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Internet of Things and Innovation Agility in Telecommunication Companies in Nigeria

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Abstract: This study investigated the relationship between internet of things and innovation 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, and 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 internet of things and innovation agility. Hence the study concludes that hike in internet of thins 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 internet of things

Keywords: Internet of Things, Innovation, Agility, Telecommunication

Introduction

We are living in a dynamic world, customers changing their preferences rapidly which enforce organizations to adopt the concept of organization agility to generate positive organization performance. The previous performance Organizational help reveal the extent at which an organization is capable of coping with environmental determinants and degree of appropriate measures the strategic objectives of the organization, resources and organizations today tend to possess a strategic vision for change to enable them to achieve organizational agility , and suggesting it is a substantial increase in the resources allocated to research and development and investment in human resource especially if they are fast, flexible and responsive to change and uncertainty and also characterized with high-quality products and these elements of organizational agility, which works to increase performance Organizational effectively .

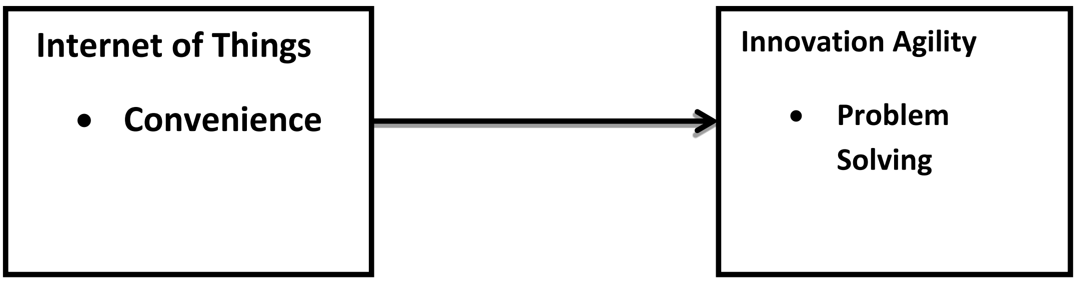
The Internet of Things makes use of synergies that are generated by the convergence of Consumer, Business and Industrial Internet Consumer, Business and Industrial Internet. The convergence creates the open, global network connecting people, data, and things. This convergence leverages the cloud to connect intelligent things that sense and transmit a broad array of data, helping creating services that would not be obvious without this level of connectivity and analytical intelligence. The use of platforms is being driven by transformative technologies such as cloud, things, and mobile. The IoT potential is analysed in (Bradley *et al.*, 2013) with examples of critical improvements such as reduction of materials, energy and costs of automated tools, which is less expensive to manufacture and implement.

Innovative firms and less innovative firms differ greatly in their risk propensity, attitude toward uncertainty, and acceptance of new technology. Highly innovative firms are more likely to engage in learning and experimenting, are able to cope with high uncertainty and are more prone to taking risks. In addition to innovativeness, firms could differ in terms of how they incubate innovations. While some scholars have argued that new initiatives are more likely to be successfully commercialized if they are separated from the core organization more recent studies have called for better integration of the new initiatives with the rest of the organization to enable their success (Ravichandran, 2017).

Such integration has not been easy for firms because it requires the ability to orchestrate complementary interactions among key business processes and resources (Barki & Pinsonneault, 2005) and overcome inherent conflicts between traditional work practices and those necessitated by the new business models. However, firms able to accomplish such complementary interactions are likely to enhance their capability to respond to changes in their business environment quickly and create competitive advantage (Oh *et al.*, 2006).

There is very scanty empirical research exploring how the technology affects the organization. Little research has been done in form of empirical studies, especially in specific contexts. Most of the research currently available is done abroad, where the job market and working conditions are different from the conditions in Nigeria, questioning if the findings from these researches are applicable in Nigeria. Hence, there is a gap in empirical studies with regards to the relationship between internet of things and innovation agility.

Operational Conceptual Framework



Hypothesis

H_{o1}: Internet of things does not significantly correlate with innovation agility of 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.

According to RBV capability can transform firm assets into superior performance. Therefore, in relation to this study, these specific capabilities are at the centre 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 touch 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.

The Internet of Things

The Internet of Things and Services makes it possible to create networks incorporating the entire manufacturing process that convert factories into a smart environment. The cloud enables a global infrastructure to generate new services, allowing anyone to create content and applications for global users. Networks of things connect things globally and maintain their identity online.

AI will lead to a redefinition and a disruption of service models and products. While the technical development leads primarily to an efficiency enhancement in the production sectors, new creative and disruptive service models will revolutionise the service sector. These are adapted with the support of big data analyses at the individual requirements of the client and not at the needs of a company.

INDUSTRY 1.0 (INDUSTRIALISATION): Industry 1.0 is known as the beginning of the industrial age, around 1800. For the first time, goods and services were produced by machines. Besides the first railways, coal mining and heavy industry, the steam engine was the essential invention of the first industrial revolution; steam engines replaced many employees, which led to social unrest. At the end of the 18th century, steam engines were introduced for the first time in factories in the UK; they were a great driving force for industrialisation, since they provided energy at any location for any purpose.

INDUSTRY 2.0 (ELECTRIFICATION): The second industrial revolution began at the beginning of electrification at the end of the 19th century. The equivalent of the steam engine in the first industrial revolution was the assembly line, which was first used in the automotive industry. It helped accelerate and automate production processes. The term Industry 2.0 is characterised by separate steps being executed by workers specialised in respective areas. Serial production was born. At the same time, automatically manufactured goods were transported to different continents for the first time. This was aided by the beginning of aviation.

INDUSTRY 3.0 (DIGITALISATION): The third industrial revolution began in the 1970s and was distinguished by IT and further automation through electronics. When personal computers and the internet took hold in working life, it meant global access to information and automation of working steps. Human labour was replaced by machines in serial production. A process that was intensified in the context of Industry 4.0 was already in the offing at that time. INDUSTRY 4.0: The term Industry 4.0 means in essence the technical integration of cyber physical systems (CPS) into production and logistics and the use of the 'internet of things' (connection between everyday objects)10 and services in (industrial) processes – including the consequences for a new creation of value, business models as well as downstream services and work organisation. CPS refers to the network connections between humans, machines, products, objects and ICT (information and communication technology) systems Within the next five years, it is expected that over 50 billion connected machines will exist throughout the world. The introduction of AI in the service sector distinguishes the fourth industrial revolution from the third

Neural Networks (NN)

Neural networks are developed by modelling the human brain, to which they are similar in two ways. First, information is acquired by networks in neural networks. Secondly, connections between artificial neurons are used to store information. In neural networks, the artificial network is a processor used to store information and to make it functional (Gelir, 1994). Neural networks consist of the combination of constant non-linear functions (Chenoweth, Obradovic & Stephen, 1996) and the authority of neural networks express the capacity of neural networks (Krose & Smagt, 1996).

Neural networks include input layer, hidden layer and output layer.

Input Layer: It is the layer in which input data groups are introduced to the network. Parameters in input layers have to be selected before analysis (Blackkard & Dean, 1999). The number of neurons in an input layer is equal to the number of input data; every input neuron is transmitted to the next layer – which is the hidden layer. Hidden Layer: The hidden layer is the basic function of the network. In this layer, data received from the input layer is processed properly and then transmitted to the output layer (Dag, 2012). Output layer: Learning takes place in the output layer. Linear units are connected to the output consisting of hidden layers (Abdi, 2003). It is the final layer in the network and it processes the data received from the hidden layer and creates the output. The number of neurons is equal to the number of outputs received by the network. Values obtained are the output values for the problem in the neural network (Dag, 2012).

Neural network has the following features:

1) Non-Linear: Neural networks emerging from the combination of cells are nonlinear and this feature of theirs is spread throughout the network. Neural networks are the most significant tool to solve complex non-linear problems.

2) Fault Tolerance: In artificial networks, fault tolerance is quite high. The reason why neural networks have fault tolerance is that information is scattered around the system in a regular way.

3) Training: Neural networks in neural networks adjusted for a purpose modify their own values and are capable of adapting themselves for the exact solution of the problem.

4) Learning: In order to obtain the data required, algorithms are identified by adjusting the load of neural networks (ANN). This process in which the load is adjusted is called "learning" (Gershenson, 2003). The process of learning is the process defining the relation between the system inputs and outputs. In order for neural networks to learn a problem, input and output data must include sufficient samples as well as a clear definition of the learning cluster.

5) Generalization: Through generalization, neural networks are capable of creating the desired response during the training process – with regard to samples it has never encountered, after studying and learning the problem.

6) Memory: In neural networks, connection loads are the types of memory and memory is distributed by creating local memories. Load values of neural networks represent the information available in the network right at that moment.

In neural networks, the artificial neuron is a model inspired by natural neurons.

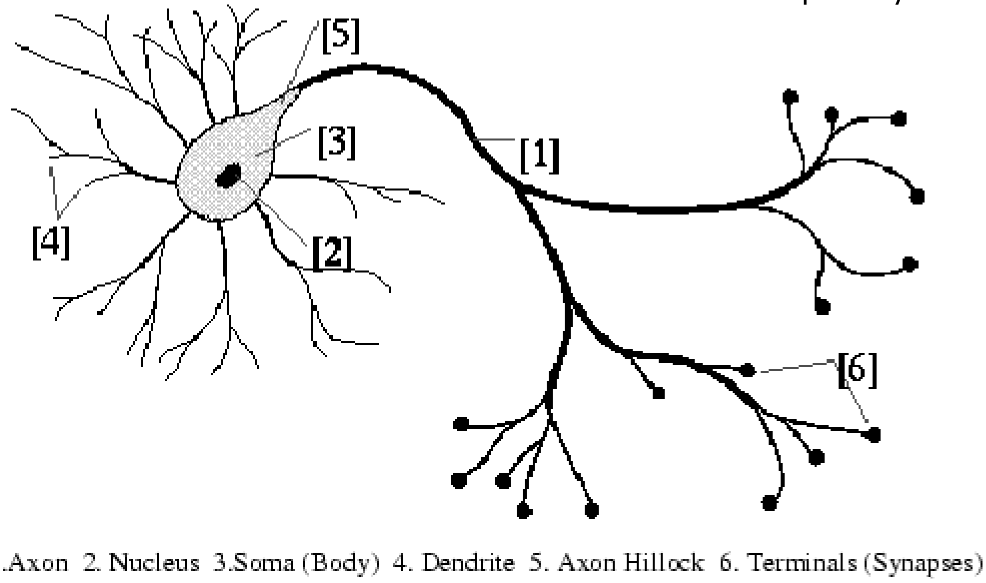


Figure 2.1: A Biological Neuron depicting a nerve cell consisted of synapse, axon, soma and dendrites

Source: Staub et al (2015),

Natural neurons receive signals through a synapse on the dendrite or membrane. Neurons distribute these signals when the incoming signals are strong enough. Signals may also be sent to another synapse and activate the other neurons there (Gershenson, 2003). When neurons receive sufficient stimulation, they immediately react to an electrical stimuli coming from an axon (Gershenson, 2003). Neural networks (ANNs)consist of traditional network compounds such as feed forward connections and linear functions (Kramer, 1991). Neural networks have two basic disadvantages. These are local minimum convergence and slow learning speed (Castillo, Guijarro-Berdinas, Fontenla-Romero & Alonso-Betanzos, 2006). Based on their architectural structures, ANNs can be subjected to various classifications such as feed forward networks, feedback networks, memory based networks, radial based networks and module neural networks. Of these network structures, the ones most commonly used in literature are feed forward networks and feedback networks: Perceptron and adaline (adaptive linear neuron). The most important feature of feed forward networks is that they are capable of detecting fake or missing data before the processing is concluded (Benell &Sutcliffe, 2003). Unlike feed forward networks, dynamic features of the network is significant in repetitive networks. In some cases, the activation values of the units go through a process of relaxation. In other applications, the change in the activation values of output neurons is important. Thus, dynamic behaviour creates the output in the network. In feed forward networks, data flows from input units to output units. Data processing might be expanded to the layers of the units; however, there are not any feed forward connections available – that means, connections spread from the outputs of the units in the same layer or previous layer to the outputs of the units (Kurkcu, 2013).

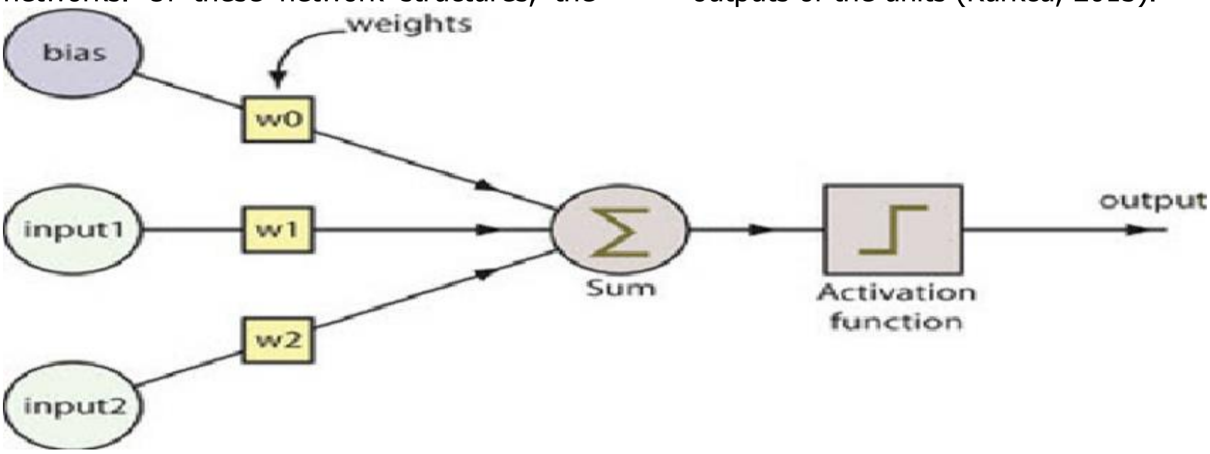


Figure 2.2: General Block Structure of ANN
Source: chip.com (2019)

In figure 2.2 (xi:i = 1……m) refers to the processor of input layer, (w1; 1……m) refers to the load of connection with hidden processor, ™ refers to deviation function, y refers to the processor of output layer. V and ij (-) refers to the load of connection with the output processor.

Neural networks are often used in deep leaning systems since both feedforward (acyclic) and recurrent (cyclic) neural networks have won early and present contests in object detection, pattern recognition and image segmentation (Schmidhuber, 2015). Neural network has thus proven to be a winning architecture and have had the greatest impact during the resent years of machine learning. Neural networks consist of elemental processors, each computing a sequence of a real-valued activations joined together in a network. The system is activated through input neurons being triggered by the environment, neurons along the network are then activated by weighted connections from previously activated neurons, sending impulses trough the network like an organic brain. When a system is learning, it is the weighted connections that are shifting to acquire desired behaviour i.e. learning. The future problems of deep learning neuron networks are to make them more optimized and energy saving (Schmidhuber, 2015).

Innovation Agility

Innovative firms and less innovative firms differ greatly in their risk propensity, attitude toward uncertainty, and acceptance of new technology. Highly innovative firms are more likely to engage in learning and experimenting, are able to cope with high uncertainty and are more prone to taking risks. In addition to innovativeness, firms could differ in terms of how they incubate innovations. While some scholars have argued that new initiatives are more likely to be successfully commercialized if they are separated from the core organization more recent studies have called for better integration of the new initiatives with the rest of the organization to enable their success (Ravichandran, 2017). This is particularly true in the case of IT-enabled innovations such as the creation of new business models, new channels to access the markets or digital products and services, because such innovations require the firm to leverage existing firm resources in new and novel ways. Moreover, unlike radical product innovations that might be driven by scientific inventions and efforts, IT enabled innovations often stem from business units and require the use of emerging and new technologies to rethink the activity systems of the firm. Large firms have resource advantages that if properly leveraged could lead to success in innovation efforts such as new business models. However, such resource leverage has to be achieved without the culture, norms and business practices of the core organization impeding the new initiatives. Tight coupling between the new initiatives and the core organization along with close intervention by the senior executives in the management of the innovation efforts are needed to balance these tensions (Govindarajan & Trimble, 2005).

Thus, the innovation capacity of a firm is both dependent on its innovativeness and the existing resource endowments of the firm. Fig. 2 depicts a framework that characterizes innovation capacity in terms of two dimensions namely, firm innovativeness and the nature of coupling between new initiatives and core activities of the organization. The upper right cell depicts firms that have high innovation capacity because they have an organizational climate that enables innovative behavior and they are capable of leveraging the resources of the core organization because of the tight coupling of the new initiatives with the core activities of the firm. The upper left and lower right cells depict firms that have moderate innovative capacity.

Methodology

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 1: Internet of Things and innovation agility

Table 2 Analysis of Relationship between Internet of Things and innovation agility.

			IoT	IA
Spearman's rho	IoT	Rho	1.000	.294**
		Sig. (2-tailed)	.	.000
		N	181	181

Source: Source: SPSS Data Output, 2020

The result in table 2 showed that there is a significant correlation between Internet of Things and Human resource agility, Information Technology Agility and Innovation Agility rate evidenced by the correlation coefficient (rho) of 0.294 at $p< 0.05$. On this premise, the null hypothesis was rejected hence there is a moderate to weak positive relationship between the adaptation to Internet of Things and innovation agility of telecommunication firms.

Discussion

Internet of Things and innovation agility:

Result of correlation analysis of Internet of Things and organizational agility divulge a low to moderate association between the use of Internet of Things and Innovation Agility. In all, the study showed a significant positive correlation of Internet of Things with innovation agility of the telecom firms. This result is in agreement with the finding of Otieno (2008) which depicted that if technological advancement which include Internet of Things are not properly implemented it can result to colossal increase in competitive advantage of the firm. It also confirms the assertion of Ovia (2000) which stated that increased dependence on the development of information technology would not be far from the high correlation of IT advancement with organizational performance of the telecommunication industry. The situation beyond the borders of Nigeria is not different as other international studies also confirmed the findings of this study. One of such is De Yong, *et al* (2007) who reported that internet adoption improved telecoms firm's profitability in U.S. community.

Conclusions

The study having taken cognizance of necessary precautions and carried out the research, carefully handling data and analyzing it, concludes that there is a positive and significant relationship between study variable (Internet of Things and organizational agility)

Based on the result it is concluded the use of various aspects of internet of things 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 internet of things positively correlates organizational agility, telecommunication firms should improve on their adaptation to internet of things 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 internet of things

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