**

Table 5 exhibits values of skewness-Kurtosis, all values are greater than +1.96 as exhibited in table, which implies that data is normally distributed and null hypotheses are reject. Skewness is 0 for data normalization (see figure 3).

3.3 Descriptive Statistics

What is the link between talent analytics and company performance? Although the mechanisms supporting this link have not been fully elucidated, research on analytics and its effectiveness suggests that analytics (and big data) are a metaphor for IT resources that will lead to business success (Groves et al., 2013; Braganza et al., 2013; Wamba et al., 2017). The resource-based view (RBV) has traditionally been used by management researchers to establish the relationship between big data and performance (Barney 1991; Verbeke and Yuan 2013). According to RBV, it is necessary to better identify the sources of competition and, once this is done, to determine which areas are most relevant to the identified causes and have a good impact. On the other hand, analysis can be seen as an investment in non-profit assets that produce value, even if their contribution to profit is difficult to measure due to their characteristics (Haskel and Westlake 2017; Brynjolfsson and Hill 2000). The statistical description of the report includes the comments of the study participants (d) regarding the evaluation of the content. The participants' evaluations were recorded using a five-point Likert scale and the experience data were reported in the study. BDA is important for managing talent and innovation. The results in Table 6 show that all participants agree or strongly agree with the questions in the survey. Managers are the key decision makers in any organization. In the business sector in Henan, China, successfully explaining their content, understanding and using big data analytics can be expensive, but over time it can become a useful and beneficial product for the economy. From operations to production, finance to information, quality control to R&D, talent management can help develop or create new products or brands. different decisions; they need a quick, fast and effective decision to create something special. According to a study conducted by Ara (2019), the service sector and

manufacturing businesses have different decisions. Efficiency requires a more focused and thoughtful solution that brings motivation ethics, negativity and the broader context. How independent factors affect the variable is different (Hutchinson, 2011).

In a linear regression study, the results are given by the intercept and slope, which show how well the X variable predicts the Y variable relative to the mean. The equation (Noon, 2003) can be used to calculate the regression line: The independent variables in this study are volume, media, variety, accuracy and cost, which are the characteristics of big data analytics; the difference is skill management.

The Adjusted R-squared value of the Model is 0.998, which means 0.998 * 100 = 99.8%. This means that the unit change in big data will account for 99% of the decision change.

Table 6: Regression Summary

Model	Change Statistics				
	R Square Change	F – Change	Df1	Df2	Sig. F Change
1	.912	779.321	2	319	.000

Variance analysis is essentially the match between the predicted values and the differences in explanatory variables. The positive expression of this difference indicates that BDA and AI may have an impact on the knowledge-driven creativity or basic skills management of the manufacturing industry in Henan, China.

Table 7: Summary

MODEL		Unstandardized Coefficient		Mean Square	F	Sig.
1		B	Std. Error			
	(Constant)	.234	.010		22.56	**.013**
	BDA	.362	.010	1.037	33.16	**.000**
	Talent Management	**.403**	**.010**	**.172**	**48.31**	**.000**

@ p = .001, .001 and .003 and .234 all the values are less than .005 model is fit and significant to predict the effect of independent variable on dependent variable. With coefficients @ 121, .234, and 3.4 values of BDA, AI and TM Linear model exhibits the values that imply research hypotheses are true and characteristics of Big Data Analyticsaffect the capacity of individuals to create new ideas and bringing attitudinal cognition ineffective patterns

$$\textit{Talent Management} = \alpha + \beta\,(BDA) + \beta\,(AI) + e$$

Therefore, researchers have tried to examine the relationship between intelligence analytics and performance using various theoretical perspectives. For example, Alar et al. (2012)

used organizational theory to show that skill analytics is associated with performance improvement because it helps managers and employees to mutually support each other. The survey shows that ICT and compensation studies are a resource that should be combined with technical analysis, meaning that these companies provide incentives and opportunities to help people. These factors can increase productivity. Some authors state that some skill tests are essentially a discount that has no impact on the company's performance. 4 Research articles can support a body of knowledge that focuses on skill and performance. Marler and Boudreau (2017) cite a publication in which researchers examined how to increase employee engagement and thus increase sales. Van Idekinge et al. (2016) investigated how social media profiles can be used to help select job applicants. According to the findings, there is no relationship between business, turnover and social media. Finally, Lin et al. (2016) argue that the value of intelligence analytics mainly comes from the changes it creates in the organization.

4. SUMMARY OF FINDINGS

According to many authors, technical analysis has become more common in organizations in the last five years (OrgVue 2019). As a result, the use of analytical skills in HR departments is more common than before (Kamp 2017; Bersin 2012) and it is now possible to show and understand that HR departments use technical analysis more (at least in large companies) in many studies. The early focus on talent is directed at specific HR processes such as recruitment and promotion in order to reduce negative performance; however, this situation is changing as HR departments begin to use analytical skills in other areas that directly support the business. (OrgVue 2019).

Analyzing the effectiveness of workforce planning and motivation policies are two applications of workforce analytics. Large companies that can invest in the technology and expertise required to support analytics appear to have the greatest impact on operational efficiency (Falletta 2014). According to a 2016 report by the Society for Human Resource Management (SHRM), data analytics now accounts for 79% of companies with 10,000 or more employees. Additionally, the strongest examples often occur in industries that emphasize technology, science, or information, such as high tech, biotech, and department stores (Falletta 2014). In this section, we discuss some of the latest applications of the technology, as well as some real-world examples of businesses using different types of analytics.

5. AI IMPACT ON TALENT MANAGEMENT

We talked about analytics and how it helps people management in the previous section. In some ways, we are writing the HR management process of the past because most companies want to know what AI can do for their HR departments (Das; Melder 2018). The goal of AI is to enable machines to follow human intelligence (Acemoğlu and Restrepo 2017). At its most basic level, the goal of AI is to use computers to perform (mostly repetitive) tasks faster than humans; in this case, automation is the main focus of AI (Acemoğlu and Restrepo 2017). Of course

Other aspects of AI are also important: for example, deep learning and machine learning are important and underpin much of the AI we use in our daily lives (Das). Machine learning is a term that refers to a set of algorithms that can be used to discover patterns in data (unsupervised machine learning) or to predict outcomes (supervised machine learning) (using supervised machine learning). In the first case, the algorithm learns from training data, and the predictive model is based on the training data. The learning model involves repetition and analysis distribution. In unsupervised machine learning, there is no information about performance; Cluster analysis is an example of such a model. Human resources, especially recruiting, have begun to use AI to perform monotonous tasks (Melder 2018; Miller-Merrell 2016). Unsupervised machine learning can help recruiters in the context of intelligent analytics. In this case, machine learning can be used to scan social media posts and identify potential candidates who are rarely listed in job postings. Machine learning can be used to recommend jobs based on past searches and posts using unsupervised machines (LinkedIn is one organization that uses this approach for its job recommendation study). On the other hand, if the goal of your professional analysis is to determine the contribution of investment training to turnover, you can choose the tracking model because there are educational materials behind it that will help you choose the benefits (turnover) and the inputs (training and other controls of the process). IBM's Watson machine learning platform has been used to develop many "artificial intelligence" applications (IBM 2016). People's potential is matched with internal career opportunities and development plans through the use of skills. The system can also identify opportunities that people may miss because they don't feel they deserve it. IBM can use tools like Blue Matching to increase workforce readiness. The process can also be used to "guide" career paths or provide training to encourage employees to learn the brilliant skills needed for the company's future development. Guenole and Feinzig (2018) support IBM's "full talent lifecycle" (p. 8), which includes attracting and hiring employees as well as providing services that promote employee engagement, retention, growth and development, and employee participation. In fact, intelligence is used to find applicants, filter them backwards, and match candidates with open positions (Miller-Merrell 2016). Organizations can adopt video conferencing and use advanced AI capabilities to analyze AI faces to better assess needs (Das). Unsupervised neural networks can be used to identify content in interview transcripts and employee surveys. Finally, a virtual assistant can help with new hire onboarding. AI can create personalized training programs based on specific preferences and interests. Similarly, AI can assist in internal job search and job development (DAS). Similarly, AI can assist in repatriation and reemployment in a way that does not harm people. Although all the results have been validated, ethical concerns regarding the use of AI in HR are still in their infancy compared to the rapid development in the literature. Recognizing some of the benefits, the company is working to educate consumers and designers. For example, IBM (Guenole and Feinzig 2018) explicitly states that its managers should be able to override AI instructions if necessary or required, and reduce the "unfair" situation built into AI systems, improved diversity, and fairness. should be considered in the design process. The main point is that AI can and should be fair and transparent (ibid.: 30), and IBM is not very clear on how to achieve this. As at IBM, we believe it is important to go beyond the company. For example, the European Commission's High-Level Expert Group on Artificial Intelligence is currently experimenting with ethics for "trusting AI" (European Commission High-Level Expert Group on Artificial Intelligence 2019). This framework emphasizes three points: AI should be "legal, ethical and efficient" (ibid.: 5). Unlike company-based methods like IBM's, it foregrounds the company and the legal system; We then propose an example that does not specifically address AI ethical issues but is based on the development of more ethical principles when using big data for analysis capabilities.

6. A FRAMEWORK FOR THE ETHICAL USE OF BIG DATA IN HR

The use of big data opens up many possibilities as it allows data to be matched and linked to find previously unknown patterns. Although big data has the potential to change the way people are managed, there are still some questions about how big data will be used in people's work. Because employee information is so sensitive, organizations need to be very careful when deciding what information to obtain and how (Cappelli 2017). For example, it is desirable to monitor the content of people's emails, but most businesses will resist anything they consider too sensitive. Employers have more responsibility when more information is obtained from sensitive data such as physical devices and mobile phone data (CIPD 2013). Essentially, GDPR limits the ability of an employer to use personal data for purposes not specified at the time of collection. GDPR requires employers to be informed about how personal data is collected and used. Furthermore, personal data is only processed if it is used for the original purpose for which it was collected. In fact, processing data for various purposes requires the explicit consent of the employee. Finally, personal data should be removed from the server when it is no longer needed, which means that HR databases should be checked and cleaned regularly.

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