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HUMAN RESOURCE DATA ANALYTICS AND MANAGERIAL EFFECTIVENESS IN MANUFACTURING FIRMS IN THE SOUTH-SOUTH, NIGERIA

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ABSTRACT

This study investigated the role of human resource data analytics in advancing outcomes of managerial effectiveness in manufacturing firms in the south-south of Nigeria. The study assessed the influence of human resource data analytics dimensions such as predictive analytics in driving outcomes of service delivery. The study adopted a correlational approach, and a structured questionnaire was used in the generation of data from 94 management staff of manufacturing firms in the south-south of Nigeria. The Spearman's rank order correlation and the partial correlation technique were used to test the bivariate and multivariate hypotheses, respectively, with the results showing that the dimension of human resource data analytics significantly impacts managerial effectiveness measures such as service delivery. This demonstrates the significance of related human resource data analytical practices to the functionality of managers and their ability to cope with the challenges associated with their role. It was concluded that HR data analytics are required for managerial effectiveness. The study affirms that the evidence of dimensions such as predictive data analytics contributes significantly to the manifestation of measures such as service delivery. In this way, the study affirms that each of these dimensions is critical to the effectiveness of the manager, enhancing their role in the organization. It was recommended that the management of the manufacturing firms focus on the development and utilization of data that ensures the strengthening of predictions and forecasts about the changes in the industry or environment of the organization and the matching of organizational skills or HR features with such changes.

Keywords: Human resource data analytics, managerial effectiveness, manufacturing firms in the South-South, Nigeria

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Introduction

Human resource analytics also reflects human resource management actions involving the use of statistical methods and data on the human resources of the organization aimed at enhancing their features and, through that, ensuring improved organizational outcomes. (Van der Togt & Ramussen, 2017), Lesser and Hoffman (2012) noted that the changing context and processes of business organizations today stem from their growing recognition and reliance on information technology and the nature of its application and use in the organization. This has also impacted the nature of human resource management, which over time has experienced a switch in form and attributes, shifting from the traditional documentation and filing of records and reports on workers to a more elaborate and systematic data-based processing of the human resource content of the organization. Levenson (2018) opined that not only have such shifts in operations and human resource management facilitated effectiveness in the coordination and harnessing of human resource capacities, but they have also enabled efficient systems and the smooth management of the organization's human resource content.

Literature on managerial effectiveness (Bran and Udrea, 2016; Hettiararchichi and Jayaranthna, 2014; Kubaisi, 2013) is increasingly aligning with emerging thoughts on the usefulness and imperatives of descriptive and predictive data analytics—promoting leadership or management capacities and capabilities through the effective discerning of their human resource gaps and shortcomings, particularly within their context of operations. Nonetheless, much more is required to bridge the observed disparities in actual practice and theorize solutions, especially within African nations, which, commendably, are beginning to pick up pace in terms of technological applications in business (Kubaisi, 2013; Jarvis, 2014). This is because, apart from improved levels of efficiency and performance outcomes, such technological and data analytical systems have the potential to boost the competitiveness of related organizations and advance their functional as well as operational features in ways that propel them beyond their local industries to a more globalized context, reinforcing their presence and success levels.

Unfortunately, the role of human resource data analytics in the outcomes of managerial effectiveness has received scant attention over the years, thereby posing a major gap in research on managerial effectiveness. This is because previous studies on managerial effectiveness have dwelled on predictors such as human resource development (Sheehan et al., 2014), knowledge management (Banki, 2010), leadership or managerial style (Sushil & Burgess, 2016), and organizational culture (Derwin, 2016), focusing mostly on related actions that deal with direct relationships and the orthodox monitoring of human resource features.

Huslid (2015) argued that the concept of human resource analytics is understudied and has little consideration in research addressing managerial outcomes. Similarly, Pape (2016) argued that the infusion of information technology and statistical analysis in the management and development of human resources enables a more controlled and well-adapted process suited to the challenges of the current business era. This study, as such, contributes towards enriching literature and extending knowledge on the relationship between human resource analytics and managerial effectiveness, as well as the influence of organizational technology capabilities on the relationship between the variables in manufacturing firms in the south-south of Nigeria.

Aim and Objectives

The aim of this research is to ascertain the nature of the relationship between human resource data analytics and managerial effectiveness. The related objectives of the study are to:

i. Examine the relationship between predictive data analytics and service delivery in manufacturing firms in the South-South, Nigeria.

Research Question

i. What is the extent of relationship between predictive data analytics and service delivery in manufacturing firms in the South-south, Nigeria?

Hypothesis

HO_1: There is no significant relationship between predictive data analytics and service delivery in manufacturing firms in the South-South, Nigeria.

LITERATURE REVIEW

Conceptual Review

Human resource data analytics can be defined as to understand relationship between performance of organization and HR practices. In case of effective HR practices, it leads to employee satisfaction and provides strong foundation where decisions regarding human capital and business strategy can be performed. Analytics enabled organization bring precision in decision making. It is possible with the use of statistical techniques and experimental approach (Lawler et al. 2004).

Bassi (2011) argues that HR Analytics can be considered both as 'systematically reporting on an array of HR metrics or more sophisticated solutions, based on 'predictive models' and 'what-if scenarios. In addition, Bassi's (2011) definition includes the notion of taking an 'evidence-based approach' to making decisions on the 'people side of the business'. She concludes HR Analytics 'is an evidence-based approach for making better decisions on the people side of the business; it consists of an array of tools and technologies, ranging from simple reporting of HR metrics all the way up to predictive modeling (Bassi, 2011).

Aral et al. (2012) explored that various practices are mutually correlated, such as HCM, performance pay, and HR analytics. HR analytics and performance pay are a set of organizational practices that complement HCM. It was elaborated by Bradford et al. (2017) that to have a competitive edge over competitors, organizations must use HR analytics for accuracy in the data and real-time information. Work force planning can be done easily and also helps in analyzing every aspect of the HR matrix by using HR analytics. It is also found that there is a consensus in regards to the importance of HR analytics in organizations and that the HR analytical skills challenge is the main hindrance to implementation. It is required that HR transform itself while ensuring that the required skills from the higher education sector are attracted and that HR practitioners are capacitated in numeracy and metrics so that the concept of HR analytics can be fully incorporated at all levels of the HR process.

Molefe (2013) said very well that the future of HR analytics is that this field will continue to grow within organizations. The process of HR analytics is very straight-forward, and the purpose is to use it to gain a competitive advantage in the industry. It is the peak time for HR managers to start focusing on business outcomes and must focus on improving employee engagement scores or increasing participation rates in their initiatives. According to Douthitt and Mondore (2014), to make HR a strategic function in any organization, proper implementation is the key initiative. According to Manuja, Casey-Campbell, and Martens (2009), the requirement of human resources analytics was viewed as a strategic collaborative partner affecting the outcome of the business. Analytics of raw data into useful information is covered under analytics, which also covers data generation, storage, and conversion. It is, however, critical that HR analytics have an integrated approach.

HR analytics implies pulling in multiple HR processes to tackle strategic issues; e.g., in succession planning using HR analytics, the components of performance evaluation, analysis of input and output from trainings, engagement of the employee in terms of contribution, efficiency, effectiveness, etc. should all be factored in a clinical and systematic manner. It has been argued that analytics can operate in a data-driven way, but it has the advantage that it can be learned from what marketing went through in those early years. It is never a simple step for some or many HR functions; a data-driven approach to decision-making has potential for HR to add, which further adds value to business (Chattopadhyay & Ashkanasy, 2010). To survive in the long run, industries need predictive analytics from human resource management. The usefulness of predictive analytics is wider, and hence its application in all related areas of HRM is essential.

Descriptive Data Analytics

Describes the organization's actions concerned with basically identifying the conditions and characteristics of the workforce in terms of size and other demographic attributes such as age, qualification, and even experience (Baesens et al., 2017; Dlomu& Spears, 2015). This reflects the organization's capacity for controlling and managing data related to the workforce. The descriptions of the workforce primarily provide knowledge on the attributes and features of the personnel and can be useful in discerning the organization's capacity and level of functionality. This dimension is primarily concerned with the internal wellbeing of the organization, as it basically creates awareness or knowledge of the quality and content of the organization's capacity through the development of a database that is accessible to key officers or management when required (Marler & Boudreau, 2017; Angrave et al., 2016; Andersen, 2017).

Taking on a retrospective view of what happened in the past, descriptive analytics present data in an understandable format and investigate the cause-and-effect relationships. Descriptive data analysis summarizes past data to provide an overview of potential patterns or trends embedded in the data, which is also known as business reporting (Demirkan & Delen, 2013). A static report relies on statistical calculations of historical data to identify the distributions over a sample or a population. A dynamic view of business performance uses a wide range of visualization techniques, such as a dashboard with a graphical interface or an interactive graph, which informs decision-makers about the current situation in a timely and continuous way. Going beyond a surface examination, descriptive analytics provides a historical account from which problems and opportunities within existing operations can be identified. Causal-explanatory statistical modeling is the normal approach employed. Relying on statistical inference, researchers test theoretical reasoning-supported hypotheses and assess the explanatory power of the causal models.

HR analytics helps organizations optimize business performance as well as employee engagement and satisfaction. HR analytics is a growing and very fast-changing technology that has 100% accuracy in HR decision-making (Denzin & Lincoln, 2005). According to Bassi (2011), HR analytics elevates the status of the HR profession and is a source of competitive advantage for organizations that put it to good use. There are various reasons for HR analytics: to improve individual and organizational performance, not to prove the worth of HR. Sharma and Dessler (2015) also found that HR analytics can help improve the quality of decisions. However, it is not clear if HR analytics can be used to improve the acceptance of decisions in any way. The insight generation and decision-making processes associated with the use of business analytics, as suggested by anecdotal research, often do not involve key stakeholders from functional areas who will all be responsible for implementing those decisions.

Predictive Data Analytics

reflect the actions concerned with assessing the future needs of the human resource in line with the goals of the organization and the changes in its environment (Marler & Boudreau, 2017). It is such a proactive action. The predictive analytic dimension, much like the diagnostic analytic dimension, focuses on both internal and external factors in its assessment and redress of its human resource content (Arora & Rahman, 2016). However, the former makes comparisons, also assesses trends, and is mostly interested in the future of the organization and what is required of its human resources for the actualization of that future, whereas the latter is more interested in existing market and industry situations and the organization's competence in scaling through its challenges and problems given the current or existing human resource content at its disposal (Marler & Boudreau, 2017).

Madueno et al. (2016) reported the biggest driver of development in the HR area to be predictive analytics. He states that in previous years, most people made the mistake of talking about predictive analytics when they actually meant descriptive analytics, i.e., reporting based on a summary of historical events. Thus, it makes sense to spend a few moments with the definitions of analysis, analytics, and predictive analytics. As said, some believe that a single report on historical events equals analysis or analytics. A report shows only one dimension of the topic under examination. Regardless of how many reports you have in the past, you need to be able to interpret them and draw some conclusions, connections, and insights between events and effects before you should state that the action taken has been an analysis. Thus, an analysis can be defined as the interpretation of the provided information (Fitz-enz and Mattox 2014). Analytics then again expands the concept of analysis. Analytics includes putting the tools into use for the analysis. Others understand analytics simply as running some statistical models.

Analytics is the transformation of the data into actionable insight. Analytics is also broadening the concept of analysis to cover the usage of different statistical techniques, but it also covers the technological aspects. In today’s world, where the amount of data grows continuously, one needs to incorporate machine power to be able to perform the analysis more efficiently. According to Naasz and Nadel (2015), the possibility of using machine power in categorizing, analyzing, and consolidating data answers today’s challenges of rapidly growing data volumes, variety, and velocity. It would be impossible for a human eye to filter out meaningful information out of masses of data without any help from machine-aided analytics.

Fitz-enz and Mattox (2014) state that the integration of HR systems, automatization, and digitalization of HR operations drive the creation of big data sets in the HR area. Luckily, the past and current development of IT systems offer manageable ways for data gathering and further analysis, for example, in the areas of candidate pool management, talent management, learning management, or performance history recordings, just to name a few. According to Harris et al. (2011), the HR department has not been the forerunner in collecting data in the most efficient way, or especially turning the collected data into information about business performance and outcomes. This is a major challenge and an improvement area for HR; instead of merely reporting their own performance, one would need to start reporting the business performance.

As Fitz-enz and Mattox (2014) describe it, around 80% of the currently produced data is unstructured, such as images, non-numeric data, text, and videos. The amount of data continues to grow alongside the rise of social media usage, and the result will be a mixture of structured and unstructured data. In order to create information from this mixture of fast-growing, variable data in HR but also in other areas, one needs to exploit the logical problem solving and statistical analysis of the data. In addition, analyzing both structured and unstructured data becomes an important source for understanding patterns in data. For example, natural language datasets present extraordinary versatility. User-generated content is frequently analyzed to understand and predict customer behavior. Coupled with unsupervised learning methods such as clustering and dimension reduction, an analysis of the semantically coherent groups and themes emerging from the textual corpus or images is found to be helpful in assisting operational decisions.

Managerial Effectiveness

Kaur and Chadha explain in Sinar (2018) that managerial effectiveness is the extent to which a manager carries out activities to achieve organizational goals and work effectively for the organization and more productively. Furthermore, Gupta (2013) uses a questionnaire developed by Kaur and Chadha using 16 dimensions (i.e., trust subordinates, communication and assignment, networking, relationships, discipline, use of resources, management of the market environment, conflict resolution, integrity and communication, management and client competence, motivating, delegating, building image, welfare management, consulting and inspection, and innovation and innovation).

Adekola in Palak and Walls (2009) describes managerial effectiveness as follows: Managerial Effectiveness It depends on the situation and the manager's ability to plan, organize, coordinate, motivate, control, and have a positive influence on organizational goals. Wang in Palak et al. (2009) identified eight different indicators to measure managerial effectiveness: supporting, caring, fair, engaging, disciplined, selfless, responsible, and knowledgeable. Based on the description above, it can be synthesized that managerial effectiveness is the accuracy of the actions of a manager in achieving work goals using methods, means, and potential, with indicators: manage and lead, interpersonal relations, knowledge and initiative, orientation of success, and contextual independence.

Managerial effectiveness, which has a significant value for management, is a type of effectiveness that appears as a result of administrator behavior. When explaining managerial effectiveness, it is necessary to mention that the manager is an individual. Theoretically, it is necessary to link organizational effectiveness to three key management theorists: Fredrick Taylor, Henry Fayol, and Elton Mayo. According to Fredrick Taylor, organizational effectiveness refers to increasing production, reducing costs associated with resource acquisition, and being technologically competent. Henry Fayol has a different point of view, according to Taylor.

According to Fayol, organizational effectiveness is an organization that has clear authority and discipline. Fayol deals with effectiveness from a managerial point of view and has dealt with a very managerial part of the process that the organization pursues to reach its goals. Mayo has criticized Fayol for ignoring employee needs. According to Elton Mayo, organizational effectiveness is the emerging production function of employee satisfaction (Pape, 2016). Mayo criticized Fayo regarding his ignorance of employee needs. According to Elton May, organizational effectiveness is a function that arises as a result of employee satisfaction (Reber and Reber, 2001).

Empirical Review

Teo et al. (2008) investigated a quantitative study examining the possible relationship between Singaporean pre-service teachers' beliefs about teaching and information use. Constructivist teaching beliefs were significantly and positively correlated with both constructivist ($r = 0.59$, $p < 0.01$) and traditional ($r = 0.50$, $p < 0.01$) technology use. On the contrary, traditional teaching beliefs were significantly and negatively correlated with constructivist technology use. The outcome of the study implies that Singaporean pre-service teachers are not adequately prepared to facilitate student knowledge construction.

Palak and Walls (2009) conducted a mixed study to investigate whether workers who frequently integrate information and work at technology-rich organizations shift their beliefs and practices toward a student-centered paradigm. The results showed that their practices did not change; neither worker-centered nor customer-centered beliefs are powerful predictors of practices. However, workers attitudes toward information significantly predict worker and customer information use, as well as the use of a variety of instructional strategies ($p < 0.05$).

Sang et al. (2010) focused on the impact of Chinese workers gender, constructivist approach beliefs, functional self-efficacy, computer self-efficacy, and computer attitudes on their prospective information use. The findings confirmed the results of the study by Palak and Walls (2009) that the strongest predictor of future information use was workers' attitudes toward it.

Methodology

This study adopted a correlational survey design. The population for this study is comprised of a total of 100 senior and middle-level managers from 20 manufacturing companies within the six states that make up South-South Nigeria (Bayelsa State, Rivers State, Cross-River State, Edo State, Delta State, and Akwa-Ibom State). The analysis of the data generated for this study utilized descriptive and inferential statistical techniques.

Data Analysis

Table 1 Distribution for Predictive Data Analytics

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Predict1	94	3.0000	1.14708	-.106	.226	-.934	.447
Predict2	94	3.3217	1.19610	-.554	.226	-.672	.447
Predict3	94	2.9478	1.21282	.011	.226	-.988	.447
Predict4	94	3.4000	1.09063	-.358	.226	-.518	.447
Valid N (listwise)	94						

Source: Fieldwork, 2023

The table above presents the result of the analysis of the third dimension of human resource data analytics, which is predictive analytics. The analysis examined the extent to which the respondents consider their organizations to be engaging in or practicing predictive data analytics for their human resources. The evidence from the analysis reveals that all four indicators of predictive analytics are significantly manifested and affirmed by the respondents to be true. The analysis points to predictive analysis as an evident attribute that characterizes the behavior and practices of the organizations of interest.

Table 2 Distribution for Dimension of Human Resource Data Analytics

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Predictive	94	3.2157	.81095	-.111	.226	-.951	.447
Valid N (listwise)	94						

Source: Fieldwork, 2023

The summary distribution for the dimensions of human resource analytics is presented in table 2. The distribution indicates that human resource analytics are to a high extent, manifested by the organizations examined in the study. The evidence presented on the table illustrates that predictive analytics mean (x) = 3.2157; approximation reveals that on the average, the organizations have a high tendency for engaging in human resource forecasting behaviour. The result from the analysis is interpreted as indicating that all three dimensions of human resource analytics are highly manifested and are an apparent feature of the organizations of interest. This goes to suggest that the manufacturing firms of interest in this study can be described as expressing human resource actions that is predictive in nature. The results point to the organizations as being functional when it comes to their human resource practices and actions.

Table 3 Distribution for Service Delivery

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Service1	94	3.6522	1.15503	-.849	.226	.068	.447
Service2	94	3.4870	1.05436	-.125	.226	-1.201	.447
Service3	94	3.4696	.99403	-.078	.226	-1.040	.447
Service4	94	3.5391	.97591	-.918	.226	.642	.447
Valid N (listwise)	94						

Source: Fieldwork, 2023

Table 3 above illustrates the distribution for service delivery, the third measure of managerial effectiveness. The distribution shows indicates that service delivery as substantial within the target manufacturing firms. This assertion is based on the distribution for the indicators which are all evidenced to have mean values equating to high extent of manifestations. The results obtained for the distribution for service delivery indicates that to a substantial and high extent, the target manufacturing firms can be considered as being highly responsive to their markets or customers in terms of their service approach.

Table 4 Distribution for Measures of Managerial Effectiveness

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Service	94	3.5617	.76772	-.483	.226	-.329	.447
Valid N (listwise)	94						

Source: Fieldwork, 2023

Presented in Table 4 is the distribution of the measures of managerial effectiveness. The results further indicate that all three measures are substantially high and well manifested within the context of the manufacturing firms in this study. The evidence shows that although service delivery is revealed to have a distribution and extent of manifestation, where mean (x) = 3.5617,

The result from the summary is interpreted as indicating that the manufacturing firms examined in this research are, to a high extent, manned by managerial personnel that can be described as effective. Their functionalities and behaviors depict significant tendencies in service delivery. This signifies substantial levels of effectiveness and indicates that the managers have a strong capacity for surmounting the changes or prevailing challenges within their market and environment.

Table 5 Predictive Analytics and Managerial Effectiveness

			Predictive	Resource	Innovate	Service
Spearman's rho	Predictive	Correlation Coefficient	1.000	.686**	.664**	.588**
		Sig. (2-tailed)	.	.000	.000	.000
		N	94	94	94	94
	Service	Correlation Coefficient	.588**	.495**	.450**	1.000
		Sig. (2-tailed)	.000	.000	.000	.
		N	94	94	94	94

Source: Fieldwork, 2023

Table 5 above illustrates the result for the test on the relationship between predictive analytics and the measures of managerial effectiveness.

Predictive analytics and service delivery: The relationship between predictive analytics and service delivery is revealed to be significant with a p = 0.000 and rho = .588. The result indicates a significant level of impact by predictive analytics on the service delivery of the managers of the manufacturing firms. It indicates that activities which express human resource assessments which are predictive in nature impact strongly on the managers capacity to respond effectively to the needs of the clients of the organization.

Discussion of the Findings

Predictive Analytics and Managerial Effectiveness

Predictive analytics is revealed to contribute significantly and positively toward outcomes of managerial effectiveness. According to Bassi (2011), elevating the status of the HR predictive analytics enhances the competitive advantage for organizations. There are various ways through which HR predictive analytics can improve individual and organizational performance, bridging the gaps between organizations and their environment. Mithas and Kankanhalli (2014), also found that HR predictive analytics can help on improve quality of managerial decisions. However, it is not clear if HR analytics can be used to improve the acceptance of decision in any way. The insight generation and decision-making processes associated with the use of HR analytics do not involve key stakeholders from functional areas who all will be responsible for implementing those decisions.

Ramanathan, Philpott, Duan and Cao (2017) attempted to explain the role of HR analytics in the outcome of decision making. Their views tallied with those of Tornatzky and Fleischer (2011), demonstrating that various elements in the context of organizations have significant influence on HR analytics adoption and its application. The researchers observed that HR analytics adoption will help influence organizational performance positively, as the level of adoption of HR analytics also moderates the link between HR analytics adoption and performance outcomes. Furthermore, the level of integration between IT and business strategies moderates the link between HR analytics adoption and performance, trust in HR systems moderates the link between HR adoption and performance.

The major factor premised on the acceptance of HR analytics in the organization is the culture of the organization; which according to Tornatzky and Fleischer (2011), drives the analytical skill of an individual. HR Analytics is applied majorly by big organizations and training and top management support are the few factors which lead to the effectiveness of HR Analytics. According to George and Kamalanabhan, (2016) the acceptance of HR analytics will be more if the technology adopted for analytics is user friendly. Gardner, McGranahan, and Wolf (2011), in their article have argued that HR analytics increases the value of organization. Predictive analytics is revealed to contribute significantly and positively toward outcomes of managerial effectiveness. According to Bassi (2011), elevating the status of HR predictive analytics enhances the competitive advantage for organizations. There are various ways in which HR predictive analytics can improve individual and organizational performance, bridging the gaps between organizations and their environment. Mithas and Kankanhalli (2014) also found that HR predictive analytics can help improve the quality of managerial decisions. However, it is not clear if HR analytics can be used to improve the acceptance of decisions in any way. The insight generation and decision-making processes associated with the use of HR analytics do not involve key stakeholders from functional areas who will all be responsible for implementing those decisions.

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The major factor premised on the acceptance of HR analytics in the organization is the culture of the organization, which, according to Tornatzky and Fleischer (2011), drives the analytical skill of an individual. HR analytics is mostly applied by big organizations, and training and top management support are the few factors that contribute to the effectiveness of HR analytics. According to George and Kamalanabhan (2016), the acceptance of HR analytics will increase if the technology adopted for analytics is user-friendly. Gardner, McGranahan, and Wolf (2011), in their article, have argued that HR analytics increases the value of organizations. When human resources and business leaders work together to address the root causes of problems and pilot new ways of solving them, HR analytics succeeds at the same time. The development of an intelligent business analytics platform is helpful to organizations.

When human-resources and business leaders work together to address the root causes of problems and to pilot new ways of solving them, HR analytics succeeds at the same moment. The development of an intelligent business analytics platform is helpful to organizations.

Conclusion

This study concludes that HR data analytics are required for managerial effectiveness. The study affirms that the evidence of dimensions such as predictive data analytics contributes significantly to the manifestation of measures such as service delivery. In this way, the study affirms that each of these dimensions is critical to the effectiveness of the manager, enhancing their role in the organization.

Recommendation

The management of the manufacturing firms should focus on the development and utilization of data that ensures the strengthening of predictions and forecasts about the changes in the industry or environment of the organization and the matching of organizational skills or HR features with such changes.

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