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# Big Data Oriented Soft-Technologies and ICT Management

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## ABSTRACT

Numerous Soft-Technologies (So-Techs) such as Information Retrieval (IR) systems are found on the Internet. The level of dynamism the Internet exhibits makes it rather tricky to manage these technologies. Part of this management as an IT concern is to evaluate and improve them towards better performance. Interestingly, evaluating IR systems come with lots of challenges, one of which is the existence of varying opinions on how IR evaluation should be done. Therefore, the choice of what methods and philosophy to adopt and/or adapt becomes necessary. With much evidence, a field advances not only by deciding on a single best compromise, but through academic discourse. This backdrop motivates the intention of this study, which is not to suggest a single best evaluation method. Therefore, one of many opinions on the evaluation of an example of soft-technology with Big data-orientation is presented. The study highlights the thrust of user-oriented soft-technologies' management from an evaluative perspective. It then concludes that the success of soft-technologies is measurable not only from the perspective of the progress of technology but also from users' requirements and other user-oriented concerns.

**Keywords:**
Information retrieval, Search engine, Big data, Soft-technologies, User-centred evaluation method, Users' requirement, and ICT infrastructure

## 1.0. Introduction

Soft-Technologies (So-Techs) exist within ICT Infrastructure (ICTI) with the Internet being the most dynamic of such infrastructure. The Internet, as an ICTI has soft-technologies that rely on different paradigms. With these paradigms, soft-technologies are able to drive and resolve communication protocol(s), provide Information Retrieval (IR) services and so on. Interestingly, this study focuses on the IR paradigmatics. Soft-technologies, which do not only draw on the IR paradigm but also demonstrate the paradigm, are known as IR systems. The IR system example considered here is Web Search Engines (WeSE) (Akhigbe, 2012). The IR paradigm is an interesting one because it drives one of the most popular So-Techs; WeSE (up to 80% of Internet users employ one type of WeSE or the other on a daily basis) (Akhigbe *et al* 2015). Since the WeSE is already live on the Internet; part of managing them as an ICT concern is to evaluate them.

Evaluation is important particularly for ICTI and the technologies that drive them because it provides the mechanism to verify and measure their level of improvement. In this case, the level of user satisfaction (and to what degree) with the effectiveness of ICTI in the delivery of services can be gauged. There are two sides to this; the system-centred (or engine) and the user-centered perspective and approach (Carterette *et al* 2012). The evaluative aspect of ICT management should provide the opportunity to track the progress of technology. This progress should include how successfully (for instance) a So-Tech (in this case the WeSE) satisfies the goal it was developed to meet. Evaluating Big data oriented technologies (BdoT) as a way of maintaining them is also a vital part of ICT management. Results from this type of evaluative exercise can be used to formulate ICT policies that ensure that there are standards in terms of what satisfies the information need of users. In Figure 1, the process of retrieval is shown to start and end with the user.

One of the key purposes of evaluation, especially from the perspective of the user is to track the progress of technology in terms of how well the technology satisfies the purpose of why it was developed.

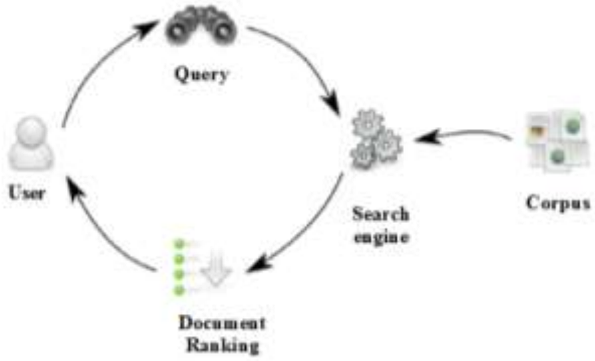


**Figure 1**: A Schematic of the Information Retrieval Process
***Source****:* Webber (2010)

Therefore, the opinion of those who have used the technology at one point in time becomes very important. For a system (or technology, which is the focus of this work) that is live in an infrastructure - in this case ICT infrastructure - the evaluative scope should be within the summative context. In this study the management (or maintenance) of ICT is being able to know the challenges to be mitigated using appropriate skills. Based on the theory of constructivism, only users who have used a technology are in the best position to evaluate it. This is because they have constructed their own knowledge based on personal experience with using a technology.

One of the major challenges with user-oriented evaluative tasks is the dearth of available metrics as measures for evaluation activity. For Big data oriented technologies like So-Techs, the dearth of available metrics introduces a different dimension. This dimension is such that metrics that completely represent users' opinion, which are nuance, are not sufficient and in most cases absent. However, there are no established evaluative methods that are certified as best practices to use the metrics even if they are available. Though, there is a paucity of methods that can be recommended based on user-centric evaluative model(s), the methods are not in one piece. What exists in literature, which could be taken as a primer can be found in just a few studies such as Kelly (2009). With the existence of "Big Data", this gap has further widened and become exacerbated, and thus in dire need of scholarly attention.

The need for the right methods, supporting theories and metrics to understand So-Techs with Big data orientation is therefore not only inevitable, but should also be studied within the summative aspect of evaluation.

The remaining part of this study is organized as follows. Section 2.0 discusses soft-technology and Big data orientation. In Section 3.0 evaluating soft-technologies with Big data orientation was presented where Section 4.0 contains suggested evaluative methodologies and theories. In this Section also concepts of user-centricity, *personas and others* are presented. Suggested Evaluative Methodologies and Theories are presented in Section 5.0. In Section 6.0 the conclusion of the study is discussed.

## 2.0. Literature Review

This section contains a succinct review of what currently obtains with respect to soft technologies and Big data orientation. The characteristic of Big data as a versatile technology is also presented.

### 2.1 Soft-technology and big data orientation

Traditionally, Information Systems (ISs) are developed with the goal of increasing corporate values and among other things accelerate decision-making. What IS is used for in terms of its purpose in an organization contributes immensely to the type of data that is generated (Shibata and Kurachi, 2015; Gavurová *et al.*, 2018). The massive generation of data is consequent upon the current quantum increases in the evolution of not only software technologies - ISs, but also hardware performance, advances in different types of sensors, digitization and so on (Shibata and Kurachi, 2015). The large amount of data, which makes the Big data concept a buzz as well as a tangible phenomenon to consider comes not only from sensors, but also from many digital devices (e.g. smart cards), log files, audio and video channels, networks, transactional applications, websites (e.g. e-commerce sites), and social media (Misra *et al.*, 2016; Wu *et al.*, 2018; Al Enezi *et al.*, 2018). Big data has also found great relevance in economic development, as every area of human endeavour stands to benefit. For example, the article "Left to Other Peoples' Devices? A Political Economy Perspective on the Big Data Revolution in Development" by Mann (2017) drew attention to the political and economic advantage of the field of Data for Development (D4D). A 'win-win' narrative was presented to establish the fact that access gained to data do allow businesses to expand and thus position them as partners that are indispensable. With an African example, the paper highlights the fact that data extraction is an on-going endeavour in the continent and is made available for expert analysis in advanced economies. The inferences made here provide an easy learning curve for foreign investors to have a commendable profit edge. The paper then argued in favour of a governance framework that may lead to data-driven restructuring as African economies become increasingly 'digital' to harness the current potential of data to become a source of power in economic governance (Mann, 2017).

The many benefits, which can result from the use of Big data make it imperative to suggest methods and models that will be useful in the evaluation of So-Techs with Big data orientation. The sum total of dynamics introduced with the advent of Big data integration into IR systems like the WeSE when conceptualized shows that with big data comes actionable intelligence. The presence of a Data Integrative Module (BDIM) highlights the existence of useable (or actionable) intelligence (see Figure 2). The BDIM is a Big data analytics mechanism with vast potentials that continue to influence the retrieval potentials of IR systems. Additionally, the Big Data Architecture (BDA), which IR leverage on for heterogeneous Big data retrieval also contributes to enhancing the retrieval potentials of IR systems (Woo, 2013). The BDA makes it possible to integrate and make real the Big data conception with IR operations.

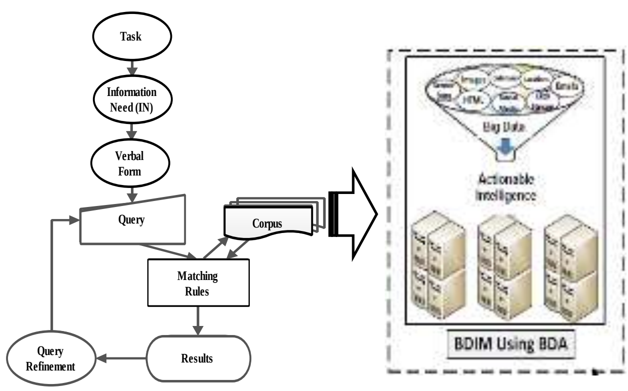


**Figure 2:** The Big Data integration into the IR paradigm
***Source**:* Akhigbe *et al.* (2016*)*

Likewise, its existence shows that the IR paradigm has the potential to become more robust and prodigious towards the provision of retrieval services. The advent of Information and Communication Technology (ICT) has continued to influence the amount of data that is available on the Internet (Coneglian *et al.*, 2016).

Users' Information Needs (INs) continue to increase and the context of the IN remains dynamic. Big data (see dimensions in Figure 3) and recently the "Internet of Things (IoT)" (AlEnezi *et al.*, 2018) has also had influence on the INs of users. This influence materializes as users attempt to meet their IN when they use So-Techs within existing ICTI. Dimensionality is an abstraction that is used in literature to reflect the attribute of "data" per time and based on how they are turned out and their degree of influence and transformation. The attribute of data based on the degree of influence and dimensionality has been conceived in terms of "Volume, Velocity and Variety" (Sowa and Marchlewska, 2016).

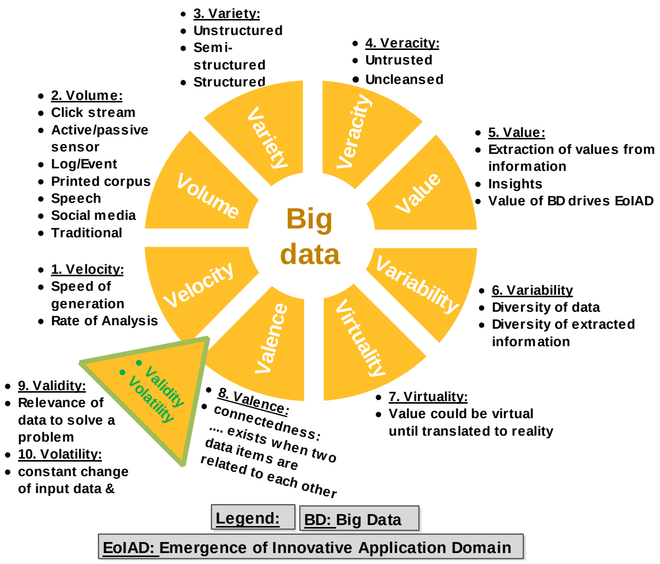


**Figure 3:** A proposed ten Vs of Big data dimensions
*Adopted from* Chen *et al.* (2014), Young (2015), Gandomi and Haider (2015), Wang and Jones (2017)

Recently, other dimensions such as the Value and Veracity have been added. In future, there is the possibility that data will be built around themselves in such a way that by using built-in-protocols, it will be self-routable and self-addressing based on the existence of meta-data. When this happens, queries which are an integral aspect of retrieval (see Figure 1) will be increasingly easy and readily possible (Sowa and Marchlewska, 2016).

## 2.2 Big data as a versatile technology

The analytics of Big data has moved beyond what was initially mere intellectual curiosity and now possesses the propensity to make impacts that transcend business operations and several other commercial activities. Its impact is such that it has become a core requirement for business enterprises to be relevant in terms of the provision of services towards end-user satisfaction (Raj, 2018; Rani and Sagar 2018). Big data is an evolving technology with the potential for application in different domains. It also has the potential to make a remarkable impact in diverse fields (Raj, 2018). For example, Big data analytics technology has inspired among many other things the move away from the Internet of electric vehicles to optimized electric vehicle charging (Cao *et al.*, 2018). This was achieved using a mobile edge computing-based system that is empowered through big data analytics. Based on this interplay, a mobility-aware mobile edge computing server with scalable ability has been developed to distribute and gather charging reservations from electronic vehicles (Cao *et al.*, 2018). Several other attempts to use Big data technology to make the dream of an electronic vehicle has been successful. One of which is the detection of cyber-threats in smart vehicles through a data-driven optimization model for transportation. This technology employs a probabilistic data structure-based approach (Garg *et al.*, 2018). The use of Big data has also found its use in detecting the intent of vehicle drivers. Within the concept of the technology, Birek *et al.* (2018) developed a fuzzy computational model that uses integrated multiple data sources to predict the intention of vehicle drivers.

Big data technology has not only been used for engineering purposes like in the case of smart cars. Data-centric architecture for robust business process analysis for distributed environments has also been made available. The data-centric software architecture supports access to key performance indicators that are used to analyse the performance of processes (Vera-Baquero and Colomo-Palacios, 2018). So also, Big data and Computational Intelligent techniques such as evolutionary algorithms, deep learning neural networks, and fuzzy logic have been successfully combined to develop technologies in different fields to produce benefits that are tangible (Iqbal *et al.*, 2018; Oliveira *et al.*, 2018; Kalantari *et al.*, 2018).

## 3.0. Available Technologies

In this Section, some tried methodologies on how to carry out user-centred evaluative exercise within the domain of end-user computing system evaluation modelling are presented and described. Particular attention was given to how soft-technologies with big data orientation are evaluated, and what theories, concepts and framework to adopt.

### 3.1. Evaluating soft-technologies with big data orientation

One of the characteristics of Big data is velocity. That is, the rate at which data is generated. It also highlights the speed at which data is analyzed and acted upon (Gandomi, 2015; Wu *et al.*, 2018). The data generated continuously change and evolve. The change can be so rapid and as such every Big data involvement poses significant challenges. For example, the creation of relevant on-demand domain models that is useful for searching, browsing, and analysing real-time content are needed. For search systems, the on-demand domain models should be able to address issues of data filtering and prioritizing as well as ranking. This is where IR can be properly utilised. The conception just discussed will be of little value if users of So-Techs cannot use them to meet their information needs. In this study the motivation is to highlight the potentials in assessing So-Techs from the perspective of users. From such an exercise, policies that will be useful in guiding the use and development of So-Techs to be better user-oriented can be formulated.

In practice, So-Techs could be designed with so much care and brilliance. Yet it is only after its launch and use that stakeholders will realize what more things could be added. Consulting the users of the system - in this case So-Techs can result in knowing in clearer terms the functionalities users would expect in a system if the purpose of designing the system will be met. And if potentials are learnt through use, then changes will be required frequently. These changes as expected will be leveraged to adjust the technology in question to the people using it as they and their needs mature. Levy (2009) referred to this as perpetual beta. The perpetual beta concept (see details in Levy, 2009) is one concept that highlights the need to evaluate So-Techs like WeSE. To develop applications that reside with ICTIs (Musser and O'Reilly, 2006), treating applications like So-Tech as a platform may be tantamount. The thinking is that its use will be oriented towards service delivery. Based on the postulations the WeSE is conceptualized as a service to be leveraged by the Big data conception. The implication of this is to focus on developing services rather than just the development of application. The perpetual beta concept supports the belief that users are at the centre of IR activities (see Figure 1).

### 3.3. Suggested evaluative methodologies and theories

In the introduction of the methodology of "User-centricity", several user-oriented techniques and theories must be drawn from. Many gainful opportunities are well associated with the Big data concept. On the other hand, lots of challenges exist. These challenges are often associated with searching, visualization, data capture, sharing, storage, and analysis. All of these are associated with Big data (Ahrens *et al.*, 2011; Chen and Zhang, 2014). Nevertheless, the focus here is on searching. This begins from when IR is used to seek and find documents in a given collection that is supposed to contain documents that may satisfy a given IN. An IN is often presented using a query that is generated by a user. Documents that satisfy a given query in the judgment of the user are adjudged to be "relevant". The challenge here is about the degree of relevance, which is measured using the metrics of precision and recall. These measures are objective measures and are not nuance enough to subjectively consider "relevance". This is because in the context of this study, "relevance" is postulated as dependent on what users feel satisfy their IN.

The absence of sufficient nuance measures to determine "relevance" is still a problem. Table 1 reveals some of the disparate sources and format of data all the way through to disparate data stores. In Table 2, the categories of the problem of data quality from data sources are presented. In most systems like the WeSE the role ofUser Interfaces

**Table 1**: Big Data in different aspects

| Data Formats | Data Sources | Data Processing | Data Staging | Data Stores |
|---|---|---|---|---|
| • Structured<br>• Semi-structured<br>• Unstructured | • Transactions<br>• Web & Social<br>• Sensing<br>• Machine<br>• IoT | • Batch<br>• Real time | • Normalization<br>• Cleansing<br>• Transform | • Column-oriented<br>• Document-oriented<br>• Key-value<br>• Graph based |

Adopted from Wang and Jones (2017)

**Table 2**: Big Data in different aspects

| Single-Source: Schema Level | Single-Source: Instance Level | Multi-Source: Schema Level | Multi-Source: Instance Level |
|---|---|---|---|
| Poor schema design, lack of integrity constraints<br>- Referential integrity<br>- Uniqueness<br>… | Data entry errors<br>- Misspellings<br>- Contradictory values<br>- Duplicates/ redundancy<br>… | Heterogeneous schema designs and data models<br>- Structural conflicts<br>- Naming conflicts<br>… | Overlapping, inconsistent and contradicting data<br>- Inconsistent timing<br>- Inconsistent Aggregating |

Adopted from Wang and Jones (2017)

(UIs) cannot be overemphasized. UIs in the domain of Man-Machine (Human Computer) interaction are seen as adequate enough to bind disparate data sources together. Big data emanates from different devices. These devices as sources of data with each of them having their individual UIs (Sowa and Marchlewska, 2016) does require UIs that are carefully designed.

## The concept of the paradigm of user-centricity

The concept of "User-centricity" is a user-centric interpretivist view of information processing. Using the concept in evaluation means that quality in terms of So-Techs' service delivery per time is sought for. One better way to achieve this purpose is to seek the perspective of users of the system. For instance, to improve the domain-based services Search Engines (SEs) offer would require consensus users' requirements. The result of user-centric evaluative methodology for evaluation will communicate users' needs as requirements. For the concept of "User-centricity" to be properly harnessed, the concept of conceptualization and operationalization must be applied to adopted measures. The need for search systems to be evaluated based on the philosophy of "User-centricity" has been stressed in literature (Carterette, *el al.,* 2012a). This is against the backdrop of the understanding that the concept of "users" in the IR model is still abstractive. The models lack the motivation to provide useful "User-centric" feedback that is capable of informing future research directions (Carterette *et al.,* 2012a).

Every IR search process is behavioural, psychological, and even cognitive in nature (Zimmer, 2010). Thus, how best can a process of this nature be addressed? In terms of methodology, the concept of "User-centricity" stands as the best possibility to achieve this.

The user-centred evaluative paradigm deals with the empirical evaluation of a system by gathering subjective user feedback on satisfaction (for instance), productivity measures and other quality of work and support measures (Mulwa *et al.,* 2011). Evidently, the concept of user-centricity focuses on the user. In Mulwa *et al.* (2011), the user-centred evaluative approach was used to evaluate an e-learning system by gathering subjective user feedback on satisfaction and productivity. Additionally, based on the data elicited about the quality of work and support the system provides, the researchers were able to assess the level of end-user experiences the system interactively provided. Other researchers (e.g. Gulliksen *et al.,* 2003; Bevan, 2008; Mulwa *et al.,* 2011; Loup-Escande and Lecuyer, 2014) have also used the user-centred evaluative approach to investigate all kinds of IS based on users' feedback (See Figure 4).

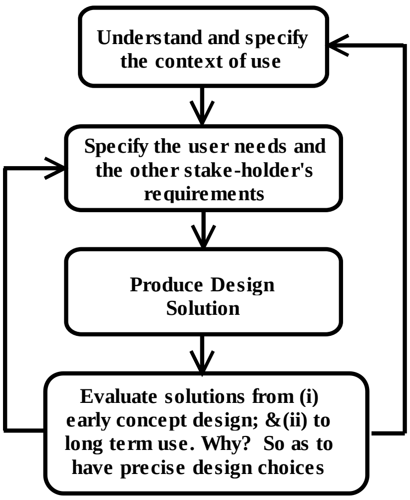


**Figure 4:** Existing User-centred Evaluative Methodology as subsumed within the User-centred System Design Process
*Adopted from* Loup-Escande and Lecuyer (2014)

This research therefore argues that user feedback should not be based only on user needs. The experience constructed by a user from using a system can be elicited as ordinal data. These ordinal data contain the judgment of users about a system. End-user experience(s) as a result of use of a system is very important. Unfortunately, existing User-centred Evaluative methodology (UcEM) does not provide sufficient information or platforms in terms of techniques to utilize user prior experience with a system as a resource to evaluate the system. The UcEM is subsumed in the User-centred System Design Life Cycle (UcSDLC). The subsumption is only a part of the larger UcSDLC process as shown in Figure 4. Though, existing UcEM process is vague, it is strongly tailored for gauging usability within the scope of system design. The UcEM is also rigid. It is the fourth process (or phase) in the UcSDLC as highlighted in Figure 4. Evaluation should not just be for evaluation sake. Evaluation exercises must use the correct method(s) and metrics (Brusilovsky *et al.*, 2004). So, the need to update and rework the UcEM in IS in general, is therefore overarching. The evaluative protocol (or framework) presented in Figure 5 is a response to the foregoing need.

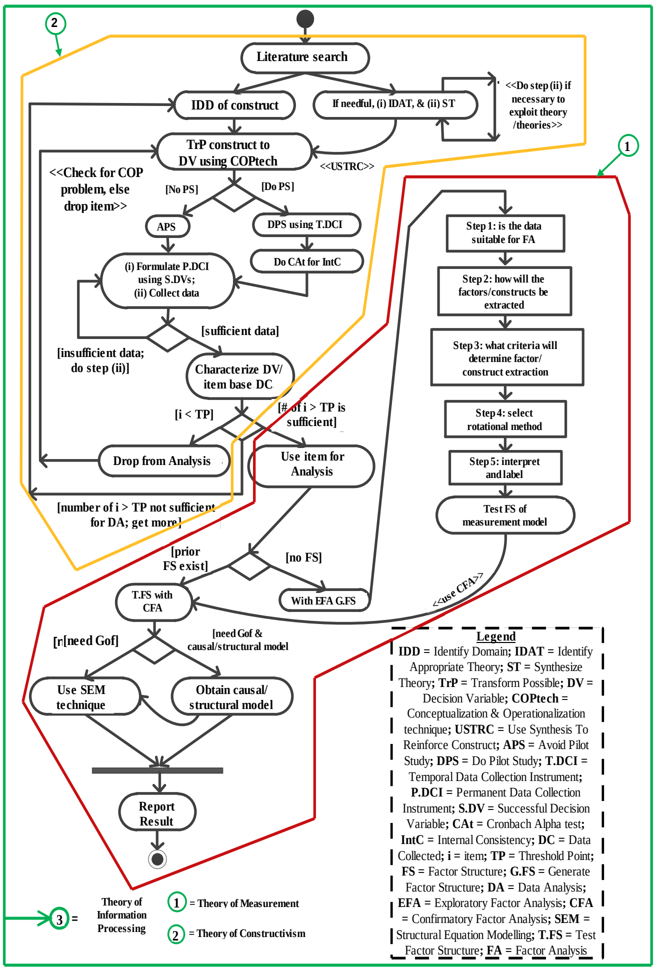


**Figure 5**: User-centred empirical evaluative protocol Adapted from Akhigbe (2015)

### 3.4. Other user-centric theoretics and methodological framework

At the core of the user-centric paradigm are the concepts of Web Analytics (WA) (Fagan, 2014) and the theory of Information Processing (TIP) (Gao *et al.*, 2012; Ortiz-Cordova and Jansen, 2012). These theoretical underpinnings offer new perspectives with clear implications for the practical use of empirical evidence towards better WeSEs (or So-Tech in general) as platforms for Big data analytics rather than just an application (Levy, 2009). The concept of user-centricity has its roots in user-centred design. Its practice represents the general philosophy that seeks to bring users into the process of design (Miaskiewicz and Kozar, 2011). Satisfying and fulfilling users' need(s) are the central concern of user-centricity. However, this can be difficult to attain; hence the introduction of personas to provide an alternative method to represent and communicate users' needs (Miaskiewicz and Kozar, 2011). The challenge of directly involving users in large design processes can be tasking based on the issues of time, cost, and logistics (Marshall *et al.*, 2015). Personas can be used to manage these constraints since it can be used to provide approximations to intended end user requirement(s).

The paradigm of user-centricity in user-centric evaluation does accommodate a persona-oriented approach. To use it; the framework in Figure 6 could be leveraged.

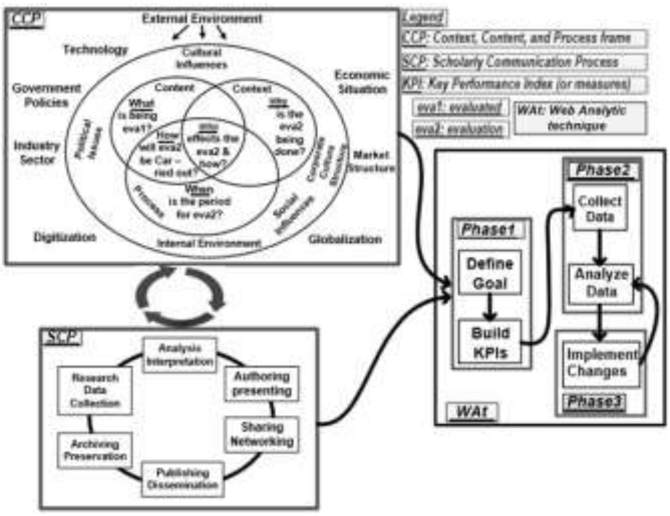


**Figure 6**: A CCP and SCP evaluative framework (*Adopted from* Akhigbe *et al.*, 2015)

Drawing from the work of Stockdale *et al.* (2008) and Rieger (2010), it presents a parsimonious frame with two parts: the CCP and SCP frames. Both the CCP and the SCP provide the context and viability to assess users based on a wide variety of evaluative situation(s) (in this case big data system). The CCP highlights user INs as being from the social and natural environments (Rieger, 2010). In synergy with the WAt, they both provide an extensible context to Identify, Conceptualize and Operationalize (ICO) intended measures broadly and qualitatively. The ICO is a qualitative and quantitative research methodology (Aladwani and Palvia, 2002; Hussein, 2015) that was leveraged in Akhigbe *et al.* (2016).

The ICO activities carried out in Phase 1, and the WAt in Phase 2 guided the quantitative aspect. The circular arrows in between the CCP and SCP means both contexts will be thoroughly considered using the participant-observatory approach as prescribed in Jorgensen (2015). With the context of big data introduced, the IR as a paradigm is more pervasive and requires broader (CCP and SCP contexts) approaches to perform the ICO activities to elicit evaluative data. Additionally, for pervasive systems like WeSEs (especially in relation to Big data) the ICO activities will be guided by the what, why, who, how and when factors of evaluation.

The WA technique has been used as underpinned by the concept of “User-centricity”, which is a process that is conceptualizable to understand and optimize the use of So-Techs (Akhigbe, 2012; Akhigbe, 2015). The WA is not a technology for producing reports. It is a process and a method that proposes a virtuous cycle for optimizing the benefits of evaluation in the assessment of Web-based Information systems. WA has been used to easily understand and improve the interactive experiences of online users (Waisberg and Kaushik, 2009). It was introduced into the framework in Figure 6 to highlight the empirical conception of “User-centricity” (Akhigbe, 2012; Akhigbe, 2015).

## 4. Expected Results

In end-user computing system interactive evaluation modelling, results are to be presented in the right way. In this way, stakeholders who may not be core computer scientists, or information system modelers, may be able to interpret the results. Therefore, the right language and notation must be used to deliver the results. In this section, discussions on personas, scenarios and how to translate user-centred evaluative results to user’s requirement are presented with a case study based on the protocol (evaluative framework presented in Figure 5).

**4.1. Personas, user profile, scenarios and users’ requirement** Personas are exemplars of the end user of a target system. They are identified through a thoroughly crafted user profile. Then based on a persona scenario, how an end-user uses a target system can be developed. Personas are used to keep precise users of a system in focus during design discussions. It is useful during the formative evaluation as well as in the summative evaluation of systems. For scenarios, they assist in system testing and in the building of (every) the functionalities users will actually want to use in a system (Baxter *et al.*, 2015). User requirements has to do with the features/attributes that a product should have in terms of functionalities (or how it should perform) from the users’ perspective (Baxter *et al.*, 2015). A standard persona should contain 1 and 7 personas that are developed to support a project.

Often, the information carried using personas are captured in form of a narrative. As a primary tool to communicate the requirement of users, it is hoped that the information will stimulate a sustained User centred Design (UCD) process (Norman, 1986; Idoughi *et al.*, 2012). The diagram in Figure 7 shows the central role that is often played by the persona tool within the confines of UCD.

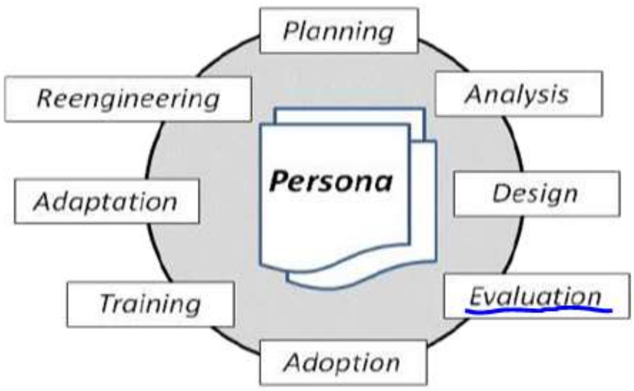


**Figure 7**: Showing the role of a persona inside a user centred design

From the diagram, it can be summarily deduced that a persona is very useful at any point in time in the eight phases of the UCD, even in the evaluation phase. However, as promising as the concept of personas is, the dearth of a common standard to design them is still evident.

This highlights the need for a standard that is clear and descriptive. The problem of usage guidelines is another challenge that is still unclear especially with respect to its integration into the process of design.
In the construction of personas, which is usually in textual format, a good knowledge of its components is important. These components are to be learned as a guide to persona construction. The first component is Identity, which has to do with the use of appropriate identification criteria such as first and last name. In most cases, the picture of the persona is included for easy identification. The other part of the Identity component includes status. This is used to describe the life goals and pursuits of the user in question. Additionally, a description of the remaining components such as Knowledge and Experience, Tasks, Relationships, Psychological profile and Needs, Attitude and Motivation, Expectations, and Disabilities are presented in Table 3 (Courage and Baxter, 2005; Idoughi *et al.*, 2012).

**Table 3**: Persona components with their description

| S/N | Persona Components/Description |
|---|---|
| 1. | Identity<br>Include a first and last name and a picture. It may include a short statement describing the overall life goals. We use also a code of colour to distinguish whether the user is a primary, secondary, tertiary, or anti-user of the application. Typically, only primary and in some cases, secondary users are included. |
| 2. | General Profile<br>A detailed description of basic demographic information including age, location, job and education degrees, and so on. |
| 3. | Goals<br>Besides goals related to the application, it includes personal and professional goals as well. |
| 4. | Scenarios<br>Three to four scenarios detail the key tasks including frequency, importance and duration. Such scenarios are described in a second stage after the validation of the key personas. Later, scenarios are reformulated in terms of specific needs (meaning usability requirements), features and interaction schema. |
| 5. | Knowledge and Experience<br>Knowledge and experience including education, training, and specialized skills. This should not be limited only to the application. |
| 6. | Relationships<br>Include information about user's associates, since this could give insight on other stakeholders. |
| 7. | Psychological profile and Needs<br>Include information about cognitive and learning styles, as well as needs such as guidance and validation of decisions. |
| 8. | Attitude and Motivation<br>Include information about the user's attitude to information technology and level of motivation to use the system. |
| 9. | Expectations<br>Information about how the user perceives the system works, and how the user organizes information related to his/her task, domain or job. |
| 10. | Special needs<br>Such as disabilities including colour-blindness, related to mobility, eyesight (wears contacts), and so on. |

*Adapted from* Courage and Baxter (2005), Idoughi *et al.* (2012)

Understanding these components contributes in no small way to making them a useful guide in the building of personas. The contents provided in Table 3 as a description of each of the persona's components have been modified into an easy to understand and adoptable version. The descriptions are meant to enlighten interested researchers on what is expected of each of the components for them to be easily used to encapsulate and communicate users' requirements. Personas are useful for communicating user requirements with a good promise, even though it is a new technique that needs to be learned. However, as promising as it seems, there is still the dearth of a common standard designed for its evolution. Time and space details of how to use personas and scenarios can be found in Idoughi *et al.* (2012), LeRouge *et al.* (2013), Salomao *et al.* (2015), and Sim and Brouse (2015).

User needs as requirements during design and implementation processes are most times extremely difficult to manage. This can be managed using personas as shown in Figure 8.

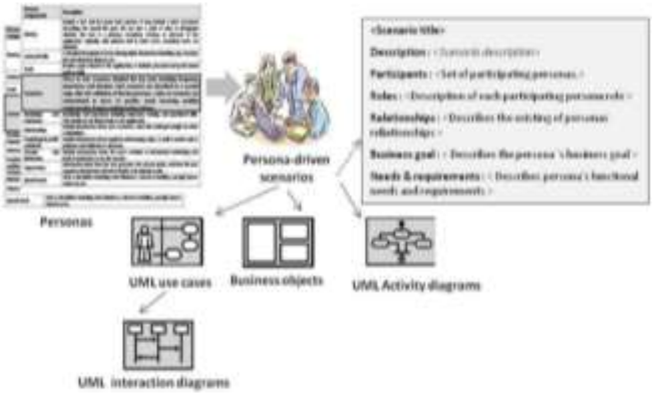


**Figure 8**: Exemplifying the translation of personas (as user's requirement) in textual format to designs with focus on implementation
*Adopted from* Idoughi *et al.* (2012)

The presentation in Figure 8 shows that personas are a summary of users' needs, and as such can be translated (as user's requirement) in textual format to designs and from there on the focus of implementation is easily achieved (Idoughi *et al.*, 2012). While the personas sufficed as users' requirements it was communicated to stakeholders, who interpreted the personas using persona-driven scenarios form where appropriate UML tools were based on business object orientation and modelling for designs. There was a mapping from the textual form (as 1st level translation) and UML diagrams (2nd level translation) for further persona description. This means that personas are a useful methodological concept in communicating users' requirements to stakeholders.

In the research work of LeRouge *et al.* (2013), the use of user-profile was recommended along with the concept of personas in the design and implementation of user-oriented technologies. A diagrammatic example is thus presented in Figure 9.

The technology described in LeRouge *et al.* (2013) is a Big data health-oriented technology. Using a

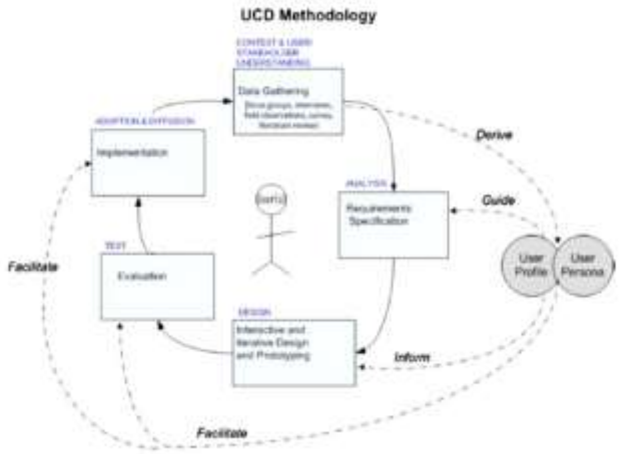


**Figure 9**: The multi-phase user-centred design approach
Adopted from LeRouge *et al.* (2013)

So-Tech example, the profile of users and their personas were applied as UCD techniques. With the techniques, a systematic way of characterizing users using text and pictorial formats were proposed. The conceptual modelling of end users, in a way that is beyond demographics was achieved using the persona methodology. As a tool, it captured users' expectations, their anticipated behaviour, and prior experiences from the use of technologies. With the technique, the mental model of users was "captured" for evaluative purpose. Based on this motivation, LeRouge *et al.* (2013) employed the persona methodology as a UCD concept in a Multi-phase approach (see Figure 9).

### 4.2. Some suggested theories

Theories help to reveal the philosophy (or thinking) behind a particular process. It is used to highlight the integrating part of the process involved in a research design (or methodology). For the UcEM, there are several theories, which could be used to underpin the concept. Three are mentioned here, but only the theory of perception is discussed in much detail. The remaining two theories are Information processing and the constructivist theory. Basically user oriented theory can be used to guide the use of the UcEM. The UcEM is judged to be flexible since depending on the goal of a particular user-oriented evaluative task, the right theory can be appropriated.

The protocol, that is, the empirical set of evaluative procedures in Figure 5 is a robust evaluative guideline to develop user-centric evaluative models. The empirical protocol with its guidelines were formulated based on the theory of information processing (Gao *et al.*, 2012), and the theory of constructivism. With these theories, the qualitative and quantitative research methodology is entrenched in the process of user-oriented evaluation of So-Tech. One way to conceptualize the operation that is highlighted with the framework as a protocol is a basic Computer Process (CP). For a typical CP, (i) there exist some inputs (which are assumed here as coming from users' interaction with a system), (ii) storage (which is a store of users' previous experiences garnered from using a system), and output information (the feedback, which can be elicited as ordinal data and analyzed to get result). Interestingly, as with any computer processes, this computational process can be exemplified formally as a 3-tuple, say;

$$CP = \langle a, Ue, q \rangle \qquad (1)$$

where;

- $a$ = the input process that results from users' interaction with So-Techs overtime;
- $Ue$ = the opinion formed by users based on the experiences garnered from using the system; and
- $q$ = the feedback, which can be elicited as ordinal data.

One of the advantages of the protocol in Figure 5 taking a cue from Williams *et al.* (2010) as an evaluative framework is that it is a procedural approach that is systematic and algorithmic-like. This quality makes it easy to adopt and adapt and at every point where the researcher needs to make a decision, it is easy for such decision to be made. For instance, the protocol was developed with the analytic concept of factor analysis. The flexibility of the protocol is that it is easy to adopt and adapt as an analytic concept for analysis. What is novel with the evaluative procedure is that it emphasizes the concept of "user-centricity" from start to finish. It seeks to underscore the importance of the evaluation of So-techs like the IR systems through the eyes of users (Norman, 1986; Hotchkiss, 2007; Patton, 2007). In Akhigbe (2015), the protocol was implemented to formulate a first and second-order evaluative measurement model as presented in Figure 10.

Summarily, the model reveals that the theoretic of the technology acceptance model is supported by

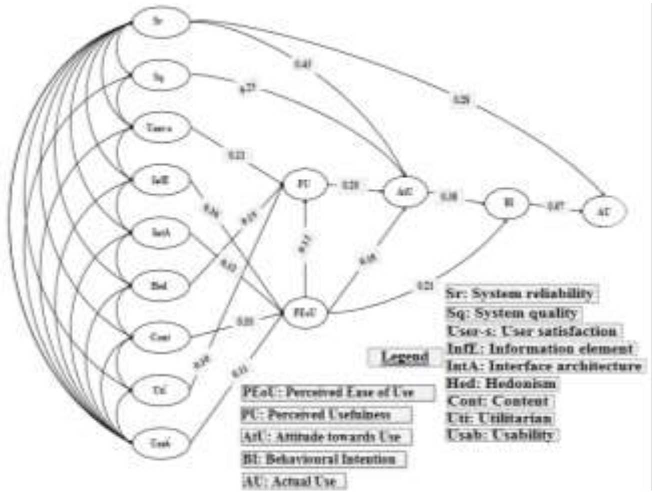


**Figure 10:** Showing the integrated evaluative mode that comprise a second -order factor analysis measurement/evaluative model with the technology acceptance model

**absolute values ≤ 0.10 $\Longrightarrow$ *"small effect"*;
**Around 0.30 $\Longrightarrow$ *"medium effect"* and
> 0.50 $\Longrightarrow$ *"large effect"*

the factors affirmed using the confirmatory factor analysis technique. Therefore, should these nine factors be taking into consideration when designing and implementing a WeSE? If they form a strong part of the functionalities of the WeSE it is certain that actual use of the system will be actualized by users. This further implies that the nine factors: *Usab* (Usability); *Uti* (Utilitarian); *Cont* (Content); *Hed* (Hedonic); *IntA* (Interface Architecture); *InfE* (Information Element); *User-s* (User-satisfaction); *Sq* (System quality); *Sr* (System reliability) are the functionalities users really want to use and experience when using the WeSE. However, the type of model to be achieved by using the procedure in Figure 5 is not specified. So, users of the procedure would need to always determine the type of evaluative model to be developed based on the goal of their evaluative research.

### 4.3. The theory of perception and ICT management

The theory of perception is from the field of cognitive science. With the laws of perception, it is possible to show that the human visual system can identify objects and put together features that are basic enough to observe; (i) surfaces coherently, and (ii) a world of things in an organized manner. It highlights the fact that users can easily segregate information that are useful and also group related information without ambiguity. As evident in Sun and Wong (2004), Ware (2000), and Wong and Sun (2006) the theory of perception is applicable to evaluate software in terms of effectiveness. The aim of such evaluation is to determine the level of service provisioning in terms of success, usefulness, and operational gain that are derivable in an ICT environment. Nevertheless, ICT management has to do with the organisation and maintenance of ICT services. It allows the proactive monitoring of the services that are provided by an organization's ICTI with a goal in mind. The goal is to monitor, manage and maintain the IT environment in such a way that the expected return on ICT (or technology) investment is achieved. The monitoring, management and maintenance activities are aimed among other things to free up resources so that additional strategic priorities can be focused on (Blue Saffron, 2018). The level of ICTI management becomes something to worry about when the business of an entity grows. Usually when a business grows, the ICT concerns grow as well. All the time when the foregoing happens, the ICT composition becomes complex. This presents a further responsibility that includes the need to support a complex mix of different So-Techs as a requirement to manage the increasingly complex systems. On the contrary, the door to outages, security threats, data loss and other impacts that can negatively affect an organizational business growth strategy must not be left open. At the granular level, an organization's ICT environment and other concerns must be looked after. Aside the need for depth in terms of skills and the know-how or resources to cope with the plethora of ICT maintenance and monitoring tasks in an ICT environment, there is the need for user-oriented feedback mechanisms. From such mechanisms inferences from users' point of view based on their experience with the use of a technology can be derived. To strengthen such feedback mechanisms based on evaluative modelling, the right theory must be applied. One of such theories is the theory of perception, which expresses the fact that visualization helps people to understand information, even though a lot of work is still needed to be able to unravel how the brain transforms, interprets, and processes the stimuli of vision.

One of the theories of perception is the Marr's theory (Marr, 1982). The theory postulates that cognitive functions are filters, and they operate on raw visual stimuli and turn them into information. This theory supports the principle of organization and explains why the attempt to make something evident and visible is profitable. Similarity, continuation, proximity, connectedness, and familiarity are some of the principles that strengthen the theory of perception. Conclusively, these perceptual theories reveal how humans perceive objects and interact with an environment.

### 4.4. Suggested data analysis tools

Basically, the evaluation of systems from the perspective of users, which this study is all about, entails the utilization of users' opinion as data for analysis. The result of such data analysis would be used for the betterment of a system, particularly to orientate the system towards the user. A longitudinal study may be employed or otherwise depending on the evaluative goal. The factor analysis tool is one data modelling technique that uses a robust statistical paradigm. It is both exploratory and confirmatory. The confirmatory aspect can also suffice for structural equation modelling. Literature is replete with primers and other detailed materials on how to use it as a veritable data analysis tool. The sample size of the population to be studied still matters because of the issue of degree of reliability of result. The amount of resources available for a particular study also influences what sample size to use for a study. The work of Norman (2010) resonates in terms of parametric powers. In statistical modelling, the choice of what data analysis technique for user-oriented modelling to use is all about parametric powers.

In Van Voorhis and Morgan (2007), it was observed that parametric power is about being able to get the probability of rejecting a false null hypothesis or otherwise correctly. And if the null hypothesis is genuinely true, then the findings arrived at will be robust. This argument is important since "attending to power during the design phase" of a data analysis is meant to "protect both the researchers and the respondents". This "protection" rule-of-thumb is often about the provision of guidance that brings one's research up to speed in terms of standard and consistency with what is in literature. In line with this thinking, the goal of a research and the technique intended for inferential statistics are two important criteria to consider. In Tables 4 and 5, the ratings of different sample sizes are presented. The ratings are based on the research findings of Comrey and Lee (1992) and Van Voorhis and Morgan (2007), who are key proponents of the qualitative and quantitative research methodology.

**Table 4**: Showing the rating of sample size

| S/N | Sample Size | Interpretation |
|---|---|---|
| 1. | ≤ 50 | Very poor |
| 2. | ≤ 100 | Poor |
| 3. | ≤ 200 | Fair |
| 4. | ≤ 300 | Good |
| 6. | ≤ 500 | Very good |
| 7. | ≤ 1000 or more | Excellent |

Comrey and Lee (1992)

**Table 5**: Showing the rating of sample size

| S/N | Relationship | Reasonable Sample Size |
|---|---|---|
| 1. | Measuring group differences (e.g., t-test, ANOVA) | Population size of 30 for 80% power, and if decreased, no power than 7 per population. |
| 2. | Relationships (e.g., correlations, regression) | ≥ 50 |
| 3. | Chi - Square | At least 20 overall, but not < 5 |
| 4. | Factor Analysis (and other variants/related statistics, such as Structural equation modeling) | ≥ 300 is "good" |

Van Voorhis and Morgan (2007)

The discussion of Norman (2010) finds relevance in the foregoing. Norman's (2010) argument accentuates the findings of many studies. It emphasized the not too obvious, which is that parametric statistics are robust despite the assumptions propagated by Lingard and Rowlinson (2006), Reise and Walker (2000), Osborne and Costello (2004), and Van Voorhis and Morgan (2007) among others. Therefore, to ignore the account and place of the robustness of parametric tests is tantamount to ignoring a substantial body of literature. The concluding counsel is evidently suggestive of the fact that parametric statistics are perfectly appropriate irrespective of sample size. So, the choice of what parametric test to carry out for statistical analysis is important. The Table 5 below provides some relevant information.

**Table 6:** Statistical software, ordered by methodological capabilities

| Statistical capabilities | | |
|---|---|---|
| **Basic** | **Intermediate** | **Advanced** |
| Excel | EpiInfo | SAS |
| Access | SPSS/PASW | Stata |
| OpenEpi | | R/S-Plus |

*Adopted from* Stanley (2012)

For brevity, interested researchers can see (http://en.wikipedia.org/wiki/List) for a list of statistical packages. The work of Stanley (2012) can also be checked out. Some common-sense information can be found in the following sources.

## 5.0. Directions for Future Research

The Big data technology has thrown the search light on sensors as having the potential to be the eyes and ears of future applications. This means that data-driven So-Techs would be able to visualize, parse and aggregate data in such a way that they can act accordingly when trends are spotted (Raj, 2018). The presentations in this study are exploratory as well as interpretive in nature and thus a number of opportunities for future research are conceivable. For example, the theoretic presented is depictedin such a way that they can aid other theory development and be used for concept validation. This means that adopting them will be needful and can thus stimulate further research, which would be necessary to extend and refine the novel findings that are reported.

The existence of Big data sources tells the fact that more information will be processed as never before in the future, which implies that more user oriented approaches to evaluating Big data oriented systems will be needed. Such an approach must be able to incorporate the wherewithal to evaluate So-Techs that were developed based on emotion and hedonic models. These types of models will be common place due to the existence of resultant Big data technologies. Definitely, such hedonic and emotion models would have been proposed based on intensive computational representations that will also need testing. The Big data technology is gaining wide application in areas such as smart cities, health care, electric cars and so on. These areas no doubt will provide veritable and fruitful opportunities to successfully develop So-Techs with affective computing tendencies. Their end-goal will be to improve the quality of human life and so many factors such as human emotions as it relates to users' activities and their interaction with several and varied services would need to be taken into consideration. Other So-Techs will also be created with the goal of adding significant commercial and scientific value to how people interact and get themselves involved in various human endeavours. Thus, smarter fault detection systems, emotion and hedonic modelling and sentiment analysis will be more popular methods of the analyses in the future. The modelling of population displacements will be rife with people drawn towards where the best services are available. Data visualization, economic strategy recommendation, personalised health services, intelligent transportation and biometrics services, e-government, and surveillance would all be relevant and prevalent (Iqbal, 2018). These are a few of the novel services that are in the offing. There will be need for measures, theories and methodologies to evaluate them so as to track their progress and as such be able to further improve them. It will be important also to translate the evaluative results from the exercise of evaluation that will result from the use of new methodologies to rethink and rework existing policies and formulate new ones to drive them.

As is, data analytics is a rapidly changing domain. As such, the traditional techniques of doing not only evaluation, but also design and modelling will require total overhaul and rethinking in order to cope with the dynamics of the Big data technology. Even current policies will need revisiting since data grows continuously. These suggestions affirm the fact that seeking for the right system - in terms of measures, theories, methodology and policies to manage the large and phenomenal growth and fusion of Big datasets would be part of the directions for future research (Rani, 2018).

## 6.0. Policy Recommendations

In the Big data technology literature, there is no report of up to ten dimensions of Big data in one article (see Figure 3) except in this study. These Ten dimensions that exist - no doubt - affect the paradigm of search with WeSE. Other Big data oriented So-techs are also positively impacted and there is dearth of policy to guide the formulation and maximization of the potentials of Big data. The immediate and complete aggregation of Big data with the IR model so that the paradigm of IR - for instance - can cope with the tones of data that is readily available even per Nano-seconds is recommended. The data science research community must take the lead as a matter of urgency.

Existing novel technologies that are Big data and Computational Intelligent-based must be well tested and guided. With this, it will be possible to harness the available strength of Big data to simplify the usual complex efforts of governments as well as that of local authorities to enhance economic development. The ultimate goal in all these is that Big data should be leveraged (especially in this part of the world - Africa) to considerably improve the quality of life of citizens. This makes the Big data technology citizen - user centred. This implies that users are and would continuously be at the receiving end of the impact of the Big data technology (Iqbal *et al.,* 2018). To this end, there is the need to carefully and cognitively analyze the technology on a continuous basis so as to inform on a lot of things with respect to policy (e.g. what responsible way to use data?), adaption and adoption issues (Raj, 2018; Iqbal *et al.*, 2018).

That the Internet - one of the ICTI - is expressly dynamic; that is ever changing and almost self-regulatory makes it imperative to act on the foregoing policies as a matter of urgency. That Big data technologies themselves are people-centred makes it overarching to want to seek new and better ways to deploy their gains.

## 7.0. Conclusion

The scope of Big Data is massive and does hamper users of the Internet - an ICTI - from locating "relevant" information (or information that satisfies their IN) except with the use of WeSE (Serrano, 2016). This is further made complex since there is no guarantee that the feedback results provided by search applications are either exhaustive or relevant to users' IN (or search needs). Despite the existence of Big data, advertorials are still ranked higher in terms of search results or recommendations. It is therefore a paradox that as the size of the Internet and Big data expands in great proportion, Web users will depend on information filtering applications like the WeSE even more. This makes the WeSE a life system and its continuous evaluation is therefore inevitable.

In IR evaluation research, experimental design should be taken as a compromise; that is there should be a balance between what an experimenter feels and the control experiments if any. Both are necessary for achieving good result (Kelly, 2009). Interestingly, without improvements in the methodology of evaluation (or measurement), this will not be possible. That is, whatever one cannot measure, its development cannot to monitored and managed towards improvement. Evaluation provides the mechanism to verify and measure improvements (Carterette *et al.*, 2012b). From the perspective of the user, which philosophy "User-centricity" emphasizes, measurement for improvement purposes should be based on how users are satisfied with a system. From the systems view, which is not the focus of this study (though), verification and measurement and effectiveness issues and how to assess them remain the focus. Going by the philosophy of "User-centricity"; when this approach is followed it would be in conformity with the measurement of how successfully an IR system meets its goal of helping users fulfil their INs.

Research experiments like evaluation design in IR is also about making choices (Kelly, 2009). Therefore, the primary goal of this study among others was to sensitize the IR and Big data community of some challenges that are bound to occur in evaluation. Valuable contributions in terms of methodology, theories, sample evaluative modelling (see the Figures presented above) have been presented using the evaluation of WeSE – an IR system - as a So-Tech. The study also sought to enlighten researchers about Big data, and its main domain of applications. One obvious motivation therefore was the fact that – using the words of Robertson (2008), "a field advances not by deciding on a single best compromise, but through different researchers taking different decisions, and the resulting dialectic". This motivation highlights the fact that there is no single best evaluation method. Like Kelly (2009) puts it, evaluating IR systems should be more than just system evaluation and retrieval effectiveness,and since IR systems require pluralistic approaches and methods (Kelly, 2009), this study's contribution especially with the advent of Big data is one of - may be - too many contributions on the subject of IR system evaluation. In this study therefore, theories, frameworks and tools to choose from have been presented with the belief that they will add to what exists in literature and assist researchers to make more informed decisions about policy formulation.

Big data is currently the focus of several researches due to its analytic orientation. This has brought about the experience of a huge growth in terms of research, adoption, use and spread. This is motivating because research into how to evaluate So-Techs (or WeSE) must be stimulated and oriented for better data retrieval. With Big data technology the data are available with even real time accessibility. But the challenge is retrieving what meets (or satisfies) the IN of users. Therefore, in future, research into how smooth and relevant the retrieval of data to analytic mechanisms due to proper aggregation and integration of data for retrieval purposes (among others) would dominate the studies in this area.

## References


Ahrens, J.P. *et al.* (2011). Data-intensive Science in the US DOE: Case Studies and Future Challenges, Computer Science Engineering, 13 (6), 14–24.

Akhigbe B.I. (2015): Development of a User-centric Integrated Evaluative Model for Information Retrieval Systems. A Ph.D. thesis submitted to the Department of Computer Science and Engineering, Obafemi Awolowo University, Ile-Ife Nigeria.

Akhigbe, B.I., *et al.* (2016). The Web Analytics Framework: An Integrated User- centric Evaluative Tool. In Proceedings of the International Conference on Transition from Observation to Knowledge to Intelligence, University of Lagos, August, 25 - 26, (pp. 331 -343). (Nigeria).

Akhigbe, B.I. (2012). Development of a User-Centered Evaluative Model for IR Systems: An empirical perspective. Saarbrucken, Germany: Lambert Academic Publishers

Akhigbe, B.I., Afolabi, B.S., Adagunodo, E.R. (2015). Modelling User-centred Attributes: The Web Search Engine as a Case. *Knowledge Organization*, Vol. 42 (1): pp. 25 - 39.

Aladwani, A.M., and Palvia, P.C. (2002). Developing and Validating an Instrument for Measuring User-perceived Web Quality, *Information and Management*, 39: pp. 467–476.

AlEnezi, A., AlMeraj, Z., and Manuel, P. (2018, April). Challenges of IoT Based Smart-Government Development. In IEEE Green Technologies Conference (GreenTech), 2018 (pp. 155-160).

Baxter, K., Courage, C., and Caine, K. (2015).Understanding Your Users: A Practical Guide to User Requirements Methods, Tools, and Techniques. San Francisco: Elsevier Publishers.

Baxter, K., Courage, C., and Caine, K. (2015).Understanding Your Users: A Practical Guide to User Research Methods. Waltham, USA: Morgan Kaufmann (an imprint of Elsevier).

Bevan, N. (2008). Classifying and Selecting UX and Usability Measures. In International Workshop on Meaningful Measures: Valid Useful User Experience Measurement (pp. 13-18).

Birek, L., Grzywaczewski, A., Iqbal, R., Doctor, F., and Chang, V. (2018).A Novel Big Data Analytics and Intelligent Technique to Predict Driver's Intent. *Computers in Industry*, 99, 226-240.

Brusilovsky, P., Karagiannidis, C., and Sampson, D. (2004).Layered evaluation of adaptive learning systems. *International Journal of Continuing Engineering Education and Life Long Learning*, 14(4): pp. 402-421.

BlueSaffron (2018). The Challenges of Successful ICT Management: Increasing Complexity and Dem - and for Improved Financial Return Drive the Need for Managed Services. Retrieved from http:// www.bluesaffron.com/ pdf/Blue%20Saffron%20The%20Challenges%20of%20Successful%20ICT%20Management.pdf on 15/07/2018 @ 17:00 pm.

Cao, Y., *et al*, (2018).Mobile Edge Computing for Big Data-Enabled Electric Vehicle Charging, IEEE Communications Magazine, 56(3), pp. 150 - 156.

Carterette, B., Kanoulas, E., and Yilmaz, E. (2012a). Advances on the Development of Evaluation Measures.In Proceedings of the 35th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 1200-1201).ACM.

Carterette, B., Kanoulas, E., and Yilmaz, E. (2012b). Evaluating Web Retrieval Effectiveness. In Proceedings of the 20th ACM international conference on Information and knowledge management, ACM, pp. 611-620.

Chen, C.P., and Zhang, C.Y. (2014). Data-intensive Applications, Challenges, Techniques and Technologies: A Survey on Big Data. *Information Sciences*, 275, 314-347.

Chen, M., Mao, S., and Liu, Y. (2014). Big Data: A Survey. *Mobile Network Application*, 19, 171–209.

Comrey, A.L., and Lee, H.B. (1992). A First Course in Factor Analysis (2nd ed.). Hillsdale, NJ: Erlbaum.

Coneglian, C., Fusco, E. and Segundo, J. (2016).Semantic Agent in the Context of Big Data - Usage in Ontological Information Retrieval in Scientific Research. In the Proceedings of the International Conference on Internet of Things and Big Data (IoTBD 2016), pages 324-330.

Courage, C., and Baxter, K. (2005).Understanding Your Users: A Practical Guide to User Research Methods. Waltham, USA: Morgan Kaufmann (an imprint of Elsevier).

Fagan, J. C. (2014). The Suitability of Web Analytics Key Performance Indicators in the Academic Library Environment, *Journal of Academic Librarianship* 40, 25–34.

Gandomi, A and Haider, M. (2015). Beyond the hype: Big data Concepts, Methods, and Analytics. *International Journal of Information Management*, 35, 137– 144.

Gao, J., Zhang, C., Wang, K., and Ba, S. (2012). Understanding Online Purchase Decision Making: The Effects of Unconscious Thought, Information Quality, and Information Quantity. *Decision Support Systems*, 53(4): pp. 772-781.

Garg, S., Singh, A., Batra, S., Kumar, N., and Yang, L.T. (2018).UAV-Empowered Edge Computing Environment for Cyber-Threat Detection in Smart Vehicles. IEEE Network, 32(3), 42-51.

Gavurová, B., Balloni, A., Tarhaničová, M., and Kováč, V. (2018).Information and Communication Technology in the Role of Information System of Healthcare Facility in the Slovak Republic.*Economies*, 6(3), 47.

Gulliksen, J.*et al.* (2003). Key Principles for User-centred Systems Design. *Behaviour and Information Technology*, 22(6): pp. 397-409.

Hotchkiss, G. (2007). User-centricity - More than just a Word. Retrieved from http://www.webpronews.com/user-centricity-more-than-just-a-word-2007-03 on 04/07/2013 @ 01:26.

Hussein, A. (2015). The use of Triangulation in Social Sciences Research: Can qualitative and quantitative methods be combined? *Journal of comparative social work*, 4(1), 1 – 12.

Idoughi, D., Seffah, A., and Kolski, C. (2012).Adding User Experience into the Interactive Service Design Loop: A Persona-based Approach. *Behaviour and Information Technology*, 31(3), 287-303.

Iqbal, R., Doctor, F., More, B., Mahmud, S., and Yousuf, U. (2018). Big Data Analytics: Computational Intelligence Techniques and Application Areas. *Technological Forecasting and Social Change*. DOI: 10.1016/j.techfore.2018.03.024. (In press).

Jorgensen, D.L. (2015). Participant Observation. In R. Scott and Kosslyn (eds.). Emerging Trends in the Social and Behavioural Sciences. Hoboken, New Jersey, United States: John Wiley and Sons, Inc.

Kalantari, A *et al* (2018). Computational Intelligence Approaches for Classification of Medical Data: State-of-the-art, Future Challenges and Research Directions. *Neuro computing*, 276, 2-22.

Kelly, D. (2009). Methods for Evaluating Interactive Information, Foundations and Trends. *Information Retrieval*, 3 (1–2): pp. 1–224. doi: 10.1561/ 15000 -00012.

LeRouge, C., Ma, J., Sneha, S., and Tolle, K. (2013). User Profiles and Personas in the Design and Development of Consumer Health Technologies, *International journal of medical informatics*, 82, e251–e268.

Levy, M. (2009). WEB 2.0 Implications on Knowledge Management. *Journal of Knowledge Management*, 13(1), 120-134.

Lingard, H.C., and Rowlinson, S. (2006). Sample Size in Factor Analysis: Why Size Matters. Retrieved from http://94.23.146.173/ficheros/c7c3f192965811945db9b57367 2781c8.pdf on 12/03/ 2013 @ 12:11pm

Loup-Escande, E., and Lécuyer, A. (2014). Towards a User-centred Methodological Framework for the Design and Evaluation of Applications Combining Brain-computer Interfaces and Virtual Environments: Contributions of Ergonomics. Project-Team Hybrid, Research Report # 8505. In hal-00965608, version 1, Inria.Fr: pp. 1-40. Retrieved from http://hal.inria.fr /INRIA-RRRT/hal- 00965608 on 17/08/2014 @ 05:04 pm.

Mann, L. (2017). Left to Other Peoples' Devices? A Political Economy Perspective on the Big Data Revolution in Development. *Development and Change*, 49(1): 3–36.

Marr, D. (1982). Vision: A Computational Investigation into the Human Representation and Processing of Visual Information. Cambridge, Massachusetts: MIT Press.

Marshall, R.*et al* (2015). Design and Evaluation: End Users, User Datasets and Personas. *Applied Ergonomics*, 46, 311-317.

Miaskiewicz, T., and Kozar, K.A. (2011). Personas and User-centred Design: How Can Personas Benefit Product Design Processes? *Design Studies*, 32, 417-430.

Misra, R., Panda, B., and Tiwary, M. (2016). Big data and ICT applications: A study. In Proceedings of the Second International Conference on Information and Communication Technology for Competitive Strategies, Udaipur, India, March 04th – 05th, 2016 (pp. 41).ACM.

Mulwa, C., Lawless, S., Sharp, M., and Wade, V. (2011).A Web-based Framework for User-centred Evaluation of End-User Experience in Adaptive and Personalized E-Learning Systems. In Proceedings of the 2011 IEEE/WIC/ACM Int'l Conferences on Web Intelligence and Intelligent Agent Technology -3, IEEE Computer Society: pp. 351-356.

Musser, J. and O'Reilly, T. (2006), ''Web 2.0 Principles and Best Practices'', (electronic version), O'Reilly Radar.

Norman, D.A. 1986. Cognitive engineering. In: D.A. Norman and S.W. Draper (Eds.), User centred system design: new perspectives on human computer interaction, Hillsdale N.J., Elbraum, 31-61.

Norman, G. (2010). Likert Scales, Levels of Measurement and the Laws of Statistics, *Advances in Health Sciences Education*, 15 (5): pp. 625-632.

Oliveira, P. *et al* (2018).CIass-Computational Intelligence as a Service with Athena. Computer Languages, Systems and Structures. DOI: 10.1016/j.cl.2018.04.003 (In press).

Ortiz-Cordova, A., and Jansen, B.J. (2012).Classifying Web Search Queries to Identify High Revenue Generating Customers. *Journal of the American Society for Information Science and Technology*, 63(7): pp. 1426–1441.

Osborne, J.W., and Costello, A.B. (2004). Sample Size and Subject to Item Ratio in Principal Components Analysis. *Practical Assessment, Research and Evaluation*, 9(11), pp. 1-9.

Patton, J. (2007). Understanding User Centricity. IEEE Software, 24(6): pp. 9-11. Retrieved from www.computer.org/software on 04/07/2013 @ 01:31am.

Raj, P. (2018). A Detailed Analysis of NoSQL and New SQL Databases for Big data Analytics and Distributed Computing. In *Advances in Computers* – Elsevier (Vol. 109, pp. 1-48).

Rani K and Sagar R. K. (2018). A Rigorous Investigation on Big Data Analytics. In: Pant M., Ray K., Sharma T., Rawat S., Bandyopadhyay A. (eds) Soft Computing: Theories and Applications. Advances in Intelligent Systems and Computing, Vol. 584. Singapore: Springer.

Reise, S. P and Walker, N. G. (2000). Factor Analysis and Scale Revision, *Psychological Assessment*, 12 (3): pp. 287-297.

Rieger, O.Y. (2010). Framing Digital Humanities: The Role of New Media in Humanities Scholarship.First Monday, 15; 10- 4.Available @ http://firstmonday.org/ojs/index.php/fm/article/view/3198/2628.

Robertson, S.E. (2008). On the History of Evaluation in Information Retrieval, *Journal of Information Science*, 34(4): 439-456.

Salomao, R.C.S., Rebelo, F., and Rodríguez, F.G. (2015). Defining Personas of University Students for the Development of a Digital Educational Game to Learn Portuguese as a Foreign Language. *Procedia Manufacturing*, 3, 6214 – 6222.

Serrano, W. (2016). A Big Data Intelligent Search Assistant Based on the Random Neural Network. In P. Angelov et al. (eds.), Advances in Big Data, Advances in Intelligent Systems and Computing, 529, Cham, Switzerland: Springer

Shibata, T., and Kurachi, Y. (2015). Big Data Analysis Solutions for Driving Innovation in on-site Decision Making. F*ujitsu Scientific and Technical Journal*, 51(2), 33-41.

Sim, W.W., and Brouse, P. (2015). Developing Ontologies and Persona to Support and Enhance Requirements Engineering Activities – A Case Study. *Procedia Computer Science*, 44, 275 – 284.

Sowa, G., and Marchlewska, A. (2016). The Internet of Things: Technological and Social Aspects. *Journal Applied Computer Science and Mathematics*, 8(1), pp. 17 -27.

Stanley (2012). Notes on Computer Programmes for Statistical Analysis. Retrieved from www.otago.ac.nz/wellington/otago048101.pdf 08-11-2017

Stockdale, R., Standing, C., Love, P. E. D and Irani, Z. (2008). Revisiting the content, context and process of IS evaluation. In Z. Irani and P. Love (eds.) Evaluating Information Systems: Public and Private Sector. Oxford, UK.: Butterworth-Heinemann (as imprint of Elsevier).

Sun, D and Wong, K. (2004). On Understanding Software Tool Adoption using Perceptual Theories.In the Proceedings of the Fourth ACSE International Workshop on Adoption-Centric Software Engineering (pp. 51–55).

Van Voorhis, C.R.W., and Morgan, B.L. (2007). Understanding Power and Rules of Thumb for Determining Sample Sizes, Tutorials in *Quantitative Methods for Psychology*, 3(2): pp. 43-50.

Vera-Baquero, A and Colomo-Palacios, R. (2018). Big-Data Analysis of Process Performance: A Case Study of Smart Cities. In *Big Data in Engineering Applications* (pp. 41-63). Springer, Singapore.

Waisberg, D and Kaushik, A. (2009). Web Analytics 2.0: Empowering Customer Centricity, *The original Search Engine Marketing Journal*, 2 (1): pp. 5-11.

Wang, L and Jones, R. (2017). Big Data Analytics for Disparate Data. American *Journal of Intelligent Systems*, 7(2): 39-46.

Ware, C. (2000). Information Visualization: Perception for Design. Waltham, USA: Morgan Kaufmann.

Webber (2010). Measurement in Information Retrieval Evaluation. An Unpublished Ph.D. Thesis Submitted to the University of Melbourne, Australia. Retrieved from http://www.williamwebber.com/research/wew-thesis-PhD.pdf on 15-10- 2018 @ 21:11 pm.

Williams, B., Onsman, A., and Brown, T. (2010). Exploratory Factor Analysis: A Five-step Guide for Novices. *Journal of Emergency Primary Health Care*, 8 (3): pp. 1-13.

Wong, K., and Sun, D. (2006).On Evaluating the Layout of UML Diagrams for Program Comprehension. *Software Quality Journal*, 14, 233–259.

Woo, J. (2013). Information Retrieval Architecture for Heterogeneous Big Data on Situation Awareness, *International Journal of Advanced Science and Technology*, Vol.59, pp.113-122.

Wu, Y., Zhang, W., Shen, J., Mo, Z., and Peng, Y. (2018). Smart City with Chinese Characteristics against the Background of Big Data: Idea, Action and Risk. *Journal of Cleaner Production*, 173, 60-66.

Young, E. (2015). Big data changing the way businesses compete and operate. Insights on governance, risk and compliance. Available at: http://www.ey.com/Publication/vw LUAssets/EY_Big_data:_changing_the_way_ businesses_operate/%24FILE/EY-Insights-on-GRC-Big-data.pdf accesed 8:34 pm 15-02-2018.

Zimmer, M. (2010). Web Search Studies: Multidisciplinary Perspectives on Web Search Engines. In J. Hunsinger, L. Klastrup, and M. Allen (Eds.), International Handbook of Inter - net Research (pp. 507-521). Dordrecht: Springer.