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DEVELOPING BIG DATA CAPABILITIES IN DEVELOPING COUNTRIES. EVIDENCE FROM A CROSS INDUSTRY STUDY IN GHANA

(Research in Progress)

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ABSTRACT

Big data is a phenomenon which is generating a lot of interest in academia and practice. In the mist of all this excitement lies a world of uncertainty that most firms seem not to be able understand, how to develop, deploy or combine the capabilities of big data to obtain the benefits that big data offers. To address this, this research uses dynamic capabilities as its theoretical lens to bring clarity to this problem. The research establishes 6 broad categories which makes up the typology of big data capabilities. The big data capabilities identified are technological, data management, legal and ethical, analytical, data sharing and decision making capabilities. The research further establishes the benefit dimensions of big data as organizational, managerial, strategic, IT infrastructure and operational benefits. Using the component factors of dynamic capabilities namely adaptive, absorptive and innovative capabilities, as well as the individual, routine/processes, organization and industry levels of analysis of dynamic capabilities, the research establishes a big data capability conceptual model which is currently being tested for understanding and possible modification with empirical data. The empirical data is being gathered from a cross industry perspective with the sector industries being healthcare insurance, banking and telecommunication.

Keywords: Big data, big data capabilities, big data benefits, dynamic capabilities

1. INTRODUCTION

The amount of data in the world is exploding. Enterprises are flooded with ever-growing data of all types, easily amassing terabytes, even petabytes, of data (Boyd and Crawford, 2012). This data comes from everywhere. These very large amounts of data which comes in structured, semi-structured and unstructured forms along with the intrinsic value that can be extrapolated from them using analytics, algorithms, and other techniques is called "big data" (Kwon, Lee & Shin, 2014).

Big data brings about a lot of interest in academia and practice (Halevi & Moed, 2012). In the mist of all this excitement lies a world of uncertainty (Boyd and Crawford, 2012) that most firms such as banks, health insurance companies and telecom companies seem not to be able understand, how to develop, deploy or combine the capabilities of big data to obtain the benefits that big data offers. This research thus seeks through theorization to bring clarity to the constituents of big data capabilities, the benefits associated with big data and how the capabilities of big data can be developed and deployed to obtain benefits.

2. <u>RESEARCH PROBLEM</u>

Big data is relatively an under-researched area (Kwon, Lee & Shin, 2014; Jin et al., 2015). In developed countries a number of research has begun to conceptualize and explore the benefit or potential gain of big data (Gandomi & Haider, 2015; Srivastava & Gopalkrishnan, 2015). Hence most of the research tends to review literature, conceptualize different characteristics of big data and explore the benefits to be gained. These research are often silent on how firms create big data capabilities and deploy them to obtain benefits. The lack of this knowledge often makes it difficult for non-adopters to chart their way through darkly waters of big data (Kwon, Lee & Shin, 2014). Thus the purpose of this study is to examine how firms develop and deploy big data capabilities and obtain big data benefits.

This said, one may say if this is of relevance to IS developing country (DC) research. This is relevant because, there is evidence to suggest that firms in Africa and other developing countries have started to experiment or deploy big data capabilities (Kuresh, 2012; UN, 2009). Academics on IS research in DCs are yet to catch up with research to explore what capabilities are been developed, what benefits are being obtained and how the often scarce IS resources in developing countries are being used to deploy the capabilities and obtain benefits.

Further, the research is opportune, as there have been growing interest in capability development research from a developing country perspective. The work of Boateng (2014) and Budu and Boateng (2015) attests to the application of the dynamic capabilities framework to explore capability development in fairly new and emerging technology research area like e-commerce and mobile business. The authors share on the complexity of factors which affect the development of such IS capabilities and thus echo that future research should explore their proposed models based on the capability development cycle and the dynamic capability framework in other IS applications. This research takes advantage of the call and intends to build on the previous understanding to understand through a dynamic capability theoretical lens the complexity of factors which enable or constrain the development and leveraging of big data in DCs.

More so, industries such as the banking, health insurance and telecommunication sectors hold a lot of promise in contributing to development in DCs (Ariss, 2010). This said, any research which offers theoretical and practical knowledge to make the sectors more efficient and productive will go a long way to contribute to development in DCs. This research holds such promise in establishing the knowledge about the application of big data in DCs context. Current research on big data in DCs are narrowly focused on the challenges and potential impacts of Big Data on DCs. This research takes a more strategic perspective to examine how big data capabilities are being developed to create benefits for DC firms.

3. <u>RESEARCH OBJECTIVES</u>

The objectives of this study are;

- 1. To examine the type and nature (constituents) of big data capabilities needed by firms to adopt big data.
- 2. To examine the benefits that are obtained by firms when they deploy big data capabilities.

3. To understand how firms the big data capabilities are developed in firms in order to obtain benefits.

4. THE TYPOLOGY OF BIG DATA CAPABILITIES

Throughout big data research mention has been made of big data capabilities (Wang et al, 2014; Kamioka & Tapanainen, 2014; Wamba et al, 2015). An academic paper search for "big data capabilities" from five academic databases returned 6 articles for ScienceDirect, 13 articles for ACM Digital Library, 13 articles for Ebscohost (13), 1 article for Emerald Insight, 4 articles for IEEE (4) and 3 articles for Sage Journals.

A review of these papers related to big data capabilities showed 6 broad categorisations of big data capabilities. These categorisations were made up of technological capabilities, data management capabilities, legal and ethical capabilities, analytical capabilities, data sharing capabilities and decision making capabilities.

4.1 <u>Technological Capabilities</u>

Technological capabilities related to big data refers to IT infrastructure that are well suited for big data. These includes building capacities in acquiring computing infrastructures (such as specialised data centres) and software frameworks (data processing technologies such as MapReduce, Hadoop, NoSQL, Machine Learning, distributed storage system, etc.), which are specifically optimised for big data applications (Di Martino et al, 2014).

Apart from physical data centres, capabilities in the acquisition of virtualised data centres in Cloud computing (Talia, 2013; Talia and Trunfio, 2010) for big data are also part of the technological capabilities needed for big data adoption. Cloud computing assembles large networks of virtualised services: hardware resources (CPU, storage, and network) and software resources (e.g. databases, message-queuing systems, monitoring systems, load-balancers). Cloud Computing services are hosted in large data centres, often referred to as data farms, operated by companies such as Amazon, Apple, Google, Codero and Microsoft.

These cloud computing services also offer big data database technologies such as Google's Big Table, Google Big Query and Mongo DB. In addition to big data base technologies these cloud computing services allows the use of traditional SQL queries to be used to access such database technologies as well as link them up to traditional databases such as MySQL which are very relevant in processing and analysing big data.

This cloud computing services seems to be on area that most organizations in developing countries trying to adopt big data are using since most of firms in developing countries seem not to have the capacity to build their own data centres.

4.2 Data Management Capabilities

Big data possess five data characteristics (White, 2012) which are crucial in the management of big data. These data characteristics are volume, variety, velocity, veracity and value. To obtain big data benefits managing big data based on these characteristics are a necessity for big data adoption. The volume characteristics refers to large volume of data that either consume huge storage or consist of large number of records (Russom, 2011). Developing capabilities to manage this volume of data is essential. According to Chen et al. (2013) managing and indexing extensive volumes is the most evident challenge with big data. Indexing helps to accelerate access to data, performing query functions such as select, insert, update and delete quickly. Developing data indexing capabilities is one component to managing big data efficiently for both querying and storage purposes. This informs the choice of database technologies to adopt for a particular big data initiative.

Big data is generated from a greater variety of sources and formats, and contain multidimensional data fields (Russom, 2011). The variety characteristics demand that firms build capabilities that correctly identify the right sources of data for the big data project being undertaken. A wrong source of data has an effect on quality of insight that is derived from big data. In addition, building capabilities in data acquisition of such variety of data sources is also essential so as to ensure the readily availability of data for analysis and processing. Data acquisition is considered as the process of gathering, filtering and cleaning data derived from heterogeneous sources, both structured and unstructured, comprehending sensor networks and data streams (Di Martino, 2014).

The velocity characteristic refers to the speed of data generation and the speed of data delivery (Russom, 2011). Developing capabilities in quick generation and delivery of data depends on the sensitive nature the data or the premium that firms place on that data (Young, 2014). For some data a minute delay is crucial whiles for others a day or two delay may not be crucial. Data integration and aggregation is one capability which is off essence if data is to be gathered and delivered based on its frequency.

The veracity of big data refers to the quality of data that is harnessed (Beulke, 2011). Data management capabilities associated with this characteristics include extraction and cleaning of data of data to conform to the quality required for the big data initiative being undertaken (Di Martino, 2014). The metadata of the data being gathered is key when it comes to veracity of big data. The much granular nature of the data ensures a greater quality and aids a much better insight to be gained from the big data. Enforcing data coherence is crucial in the development of this capability.

Value refers to the extent to which big data generates economically worthy insights and or benefits through extraction and transformation (Chen et al., 2013). Deriving value from big data is the ultimate goal of undertaking big data projects as it is out of that much benefit can be gained. Data management capabilities within this characteristic include data analysis and interpretation. Data analysis and interpretation refers to the application of analysis techniques on the acquired data, in order to support business intelligence, decision-making and support, forecasting; extraction of new data from the analysed sources.

4.3 Legal and Ethical Capabilities

In the era of big data, much personal and sensitive information including health data, security data, location data and browsing data just to mention a few are constantly being gathered (Zwitter, 2014). Capabilities in big data ethics which comprise of a set of four-high level principles according to Richards & King (2014) is essential to be developed by firms in carrying out big data initiatives. The four high-level principles are

- Privacy Rules (i.e. information rules that manage data and information flows in ethical ways)
- Confidentiality of shared private information
- Transparency in big data
- and a recognition that big data can comprise identity

These ethical considerations in big data requires the need to build capabilities in legalities that can protect firms as well as their clients in the adoption of big data initiatives. These legal capabilities may vary from place to place as well as from industry to industry. An IBM white paper by Chessell (2014) suggest that firms in developing ethical capabilities need to consider the following;

- **Context** The purpose for which the data was surrendered as well what it is being used for now. It is important to consider how far from the usage original context the current use has moved from.
- **Consent & Choice** Are the affected parties aware of the choice they are making in giving off data as well as their understanding of the choice they are making.
- **Reason** This considers the depth and breadth of the data collected and used. It establishes the reasonable relationship between the data collected and its usage.
- **Substantiation** This looks at whether the sources of data used are suitable, convincing, complete and appropriate for the big data initiative.
- **Ownership** This looks at who actually owns insights gained from the big data and how the owner protects the big data.
- **Fairness** This considers how parties involved in the big data initiative are properly compensated.
- Access In sharing data it is important for firms to consider who has access to what data.
- Accountability This looks at how mistakes, errors and unintended results are detected and handled.

Chessell (2014) indicates that these considerations put together forms the ethical awareness framework for big data.

4.4 Analytical Capabilities

Harnessing value from big data or gaining insights into the data gathered is the ultimate objective of big data (Wu et al., 2014). Analytical capabilities refers to capacities that enables firms to gain insights or values from big data. Analytical capabilities include data and text mining for business intelligence, statistical analysis, data modelling, machine learning and data visualization (Ohlhorst, 2012).

Business intelligence involves delivering actionable information obtained from in-depth analysis of data driven systems (Chen, Chiang & Storey, 2012). Business intelligence comprise of tools and techniques to turn raw data into meaningful and useful information for business analysis purposes.

Data mining involves data analysis from varied perspectives and delivering them in summarised forms which are useful to organizations. It makes use of archival data using mining

techniques which focuses on modelling and knowledge discovery for predictions (Wu et al., 2014). It is an ideal technology for unearthing new patterns in data.

Statistical analysis involves looking data based on statistical oriented algorithms (Ohlhorst, 2012). Data sets involved are normally related to census, polls and other statistical data sets. They normally lead to estimations, testing and predictive analysis to a large population from a sample size that has been analysed.

Machine learning involves the construction of algorithms that can learn from and make predictions on data (Madden, 2012). The models work by building a model from sample inputs in order to make data-driven predictions or decisions, rather than following strictly static program instructions.

Data modelling comprises of multiple "what if" scenarios for whose algorithm multiple data sets can be used on (Chatti et al., 2012). Information modelled out of these algorithms changes depending on the data set made available to the algorithm.

Data visualization is seen as a substitute for visual communication of data (LaValle et al., 2013). The principal goal of data visualization is to communicate information unambiguously and efficiently to users through statistical graphics, plots, information graphics, tables, and charts. Effective visualization helps users in analysing and reasoning about data and evidence. It makes complex data more accessible, understandable and usable.

4.5 Decision Making Capabilities

Having analysed big data is great however how one interprets the insights obtained and how decisions are made with the analysed data makes a great difference. It determines which firms succeed or fail in a competitive world. Making data driven decisions or gut feeling decisions are crucial thus decision making capabilities are necessary for firms to develop if they are to improve organizational performance and gain competitive advantage. Developing capabilities in decision-making begins with recognising the four broad categories of decision-making and how big data affects them (Yulinsky, 2012):

Episodic decisions: These are decisions that are infrequent, based on a regular cycle and in response to triggering events. These decisions are strategic in nature. These decisions are highly discretionary in nature, and require synthesis of multiple information sources. Decisions in this realm are increasingly relying on simulation models (combining descriptive and predictive approaches) to drive scenario analyses and make trade-offs more clear. Big data offers predictive and descriptive analytics for making such decisions.

Fixed cycle decisions: All businesses have an ongoing cadence for key processes (demand forecasting, sales calling, marketing campaigns, pricing, and inventory replenishment). Historically made as discretionary decisions backed by "rear view mirror" performance data, they are now often supported by predictive analytics leveraging Big Data flows.

Embedded algorithmic decisions: These are "machine-made" continuous decisions driven by optimisation algorithms built-in to consumer (or frontline) facing interfaces are most often the face of Big Data decision making. They include dynamic online offers, real-time credit and

pricing decisions, automated underwriting and call routing. These decisions driving "personalised" outcomes are the type most often changed by the data explosion.

Controller decisions: Evaluation, iteration and refinement of decision-making is usually focused on the effectiveness and ROI of algorithmic decisions. Machine learning based on big data ensures that the algorithms constantly get better, but there also has to be a rigorous layer of analysis to make sure these algorithms stay aligned with the company's objectives and targets.

4.6 Data Sharing Capabilities

Data sharing is complex and inconsistent within and across the many classes of stakeholders (Young, 2014) in a firm and within its industry. The stakeholders within a firm and its industry may include the staff, customers, suppliers, competitors and government (Young, 2014).

After data has been analysed for decision making, the data needs to be shared with those who need it to make relevant decisions. Privacy issues as well as other ethical and legal considerations are of essence at this stage. Furthermore the timely fashion the data gets to stakeholders is crucial to gain competitive advantage. Thus data sharing capabilities such as sharing information via web services, mobile services and many others are relevant within and outside the organisation. However in developing these capabilities they must be done in tandem with the Legal and ethical capabilities that guides the sharing of big data insights. Data sharing capabilities also include sharing the information in real-time or in a timely fashion so as to gain obtain the maximum benefit (Wamba et al, 2015) needed from big data initiatives.

5. THE BENEFITS OF BIG DATA

The benefits that big data offers to organisations has been variously looked at by several authors – both academic authors and practitioner authors. Mayinka et al., (2011) viewed at the benefits of big data from five broad perspectives. These perspective include making information transparent and usable at a higher frequency; exposing variability and boosting performance accurate and detailed data from varied sources; an ever-narrowing segmentation of customers to offer tailored services and products; improving decision making through sophisticated analytics and development of the next generation of products and services.

Kobielus (2013) also looks at the benefits of big data based on four dimensions of big data (i.e. volume, variety, velocity and veracity). Out of this Kobielus (2013) creates a taxonomy of big data value. This taxonomy consist of volume-based value which consist of a 360 degrees view of customers from more historical data on customers; velocity-based value which looks at the quick decision value derived from rapidly ingesting data in big data platforms; variety-based value which looks at the value of decision making derived from varied data on customers and finally the veracity-based value which looks at the value of decision making derived from a more pure and accurate data on customers.

ISACA (2013) also looks at big data benefits for organisation from the perspective of product development benefit, market development benefit, operational efficiency benefit, customer experience and loyalty benefits and market demand and predictions benefit.

A study by Wang et al. (2014) looking at the benefits dimensions of big data concluded on five potential benefits of big data. The study used Shang and Seddon's (2002) potential benefits of enterprise systems as its basis to draw out the benefits that big data offers. Five broad categories of big data benefits were identified. These categories of big data benefits are organizational benefits, managerial benefits, strategic benefits, IT infrastructure benefits, and operational benefits. Shang and Seddon's (2002) benefits dimension has been applied over the years to several studies in different areas. Among these studies are Monem et al. (2013) for the healthcare studies, HassabElnaby et al. (2012) for organizational studies, Tsai et al. (2013) for internal audit studies and Alshawi et al. (2011) for customer relationship management studies.

This study uses Wang et al. (2014) benefit dimensions to look at the benefits derived from big data.

5.1 IT Infrastructure Benefits

Acquiring IT infrastructure such as big data cloud servers, big data database and analytic technologies to carry out big data initiatives is one key component that is crucial to the success of any big data project (Di Martino, 2014). IT infrastructure is made up of IT resources that are sharable and reusable and provides a basis for current and future business applications (Davenport & Linder, 1994; Shang & Seddon, 2002). Big data IT infrastructure benefits refers to the potential of benefit of big data to enhance business flexibility and future changes through IT infrastructure; the potential of big data to reduce IT costs and marginal costs of business units; and an increase in the ability of big data to prompt and implement economically new applications (Shang & Seddon, 2002; Wang et al., 2014)

5.2 **Operational Benefits**

Organizations perform several operational activities on daily basis. These processes are quite time involving and time consuming. The operational activities may include those performed daily, weekly, monthly or by the minute or second. Big data offers quite an improvement in the execution of these operational process by making available relevant information and analytics which aids some of the repetitive actions (Wang et al., 2014). In some instances, it offers better alternatives to performing certain operational activities. Thus big data in terms of operational benefits looks at increasing operational efficiency; reducing operational cost, reduction in cycle time, improving productivity, improving quality and ultimately improving customer service (Shang & Seddon, 2002; Wang et al., 2014).

5.3 Managerial Benefits

Organizational activities comprises of allocation and control resources in a firm, the monitoring of operational activities and strategic decision support (Peters & Waterman, 1982). Managers primarily are the backbone of these organizational activities. Managers in performing these organizational activities primarily rely on analysed data which generates reports and insights to aid in decision making and planning (Shang & Seddon, 2002). Big data in terms of managerial benefits offer organizations the potential to obtain real-time information that help organizations to efficiently use resources, improve decision making and planning as well as improve the performance of organization (Shang & Seddon, 2002; Wang et al., 2014)

5.4 Strategic Benefits

Big data offers competitive advantage to organizations (McAfee et al., 2012) through the use action strategies that innovative in contrast to "being first on the scene" (Kettinger et al., 1994). Strategic actions comprise of long-term planning with respect to decisions at the high-level, such as mergers and acquisitions, competition in the market, planning of products, retention of customers and the sourcing of capital (Shang & Seddon, 2002). Big data offers organizations the potential to have relevant analysed data and insight to aid strategically in product differentiation, business growth, innovation, cost and external linkages (Shang & Seddon, 2002; Wang et al., 2014). These ultimately helps in improving organizational performance and strategically positioning an organization by ensuring that data-driven decisions are made at high level decision making.

5.5 Organizational Benefits

Organizational benefits are seen in the focus, cohesion, learning and the execution of strategies in an organization (Shang & Seddon, 2002). Big data helps in having an integrated look at the organization, providing shared organizational information to improve employee communication, build up the development of a 'common vision' and the empowerment of users, support customer services and promote a much horizontal organizational structure (Peters & Waterman, 1982; Shang & Seddon, 2002; Wang et al., 2014). Generally, big data organizational benefits refers to big data benefits that have the potential to improve working patterns, promote organizational learning, empower workers, helps in achieve a common vision across the organization and also improve organizational culture (Shang & Seddon, 2002; Wang et al., 2014).

6. <u>A DYNAMIC CAPABILITY MODEL FOR FORMING BIG DATA</u> <u>CAPABILITIES TO OBTAIN BIG DATA BENEFITS</u>

Big data is seen as the next 'Blue Ocean' in nurturing business opportunities which offers firms competitive advantage (Mayinka et al., 2011). Competitive advantage has been a driving force which many firms have sought after for many years to outwit their competitors. Theories which have been used in IS to analyse competitive advantage include Resource-based view theory, Porter's five competitive forces and dynamic capabilities.

6.1 <u>Why Dynamic Capabilities as a Theoretical Lens</u>

Dynamic capabilities theory was introduced by Teece et al. (1997). Dynamic capabilities criticises the resource-based view theory as being static and neglecting the market dynamism that occurs in a firms competitive environment (Teece et al., 1997). Dynamic capabilities also fails to define mechanisms for resource transformation to competitive advantage (Mosakowski & McKelvey 1997; Priem & Butler 2001). For Michael Potter's five forces dynamic capabilities also criticises it as being static and failing to recognise the internal perspectives of competitive advantage (Teece et al., 1997).

Teece et al. (1997) defined dynamic capabilities as the ability of a firm to integrate, build and reconfigure internal and external competences to address rapidly changing environments. Beyond Teece et al.'s (1997) definition many other definitions have evolved including revised definitions by Teece. Some of these definitions have looked at dynamic capabilities as abilities or capacities (Helfat et al., 2007; Teece, 2007; Winter, 2003; Zahra et al, 2006). Others have looked at it from the perspective of processes or routines (Eisenhardt & Martin, 2000; Winter 2003). However, Wang and Ahmed (2007) review of dynamic capabilities is one of the most recent.

6.2 Wang and Ahmed's View of Dynamic Capabilities

Wang and Ahmed (2007) looks at dynamic capabilities not from a piecemeal and disconnected orientation but from a synthesis of conceptual debates and empirical findings towards a more integrated understanding of dynamic capabilities. This research thus falls on Wang and Ahmed's (2007) view of dynamic capabilities as its theoretical lens to analyse the big data capabilities.

By definition Wang and Ahmed (2007) define dynamic capabilities as the "behavioural orientation of a firm to constantly integrate, reconfigure, renew and recreate its resources and capabilities, and most importantly, upgrade and reconstruct its core capabilities in response to the changing environment to attain and sustain competitive advantage".

In Wang and Ahmed's (2007) review they identified four hierarchical levels for a firm's resources and capabilities. The hierarchical levels are;

- Zero-order: These are the resources of a firm that forms the basis for firm capabilities.
- **First-order**: This enables firms to deploy resources to attain a desired goal for improving firm performance.
- **Second-order or core capabilities**: It refers to bundle of a firm's resources and capabilities strategically key to competitive advantage at a certain point in time.
- **Third-order or dynamic capabilities**: This is a firm's constant pursuit of renewal, reconfiguration and re-creation of resources, capabilities and core capabilities to address environmental changes of a firm.

Beyond the hierarchical levels of a firm's resources and capabilities Wang and Ahmed (2007) identified three component factors of dynamic capabilities which as exist across firms. These component factors are adaptive capability, absorptive capability and innovative capability. Wang and Ahmed (2007) suggested that these factors are correlated but conceptually distinct and underpins a firm's dynamic capabilities. Wang and Ahmed (2007) called for the adoption these component factors in future research. This research draws on this call to explain how conceptually this component factors each distinctively form part of a capability and how the component factors correlate to form a particular capability.

The research in explaining the distinctiveness of the component factors in capability formation also takes into consideration the role that the various actor in capability formation perform in the generation of the capability. These actors include the individuals in an organization, routines/process in an organization, the organization itself and the environment the organization finds itself (Hess, 2008; Ibrahim, 2006; Gajendran, 2014; Zollo & Winter, 1999).

6.3 The Component Factors of Dynamic Capabilities

Wang and Ahmed (2007) looks at dynamic capabilities not from a piecemeal and disconnected orientation but from a synthesis of conceptual debates and empirical findings towards a more integrated understanding of dynamic capabilities. This research thus falls on Wang and Ahmed's (2007) view of dynamic capabilities as its theoretical lens to analyse the big data capabilities.

6.3.1 Adaptive Capability

Adaptive capability is defined as a firm's ability to identify and capitalize on emerging market opportunities (Chakravarthy, 1982; Hooley, Lynch & Dobber, 1992). It focuses on organisations' ability to adapt themselves in a timely fashion to environmental change through flexible resource management and alignment of resources and capabilities (Wang & Ahmed, 2007). Thus adaptive capability aligns internal organisational factors with external environmental factors. This implies that it enables firms' to have the maturity and capacity to adjust their managerial, strategic and operational capabilities by sensing, preparing and responding to environmental change. The development of adaptive capability is often accompanied by the evolution of organisational forms. Wang & Ahmed (2007) indicate that measures for adaptive capability are multi-dimensional and includes a firm's ability to adapt their product-market scope to respond to external opportunities; to scan the market, monitor customers and competitors and allocate resources to marketing activities; and to respond to changing market conditions in a speedy manner (Oktemgil & Gordon, 1997). Firms that have high levels of adaptive capability exhibit dynamic capabilities (Teece et al., 1997).

6.3.2 Absorptive Capability

Cohen and Levinthal (1990) gave birth to absorptive capacity in their seminal paper "Absorptive Capacity: A New Perspective on Learning and Innovation". From their paper they defined absorptive capacity as the ability to identify, assimilate, transform, and apply external knowledge. Through its research and development activities, a firm develops collective knowledge about certain areas of markets, science, and technology and how those areas relate to the firm's products and services (Cohen & Levinthal, 1989). This knowledge base enhances the firm's ability to identify and value external knowledge. However, sheer exposure to related external knowledge is not sufficient to ensure that a firm will absorb it successfully (Pennings & Harianto, 1992). The knowledge must be assimilated or transformed into the firm's knowledge base. While a knowledge base enables the associative connections needed for insights related to new knowledge, the organizational assimilation of new knowledge depends more so upon the transfer of knowledge across and within subunits (Cohen & Levinthal, 1990).

Firms apply their newly absorbed knowledge in a variety of ways, for example, to replenish their knowledge base (Van Den Bosch, Volberda & De Boer, 1999), to forecast technological trends (Cohen & Levinthal, 1994), to reconfigure existing capabilities (Pavlou & El Sawy, 2006), and to create innovative products and services. A substantial body of research finds that absorptive capacity contributes both directly (Lichtenthaler, 2009) and indirectly (Lane, Koka & Pathak, 2006) to firm performance. Firms with higher absorptive capability demonstrate stronger ability of learning from partners, integrating external information and transforming it into firm-embedded knowledge. Ultimately the absorptive capability of firms highly contribute

to their dynamic capabilities (Wang & Ahmed, 2007). A significant number of prior studies use R&D (research and development) intensity (defined as R&D expenditure divided by sales) as a proxy to measure absorptive capability (e.g. Tsai 2001). Other studies (e.g. Chen, 2004) use multiple indicators to measure the extent of the firm's ability to assimilate and replicate new knowledge gained from external sources. Zahra and George (2002) reckon that absorptive capability is a multi-dimensional construct and propose four components of the absorptive capability construct: knowledge acquisition, assimilation, transformation and exploitation.

6.3.3 Innovative Capability

An organisation's ability to innovate is recognised as one of the determinant factors for it to survive and succeed (Doyle, 1998; Quinn, 2000). Innovative capability refers to a firm's ability to develop new products and/or markets, through aligning strategic innovative orientation with innovative behaviours and processes (Wang & Ahmed, 2007). Innovative capability is thus multi-dimensional in nature. Researchers over the years have addressed the concern of effectively measuring organisational innovative capability, and multiple indicators have been developed to measure the dimensions of innovative capability (i.e. strategic innovative orientation, behavioural, process, product and market innovativeness) (Miller & Friesen, 1983; Avlonitis, Kouremenos & Tzokas, 1994; Wang & Ahmed, 2004). These multi-dimensions are important in measuring the overall innovative capability of a firm as a component factor of the dynamic capabilities construct (Wang & Ahmed, 2007).

6.3.4 Why the Component Factors

Adaptive capability, absorptive capability and innovative capability are correlated but conceptually distinct and underpins a firm's dynamic capabilities – the ability for a firm to integrate, reconfigure, renew and recreate its resources and capabilities in line with external changes (Wang & Ahmed, 2007). Each component factor of dynamic capabilities has a particular emphasis: the focus of adaptive capability is to align internal organisational factors with external environmental factors. Absorptive capability highlights the importance of taking in external knowledge, combining it with internal knowledge and absorbing it for internal use. Innovative capability effectively links a firm's inherent innovative capability explains the linkages between a firm's resources and capabilities with its product-market.

For this research it is proposed that these component factors come together to generate a particular capability. Thus each capability can be measured by measuring the component factors that the capability is derived from. A measurement of these component factors will ultimately result in a measuring construct for the overall dynamic capability of a firm. However, it must be noted that the dynamic capability formation has a complex and multi-level nature (Hess, 2008).

6.4 Levels of Analysis for Dynamic Capability Formation

Dynamic capability formation analysis requires a multi-level approach (Hess, 2008). Dynamic capability itself represents change at the routine or capability level of analysis (Helfat et al., 2007). A change in an organization's resource base is a direct result of the collective actions of

individuals. Three levels of analysis are required to fully understand both the inputs and outputs of dynamic capabilities: the individual, routine, and organization level (Hess, 2008).

Beyond the three levels of analysis this research proposes a fourth level –the industry within which the firm exist- which affects how the three levels work together to generate the capabilities resulting from the component factors (adaptive, absorptive and innovative capability). The individual is considered the building block of dynamic capabilities (Lane, Koka, & Pathak, 2006; Hess, 2008). To a number of researchers dynamic capabilities is seen through the lens of routines or processes that use resources to integrate, reconfigure, gain and release other resources so as to cause change (Eisenhardt & Martin, 2000; Winter 2002). Ultimately the organizational level is the point where dynamic capabilities are exhibited to gain competitive advantage (Helfat et al., 2007; Hess, 2008; Wang & Ahmed, 2007). The environment is the medium through which market dynamism is taking place and is in constant flux with the individual, routines and organization and this ultimately leads to changes which results in dynamic capabilities being formed (Hess, 2008).

Based on the levels of analysis and the component factors of dynamic capabilities, this research proposes a capability formation model in Fig 6.1.



Fig. 6.1: A Conceptual Model for Dynamic Capability Formation

The model suggest that for any capability to be formed the three component factors will work distinctively in separate proportions and dimensions but combine collectively to result in the particular capability formed. Furthermore the three basic levels of analysis (individual, routines/processes, organization) will each separately interact with the component factors

(adaptive capability, absorptive capability and innovative capability) to generate a particular capability. The three basic levels collectively constitute the firm. However, the firm is and its levels of analysis are constantly being influenced by the industry the firm finds itself in as a fourth level of analysis. Thus, the firm and the industry are in constant flux.

6.5 The Stages of Capability Formation

Several researchers have looked at the stages through which capabilities travel. From the foundation, to development, deployment and finally retirement or redeployment (Boateng, 2014; Budu & Boateng, 2015). Budu and Boateng (2015) proposes a Mobile Service Capabilities Framework depicting how the capabilities evolve. Boateng (2014) further enhances the earlier framework to create a Resource-based model of e-commerce capability evolution. This research combines the capability evolution frameworks and the proposed capability formation model to develop a big data capability model.



Fig. 6.2: Mobile Service Capabilities Framework (Budu and Boateng, 2015)

Budu and Boateng (2015) suggest that a capability is generated based on resources as inputs which goes through a process of resource development which involves coordination, learning and reconfiguration to produce a capability. When a capability is developed it may cease or enter a maturity phase where capability may be used till it becomes part of an organizations memory and culture and thereby growing into a new capability.

Beyond this work, Boateng (2014) suggested an enhanced Resource-based model of ecommerce capability evolution as shown in Fig 6.3.



Fig 6.3: Resource-based model of e-commerce capability evolution (Boateng, 2014)

In Boateng (2014), the author suggest that a capability begins at the foundation stage where the firm identifies the relevant asset positions or resources as well as processes, and organize them based on the objective of developing a capability. From the foundation stage comes the developing stage. The developing stage is where resource development occurs through coordination, learning and reconfiguration processes. Beyond the development stage, a capability becomes a learned organizational skill; the development of such as capability may cease and enter the maturity stage. At the maturity stage, the capability becomes more routine and entrenched in organizational memory and culture. Beyond the maturity stage, the capability may branch into two key phases: rebuilding or declining. In the rebuilding phase, the capability may be renewed, redeployed, recombined or replicated, and thus, initiate another evolution process. In the declining phase, the capability may be retrenched or retired and this may also affect other resources which contribute to the development of the capability.

This research moves further to develop a Big Data Capability Model which combines proposed model of dynamic capability formation, Budu and Boateng's (2015) Mobile Service Capabilities Framework and Boateng's (2014) Resource-based model of e-commerce capability evolution. The resulting Big Data Capability Model is as shown in Fig 6.4.



Fig 6.4: A Big Data Capability Model

The conceptual model posits that to form a Big Data Capability the requisite inputs must be placed in the firm through the process of resource identification. Within the firm, the need for the required capability may be instigated as a result of the need to adapt to changes in the environment of the firm which includes the industry within which the firm is placed. This need for adaptation may emanate from an individual within the firm, a process, the organization itself or as an influence from the industry of the firm. This adaptation process links intenal organisational factors with external environmental factors. Adaptive capability thus exhibits itself through this stage of the capability formation process. Beyond the adaptive capability the individual, process or organisation may need to identify and value external knowledge which is relevant to the type of big capability being formed.

Beyond the identification and valuing of external knowledge, the individual, process or organisation will have to assimilate the knowledge and transform it into the firms' knowledge base and apply it accordingly. This identification, assimilation, transformation and application of external knowledge constitute the absorptive capability component of the big data capability formation process. In the application of the knowledge base formed out of the external knowledge, the knowledge may be applied in varied ways (e.g. forecast technological trends, reconfigure existing capabilities and create innovative product and services). This application of knowledge shows forth the innovative capability component of the big data capability being formed through the development of new products and/or markets and the aligning of strategic innovative orientation with innovative behaviours and processes.

Beyond this innovative capability the specific big data capability is created. The big data capability formed when put to use leads to big data benefits. The capability may also enter the maturity stage after sometime and subsequently result in the capability being retired or renewed, redeployed, recombined or replicated to serve as input for the formation of a new big data capability.

Based on this big data capability conceptual model, this research proposes to gather empirical evidence to understand and critic the model so as to refine the model.

7. <u>RESEARCH METHODOLOGY</u>

7.1 <u>A Critical Realist Perspective to Big Data Capability</u>

To carry out this research, the study proposes to employ a critical realism philosophical stance and qualitative methods to unearth structures and mechanisms of big data capabilities and their attending benefits (Mingers, Mutch & Willcocks, 2013). The choice of CR will enable an IS researcher to unearth the capability constituents needed for a firms adoption of big data. Bhaskar (2010) argues that these constituents are not apparent in the observable pattern of events, and can only be identified through the practical and theoretical work of the social sciences. As a result, CR gives way for the complex and detailed unearthing of structures of a social reality (Elster, 1998) like the capabilities needed for the adoption of big data.

To unearth the big data capabilities constituent, critical realism adopts a retroduction research methodology (Bhaskar, 2010). Retroduction enables the CR researcher to establish the basic conditions for a phenomenon, such as for big data capability to exist. Hence, without these

conditions big data capability will not exist. These conditions may be based on the steps involved in the big data capability formation processes described in Fig. 6.4.

The use of retroduction as a research strategy involves three main steps. First, the researcher begins by examining the observed events and connections between/in a social phenomenon. In this study, this requirement leads to a thorough review of previous research on big data to explore the different theoretical and conceptual underpinnings which explain the previously observed events. The review will aim to a) identify and categorise the dominant theoretical and conceptual approaches that have been used in analysing big data capabilities; b) identify the benefits that firms derive out of big data; c) a categorisation and analyses of the various type of big data capabilities firms have, use, acquire and develop in the adoption of big data from a dynamic capabilities perspective; and d) the future research direction of big data capabilities.

Second, the researcher needs to postulate the existence of real structures and mechanisms, and how they would describe and explain relationships observed, if they existed (Easton, 2010). The CR researcher "theorizes a model of an underlying mechanism which might have produced patterns seen in the data, and then works backwards from the data towards verifying or otherwise that model" (Mason, 2002, p. 181). Thus, this research will need to develop/postulate models or hypotheses based on a theory to explain how big data capabilities may occur if they existed and also postulate the constituents of these capabilities. This research will be carried out through the theoretical lens of the dynamic capabilities (Teece et al, 1997). The postulated model will be the big data capability formation model which has been proposed in Fig. 6.4.

The third step is to attempt to demonstrate the existence and operation of these structures and mechanisms postulated in the big data capability formation conceptual model. To do this the researcher needs to select appropriate data collection methods which fits the research paradigm and support the research purpose. Critical realism is supportive of methodological pluralism - quantitative or qualitative data collection methods- as it acknowledges that a variety of objects of knowledge exist and each of these objects requires different research methods to unearth them (Carter & New, 2004). For the purpose of this research a qualitative research methodology is adopted.

Qualitative methods within CR have a more profound role, as they are more capable of describing a phenomenon, constructing propositions, and identifying structured interactions between complex mechanisms. Thus for a deeper understanding of how big data capabilities are formed and developed a qualitative research methodology will be much suited.

Several CR researchers have identified the case study method as the best approach to explore the interaction of structure, events, actions, and context to identify and explicate causal mechanisms (Ackroyd, 2010; Easton, 2010; Miles, Huberman & Saldaña, 2013; Mingers, 2004). Thus the study will employ a case study research design with a qualitative research methodology.

7.2 <u>Research Design and Methods</u>

The purpose of a research design is to make sure that as unambiguously as possible the research problem is effectively addressed by the evidence found. A case study "involves investigating one or a small number of social entities or situations about which data are collected using multiple sources of data" (Easton, 2010 p. 119). "A case study is an empirical inquiry that

investigates a contemporary phenomenon - such as big data capabilities - in depth and within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident" (Yin 2003, p. 13). By focusing on a "sustained consideration of activities and behaviour in a particular location" (Ackroyd, 2010, p. 535), the case study inquiry copes with the technically distinctive situation in which there are many more variables of interest than data points, and relies on multiple sources of evidence, with data needing to converge in a triangulating fashion.

The study will begin with the development of the big data capability construct model. This will involve the use of qualitative research methods to give an in-depth understanding of the big data phenomenon, including contextual issues that can be gained (Creswell, 2012).

The research will be guided by the theory of dynamic capabilities to provide an understanding of the big data capability phenomenon and to generate ideas and theories. It will begin with a thorough desk research and extensive review of existing practitioner big data white papers, consultant reports and academic literature.

This desk research will lead to development of the big data capability conceptual model. Secondly, a cross industry study of the top 2 firms in the banking industry of Ghana, health insurance industry of Ghana and the telecommunication industry in Ghana will be carried out. This is to ensure that elements of the conceptual model are well looked out for in each of this industries. This will ensure that all commonalities of big data capabilities occurring irrespective of industry is looked at. In addition, a cross industry study will permit potentially new capabilities not stipulated in literature to be found irrespective of industry.

For each firm in an industry a heterogeneous purposive sample of staff categories using the different types of IS (TPS to ESS) will be used as sampling units. To ascertain the exact sampling units a pilot single case study of one of the firms will be conducted (Easton, 2010).

For data collection the primary source of data from the firms will be from focus group discussions and interviews given the qualitative nature of the research. The interviews will be taped and transcribed with the permission of interviewees. Copies of transcribed interviews will be returned to interviewees and any discrepancies detected will be resolved. Secondary data sources will be obtained from documents of the firms. To analyse the qualitative data obtained, Miles and Huberman's data analysis (Miles, Huberman & Saldaña, 2013) approach will be used.

8. CONCLUSION

This research which is part of a doctoral thesis is currently at its conceptual stage with data collection currently started. The research began with the type and nature (constituents) of big capabilities being established. These capabilities based on a desk research as stipulated by the research methodology detected 6 broad categories of big data capabilities. The big data capabilities, analytical capabilities, data sharing capabilities and decision making capabilities. Beyond the big data capabilities, The research has currently established the broad categorisation of big data benefits based on Wang et al.'s (2014) classification of big data benefits drawn from Shang and Seddon's (2002) benefit dimensions. These categories of big

data benefits are organizational benefits, managerial benefits, strategic benefits, IT infrastructure benefits and operational benefits. The big data capability conceptual model has also been established through the dynamic capabilities theoretical lens.

As an ongoing research empirical data is currently being gathered and very interesting results seems to be emerging in the interviews currently carried out. The interviews depict new capabilities which are being developed due to the developing country context as well the industry specificity of the firms being investigated. These results from a preliminary look seems to possible modify the big data conceptual model proposed.

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