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MACHINE LEARNING AND ORGANIZATIONAL AGILITY IN TELECOMMUNICATION COMPANIES IN NIGERIA

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ABSTRACT

This study investigated the relationship between machine learning and organizational agility. The study was carried out in telecommunication firms in Nigeria.. Survey design was adopted in the generation of data. The instrument for data collection used in this study was the questionnaire. The target population of the study comprised the three hundred and sixty (360) employees in four telecommunications companies. From the population, using Krejcie and Morgan sample determination table a sample size of one hundred and eighty-six (186) respondents was used for the study. Descriptive statistics (mean, standard deviation, percentages) were used as statistical tools for analyzing the data, while Spearman Rank Order Correlation was used as statistical tools to test the hypotheses with the Statistical Package for Social Sciences (SPSS). Findings revealed that there is positive relationship between machine learning and organizational agility. Hence the study concludes that hike in machine learning improves the agility of telecommunication companies. Therefore, among other recommendations, the study strongly suggests that telecommunication firms greatly build a strong organizational culture in order to adapt to emerging change brought about by the adoption of machine learning.

Keywords: Machine Learning Organizational, Agility, Telecommunication

INTRODUCTION

Companies in developing and developed countries are aware that agility is a must in order to meet the competitive factors and environmental pressures. Agility in global markets has been defined as a capacity to work in a profitable way with renewed changes in a global competition environment (Boehm & Turner, 2003, p.16). Agile entrepreneurship makes it possible to shift from one task to another and through unexpected variables; it offers short delivery times, high quality and low-cost. Therefore, in addition to several basic variables introduced by globalization, business enterprises in the market change more rapidly and variables such as innovation, flexibility and efficiency ease the advancement of enterprises (www.codecentric.com, 2010).

As literature review revealed, organizational agility has its roots in manufacturing context and started as a research by Nagel & Dove (1991). It was defined as a manufacturing system which is able to meet the needs of a changing marketplace, shifts quickly between products, in real time in order to adapt to changing customer needs. Early agility research (Goldman, Nagel, & Preiss, 1995; Sharifi & Zhang, 2001; Yusuf, Sarhadi & Gunasekaran, 1999) characterized agility as an ability to reconfigure manufacturing system in order to respond to unpredictable changes in the market. The ability to reconfigure entails

utilization of structural and infrastructural elements, which adds to the position that agility is a more encompassing capability compared to flexibility (Attafar, Ghandehari, & Momeni, 2012). By synthesizing existing technologies and production methods (Goldman *et al.*, 1995), combining managerial and manufacturing tools (Sharifi & Zhang, 2001) with the help of people and processes (Brown & Bessant, 2003) organizations are able to reach agility. Literature often confuses definitions of organizational agility and manufacturing agility, due to mixing performance outcomes and manufacturing processes (Narasimhan, Swink, & Kim, 2006). Researchers conceptually differentiate organizational agility – a performance capability, from agile manufacturing systems – cluster of related practices (Attafar *et al.*, 2012). Authors of early research into organizational agility focused mainly on manufacturing organizations, thus agility definitions are concentrated around manufacturing processes and new products.

Machine learning methods require data. Deep learning, subfield of machine learning has become popular over past decade as it has shown great potential in several fields including image recognition and natural language processing. Techniques of deep learning have developed but are still rather close to ones that have been developed decades ago. What has improved and made possible to harness true potential of deep learning is the availability and amount of data. Deep learning algorithms, models, become more and more accurate when data volume that is used for training increases. Typically, a model becomes accurate enough when training data consists of at least 5000 labelled samples. Achieving and exceeding human level accuracy requires millions of labelled samples. There are research areas that focus on the techniques that would achieve good results with smaller sample volumes and with unlabelled data. However, larger volume and better quality of data are always welcome. (Goodfellow, Bengio, & Courville, 2016, pp. 18-21) Therefore, to apply machine learning and especially deep learning methods to solve an issue or to analyze a phenomenon, sufficient amount of data is required.

Machine Learning and Organizational Agility

The field of AI, short for Artificial Intelligence, has been gaining much attention due to its ability to effectively analyse and act upon a vast amount of collected data (Bughin et al. 2017). The technology has been recently featured frequently both in media and in companies' public relations. However, as a research subject, it has been around since the 1950s, during which it has survived a few "winters" of deflated interest and is now experiencing a summer again (Ning & Yan 2010). This spike in interest is mostly due to the advances in the subfield of machine learning and supporting factors such as data storage and computational power (Quan & Sanderson 2018).

The science of machine learning is translated to business applications in numerous ways which influences business models and employees. Marketing, risk management, logistics, legal departments, finance departments, health care and even education have started to use machine learning applications (Baesens, 2014; Frey & Osborne, 2013). Big data and machine learning have the potential to transform virtually any business (McAfee & Brynjolfsson, 2012; Yeomans, 2015) and machine learning is "likely to change the nature of work across a wide range of industries and occupations" (Frey & Osborne, 2013, p. 17). However, unlike in other business domains, Human Resource Machine Learning (HRML) is not – yet – commercially ready.

Machine learning can, in theory, help us moving further away from the universalistic paradigm in HR. When HR and business data is combined with big data (e.g. information on competitors, the labour market, etc.) it allows for the creation of context specific HR models that have a high internal validity. In plain language, HRML gives better, individualized and tailor-made HR advice than HR professionals ever could give. Several researchers have already investigated HRML. Examples include, among others, (1) how to reduce selection criteria for hiring managers, (2) to predict turnover intentions of employees, (3) extract information from resumes and motivation letters, or (4) to improve employee selection (Wang, Li & Hu, 2014; Fan, Fan, Chan & Chang, 2012; Kaczmarek, Kowalkiewicz & Piskorski, 2005; Chien & Chen, 2008). These examples show how HRML can be used to improve HR outcomes. Therefore, it is the working proposition of this paper that HRML increases the quality of HR advice.

Prieto and Revilla (2006) stated that while numerous organizational learning scholars demonstrate the significance of learning capability, no clear definition is establishe for the subject. Moreover, Hull and Covin (2010) defined learning capability as an organizational competence to produce new products using innovative insights or new obtained capabilities. Additionally, Limpibunterng and Johri (2009) defined "organizational learning capability as an intrinsic ability of an organization because of which the organization creates, enriches, and utilizes knowledge to outperform its competitors in terms of its competitiveness and performance" (p. 328). Teo et al. (2006) specified that organizations with the capabilities to learn could adopt to new technologies faster that organizations are lacking learning capabilities.

In addition, Organizations can acquire competitive advantage by adapting learning capabilities that include assets and perceivable or unperceivable capacities (Alikhani and Fazlollahtabar, 2014). Weerawardena (2003) stated, "Learning processes must be translated into the acquisition of managerial competencies that permit the organization to be more efficient than competitors" (p. 411). Correspondingly , Prieto and Revilla (2006) "conceptualize learning capability as the potential to explore and exploit knowledge through learning flows that make possible the development, evolution and use of knowledge stocks that enact organizations and their members to add value to the business" (p. 169).

Machine learning is associate degree application of computing (AI) that gives systems the power to mechanically learn and improve from expertise while not being expressly programmed. Machine learning focuses on the event of pc programs that may access knowledge and use it learn for themselves. The process of learning begins with observations or knowledge, like examples, direct expertise, or instruction, so as to seem for patterns in knowledge and create higher selections within the future supported the examples that we offer. the first aim is to permit the computers learn mechanically while not human intervention or help and modify actions consequently. Machine learning algorithms are usually classified as supervised or unsupervised. (Varone, Mayer & Melagari 2019)

Machine learning permits analysis of large quantities of knowledge. whereas it usually delivers quicker, a lot of correct leads to order to spot profitable opportunities or dangerous risks, it's going to conjointly need beyond regular time and resources to coach it properly. Combining machine learning with AI and psychological feature technologies will create it even simpler in process giant volumes of data. Probably the most discussed

today is artificial intelligence (AI), which in general terms is defined as a field in computer science that refers to an IT system that can act, learn, comprehend and sense (Kolbjørnsrud et al., 2015). In particular, AI involves machine learning; "the machine's ability to improve its performance without people having to explain to it exactly how to perform all the tasks to be completed" (Antonescu, 2018, p.16).

The effect of these developments on businesses is not just due to their direct contributions but also by inspiring new innovations. The outcome can be new products in artificial vision and audio/speech recognition, natural language processing, and many other possibilities with machine and deep learning (Antonescu, 2018). In fact, Statista company has estimated that the market global earning from AI for enterprise applications will rise to over 30,000 million dollars in the year 2025.

Although machine learning presents unprecedented opportunities for value creation, it also creates daunting challenges for managers and executives as they will be forced to reconsider their own roles and re-evaluate the fundamental operating principles presently guiding their organization (Kolbjørnsrud et al., 2015). Collaboration among machines and humans will increase, and the division of labor will change (Kolbjørnsrud et al., 2015). Therefore, companies will have to reinforce their performance, training and talent acquisition strategies to place newfound emphasis on work that depends on human judgment and skills, along with experimentation and collaboration. (Kolbjørnsrud et al., 2015). As MIT Sloan professor Erik Brynjolfsson, a well-known management expert explained, the difficulty we face today is not explained as a world without a work, rather as a world with constantly changing work (Chopra, 2018). Consequently, managers will need to keep on their toes and to keep on taking advanced steps in order to continually evolve companies (Chopra, 2018).

To sum up, AI will in general change all levels of management, where key manager's tasks such as coordinating, controlling, collaborating and problem solving are most likely to be automated. Furthermore, AI will automate scheduling, reporting and resource allocation, along with taking time-consuming and administrative tasks off managers' shoulders, giving them more time to spend on innovation, strategy and the people within the organization. However, this challenges managers to reconsider their role in this constantly changing work environment. Hence, it has become imperative to examine how machine learning specifically correlate with various dimensions of organizational agility as operationalized in this thesis. Accordingly, the following null hypotheses were formulated and tested:

H_{o1}: Machine learning strategies do not significantly correlate with human resource agility of telecommunication companies in Nigeria.

H_{o2}: Machine learning strategies do not significantly correlate with Information Technology agility of telecommunication companies in Nigeria.

H_{o3}: Machine learning strategies do not significantly correlate with innovation agility in telecommunication companies in Nigeria.

Resource Based View

According to the Resource Based View Theory, competitive advantage stems from a firm's unique resources that are valuable, rare, and inimitable (Barney, 1991). Firm resources include both assets and capabilities. Assets are observable and can be valued, such as spatial preemption, brand equity, and patents. In contrast, capabilities are not observable

and difficult to quantify; they are the glue that brings the assets together and deploys them advantageously (Makadok, 2001). Because capabilities are deeply embedded in organizational routines, they are idiosyncratic and difficult to imitate or duplicate, which makes them the most likely sources of competitive advantage (Day, 1994).
According to RBV capability can transform firm assets into superior performance (Hult, Ketchen & Slater, 2005; Zhou, Yim & Tse, 2005). Therefore, in relation to this study, these specific capabilities are at the center stage in determining how an organization responds to changes in the environment in which it operates. In this study, the capabilities are seen in form of artificial intelligence, IT adoption, strategic alliances and human resources management practices. Further, capabilities touches on the intricate aptitude for the firm to offer high quality services to match customer needs and expectations. This to a great extent would enhance agility of the firm.

Research Design

The research design adopted in this study by the researcher was the cross sectional correlational survey design.

Population of the Study

The targeted population was obtained from four Telecommunication companies in Nigeria and with offices in Port Harcourt, Rivers State. These companies were: MTN, Global-com, Airtel, and 9mobile. The population consists of these four organizations with a size of three hundred and sixty (360) employees comprising one hundred and one (101) employees of MTN, eighty-five (85) employees of 9mobile, eight-five (85) employees of Airtel and eighty-nine (89) employees of Global-com.

Sample and Sampling Techniques

The sample size for the study was determined using Krejcie and Morgan (1970) sample size determination table. The table was used to obtained the sample size of 186 employees based on the total population of 360 employees in the four Telecommunication companies. The sampling technique was purposive sampling for top and functional management and random sampling for supervisors and workforce. Bowley (1926) proportional allocation formula was used to allocate sample size for each company.

TABLE 1 Summary of Sample Size

S/N	TELECOM COMPANIES	Top Mgt	Functional Mgt	Supervisors	Workforce	Total
1	MTN	5	10	7	30	52
2	9mobile	4	10	7	23	44
3	Airtel	5	11	7	21	44
4	Global-com	5	12	8	21	46
	Total	19	43	29	95	186

Source: Field Survey, 2019.

Methods of Data Analysis

The copies of questionnaire were coded for analysis using SPSS version IBM 23. Descriptive statistics of percentage, mean and standard deviation was and Inferential statistics (Spearman's Rank Order Correlation Co-efficient) were used for data analysis.

Results

Hypotheses 7-9: Machine Learning and organizational agility

Ho -There is no significant relationship between Machine Learning and organizational agility.

The independent variable in this hypothesis was machine learning, while the dependent variables are Human Resource Agility, Information Technology Agility and Innovation Agility rate. Spearman's Rank Order Correlation Co-efficient was used to test this hypothesis. The result of the analysis was presented on table 4.16.

H_{o1}: Machine learning strategies do not significantly correlate with human resource agility of telecommunication companies in Nigeria.

H_{o2}: Machine learning strategies do not significantly correlate with Information Technology agility of telecommunication companies in Nigeria.

H_{o3}: Machine learning strategies do not significantly correlate with innovation agility in telecommunication companies in Nigeria.

Table 1 Analysis of Relationship between Machine Learning and Organizational agility.

			ML	HRA	ITA	IA
Spearman's rho	ML	Rho	1.000	.278**	.289**	.351**
		Sig. (2-tailed)	.	.000	.000	.000
		N	181	181	181	181

Source: Source: SPSS Data Output, 2020

The result in table 1 shows that the sig (2 tailed) value of Innovation Agility, Human Resource Agility and information technology agility when compared to machine learning with rho =0.278, 0.289 and 0.351 respectively are less than the p value at $P<0.05$ significant level. With this result, the null hypotheses were rejected. The result therefore implies that machine learning has a significantly weak association with Innovation Agility, Human Resource Agility and information technology agility in telecommunication firms. On the basis of this outcome, I reject the null hypotheses hence there is a significant relationship between machine learning and organizational agility.

Machine learning and Organizational agility

Correlation analysis of the relationship between machine learning and measures of organizational agility (Human Resource Agility, Information Technology and Innovation Agility) of telecom firms showed a positive low relationship. The result as revealed by this study following a p-value of 0.00 showed that there is positive and significant relationship between Machine Learning and Innovation Agility, Human Resource Agility and Information Technology Agility. This confirms the earlier assertion of Smola and Vishwanathan, (2008) that Machine learning comes to stage as a necessary ingredient for technological progress and ultimately impacts overall organization's performance. Also the findings supported the work of Soliman (2011). He evaluated the relationship between Information Technology advancement and organizational agility. He concluded that there

is positive relationship between information technology advancement and organizational agility.

CONCLUSIONS

The study having taken cognizance of necessary precautions and carried out the research, carefully handling data and analyses, it concludes that there is a positive and significant relationship between study variable (Machine learning and organizational agility). Based on the result it is concluded the use of machine learning has a great effect on the organizational agility of telecommunication companies.

RECOMMENDATIONS

Judging from the findings of the study, the researcher hereby makes the following recommendations:

1. Since machine learning positively correlates organizational agility, telecommunication firms should improve on their adaptation to machine learning system as well as other emerging technological advancement in to further improve their organizational agility.
2. Since Competitiveness of a telecom firm's product in the market is dependent on its agility which is dependent on strong cultural practice, it is therefore important that telecommunication firms greatly build a strong organizational in order to adapt to emerging change brought about by the adoption of artificial intelligence system.

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