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Understanding big data analytics and the Interpretive approach for analysis purposes

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ABSTRACT

Big data is a complex sets of data based on its unprecedented, structured, and unstructured nature of its volumes, varieties and velocities. This makes it difficult for many organisations to achieve their objectives from a mono-approach in the use of analytics tools such as descriptive, predictive and prescriptive for big data analysis. The focus of this research was to explore and examine the possibility of combining the interpretive approach with the analytics tools for big data analysis purposes in an organisation, towards enhancing business objectives. Thus, the interpretive approach, from the perspective of subjectivism is required to enact and bridge that gap created from the mono-approach in using the analytics tools. The objectives of this research emanates from this point, and therefore were to: (1) identify some of the gaps in the application of big data analytics; and (2) propose methods through which the interpretive approach can be combined with the analytics tools, for big data analysis, to leverage business objectives. Existing related materials were gathered to achieve the objective from the perspective of qualitative methods. The analysis of the materials followed the interpretive approach from an epistemological standpoint in order to gain a better understanding of the knowledge that is obtainable about combining analytics tools with the interpretive approach for the analysis of big data. Based on the findings from the analysis a complementarity data analytics and interpretive approach model was developed and proposed, for organisational purposes.

Key phrases

Big data; big data analytics; interpretive approach and qualitative methods

1. INTRODUCTION

In an ever-growing knowledge driven society, big data and analytics are said to be fuelling the digital revolution (Maniak, Jayne, Iqbal & Doctor 2015:602). Big data is produced regularly from information systems and various digital technologies such as cloud computing, social media and Internet of Things (Zakir, Seymour & Berg 2015:82). The analysis of big data is useful in revealing patterns that exist within datasets, from which knowledge is gained to assist in decision-making (Iqbal, Doctor, More, Mahmud & Yousuf 2017:5). Big data analytics is defined as the methods that are used to study and process high volume and varied types of datasets (Gandomi & Haider 2015:138). Iqbal *et al*. (2017:8) assert that big data analytics is the use of techniques to uncover hidden patterns and identify relationships within big data. Similarly, Acharjya and Ahmed (2016:512) state that big data analytics processes data that is of high volume, variety, veracity and velocity by means of different computational techniques.

Taken into consideration that big data analytics does come with challenges, Acharjya and Ahmed (2016:514) explain that most of the methods of data analytics, such as data mining and statistical analysis are not able to handle large volume of datasets successfully, because of synchronisation challenges between analytics tools and database systems. Katal, Wazid and Goudars' (2013:408) postulate that one of the challenges of analytics tools include the designing of systems that can handle big data efficiently and have the ability to filter out vital data from the large volumes of data collected. The challenges of analytics tools can be attributed to the mono-approach in the use of analytics tools for analysis of big data, to find business leverage solutions for an organisation.

Along the same line of argument, Kaisler, Armour, Espinosa & Money (2013:996) state that another problem with analytics tools is how to describe the essential characteristics of big data, from a qualitative perspective. This is attributable to Sharmas' (2015:3) concern about the capabilities of the existing analytics techniques to enable and support business aims and objectives. According to LaValle, Lesser, Shockley, Hopkins and Kruschwitz (2011:23), the current single approach lacks detailed examination of huge data sets, which big data deserves in order to increase purposefulness and usefulness. Iyamu (2018:2) therefore suggest that there is a need to explore alternatives, which will combine big data analytic tools with a methodological approach. Such an approach should be able to increase the value of big data through an understanding of why and how data sets transform from one point to another (Gandomi & Haider 2015:138).

The interpretive approach allows for alternative options which again will lead to alternative interpretations, meaning that there is no correct or incorrect route to reality or knowledge (Antwi & Hamza 2015:219). Walsham (1995:378) argues that there are no 'correct' or 'incorrect' theories, if viewed from the interpretive perspective. The interpretive approach helps to gain knowledge of reality through social constructions such as language, shared meanings, tools and documents (Walsham 2006: 321). This means that the approach can be used complementarily with analytics tools to unpack and gain a deeper understanding of data sets (Iyamu 2018:3). According to Myers (2009:67), within the interpretive premise, access to reality is socially constructed through means such as consciousness and shared meanings. Arguably, this means that an entity can have value only if meaning is associated to it. According to Marshall, Cardon, Poddar and Fontenot (2013:14), through social construction realities are revealed by a process of enquiry and interaction.

Various stakeholders, such as software developers, business managers, users and suppliers are involved in the use of analytics tools for analysis of big data in organisations (Skok & Legge 2001:190). Due to the variety of stakeholders and interrelationships between them, examining big data analytics becomes a complex situation in a social context such as an organisation (Watson 2014:1251). Giddens (1984: 24) refers to social context as a society of people governed by policy and culture. In such a social context, Abdel-Fattah (2015:311) states that an interpretive research approach is suitable to comprehend the influences that are at play and to capture the complexity and contextual richness. Lukka (2014:563) states that the interpretive research approach offers a deep insight into social reality. The use of interpretive approach is often intended to gain better understanding of a phenomenon by examining it in its natural context (Butler 2016:17). From the interpretive perspective, Iyamu (2018:4) employed actor-network theory to complement analytics tools, to propose a multilevel approach for analysis of big data. Actor-network theory is a sociotechnical theory that is primarily concerned about actor (human and non-human), network, and the relationship and interactions that happen between actors within heterogeneous networks (Callon 1986:196). According to Iyamu (2018:2), the theory can be used to define data sets and human actors; examine how the actors' networks are formed and stabilised; how data sets are categorised into networks; and how to gain a better understanding of the data sets and actors' relationship and interaction.

From the discussion above, the objectives of this research were formulated as, to: (1) identify some of the gaps created from the mono-approach in using the analytics tools for big data analysis; and (2) propose a model through which the interpretive approach can be combined with analytics tools, for big data analysis and to leverage business objectives. Based on these objectives; the study was carried out and is documented in six main sections as follows: the introduction of the research is first presented, followed by a review of literature. The third section covers the methodology that was applied in the study. The relevant factors to this study that were discovered from existing literature are discussed in the fourth section. In the fifth section, a complementary approach is proposed, as well as discussion about the implications of use. Finally, a conclusion is drawn.

2. LITERATURE REVIEW

Based on the objectives of the research as stated above, a review of recent works in the areas of big data analytics, such as Gandomi & Haider (2015:141); Sharma (2015:3); Côrte-Real, Oliveira and Ruivo (2017) and interpretive approach (Marshall *et al*. 2013:14; Walsham 2006:322) was conducted. Through the review, historical insight into the possibility of combining the two concepts, big data analytics and interpretive approach for big data analysis was gained. According to Iyamu and Roode (2010:2), the combined use of two approaches is not necessarily to compare, but to highlight the importance and usefulness of the approaches in a complementary fashion.

Big data analytics encompasses the various techniques such as descriptive, predictive and prescriptive analytics for analysing large volume and variety of datasets, which are both structured and unstructured (Sun, Sun & Strang 2018:164). The descriptive analytics deals with describing past events; while predictive analytics focuses on future activities and how to possibly influence it; and prescriptive analytics refers to decision-making mechanism and tools (Rehman, Chang, Batool & Wah 2016). According to Wang, Kung and Byrd (2018:5), big data analytics has the potential to provide fresh business insights and improve business processes for many organisations. This is due to the ability of big data analytics to improve quality and accuracy of business decisions, boost business growth through effective decision making and offer a holistic view for meeting future organisational needs (Sun, Song, Jara & Bie 2016:767).

Big data analytics lead to valuable knowledge for many organisations. LaValle *et al*. (2011:27) classify the capability of big data analytics into three categories, namely, aspirational (future or intended use of data sets), experienced (practical use of data sets), and transformed (manipulation of data sets). The classifications make an attribution to business operations and risk management (Sivarajah, Kamal, Irani & Weerakkody 2017). The aspirations of many organisations are to seek meaning of lived experiences, and a deeper understanding from data sets through the interpretation of text (Jha & Bose 2016). Chen, Preston and Swink (2015:6) assert that insights resulting from big data analytics can transform business models and strategies. Akter, Wamba, Gunasekaran, Dubey and Childe (2016:115) states that big data analytics has the potential to deliver competitive advantages and returns on investments for organisations.

Datasets are generated from various sources and for this reason, data heterogeneity poses a challenge for big data analytics. (Sun *et al*. 2016:769). For various reasons, some organisations struggle to gain from the benefits, such as transformation, which big data analytics potentially presents (Wang *et al*. 2018:7). From the explanation in Katal *et al*. (2013:407), there are four main analytical challenges with big data, which are: (1) the inability to effectively deal with data that comes in large volumes and varied in nature; (2) the availability of data storage systems that can efficiently store big data; (3) making decisions as to which data is necessary for analysis; and (4) to gain the most value out of the data that has been analysed previously. The challenges currently encountered with big data analytics can be addressed by making use of the interpretive approach as this approach allows for various alternative approaches and perspectives.

Irrespective of the tools or viewpoints (descriptive, predictive or prescriptive), analytics of big data does require interpretation to gain deeper insight. Iyamu (2018:7) demonstrates how big data analytics tools can be combined with actor network theory from an interpretive perspective. Najafabadi, Villanustre, Khoshgoftaar, Seliya, Wald and Muharemagic (2015:2) argue that the difficulty of big data analytics is caused by the increase in data sources and data types that are associated with big data analytics, thus presenting inherent practical challenges. Also, there are some unique challenges that are faced by big data analytics, such as: (1) effectively dealing with streaming data that is moving at a rapid rate; (2) the distributed nature of the data sources; (3) the expansion capabilities available for analysis algorithms; and (4) the high dimensionality of data - large number of features and attributes in a dataset (Najafabadi *et al*. 2015:3; Rumsfeld, Joynt & Maddox 2016:352; Wilder-James 2012:2).

The interpretive approach can be useful to analytics tools in the analysis of big data, in that approach guides enquiry on why things are the way they are. The interpretive approach aims at probing for meaning from existing facts or materials, such as big data (Botes & Smit 2015:447). The intentions of the interpretive approach are grounded in theory building and conceptual thinking, which can be of use in examining big data, from its numerous sources, varieties and velocity (Khan 2014:237). Ultimately, the application of the interpretive approach for investigation depends on the investigator (researcher) and the amount, and types of available data, which are viewed from scientific and social worlds.

It is assumed that the validity of research that is conducted from an interpretive approach by the gathering of in-depth and rich qualitative data focuses on reality and context according to Wohlin and Aurum (2015:1430).

In either the qualitative or the quantitative enquiry the interpretive approach can be employed. Wu and Chen (2005:9) state that the strengths of the interpretive approach are threefold:

(1) the ability to provide valuable information and the generation of new knowledge;
(2) the flexibility in the creation of meanings introduced by unanticipated data; and

(3) providing a means in which meaning about a phenomenon can be described and discovered through the analysis and understanding of big data, from its complex volume, velocity and variety.

Some of the challenges of analytics tools include analysis of integrated (variety of) data and transformation of big data (Sivarajah*et al*. 2017:265). According to Mikalef, Pappas, Krogstie and Giannakos (2018:561), analytics tools lack the capability that is required to transform big data into actionable insight for organisations. The interpretive approach can be employed from this angle to close this gap. This is because the interpretive approach allows and enables analysis of multiple stages of innovation and can be linked to different theories (Jha & Bose 2016: 300).

3. RESEARCH METHODOLOGY

The qualitative methods were applied in the study. This was primarily because the methods help to gain an understanding about social phenomena, within context (Lewis 2015:473). Qualitative data were gathered from existing materials. The hermeneutic approach from the interpretive stance was employed in the analysis of the data.

Based on the objectives of the study, existing research articles published within ten years, between 2008 and 2018 were gathered. That was primarily to have a reasonable historical spread of the big data analytics challenges, as well as the consistency of meaning that has been associated with the interpretive approach over the years. According to Iyamu, Nehemia-Maletzky and Shaanika (2016:171), an historical spread helps to gain better understanding of perspectives; consistency and meaning that are associated with a concept over a period. A total of 46 peer-reviewed articles were gathered and used as data, from both big data analytics and interpretive approach viewpoints.

The hermeneutic approach focuses on the process of developing an understanding of data, from a qualitative perspective, as explained by Boell and Cecez-Kecmanovic (2014:2). The qualitative research methods are more about social worlds, with specific focus on reality and cultures (Silverman 2013:2). These are some of the reasons the qualitative methods are often applied to scientific phenomena, to seek answers to questions, collects evidence, and produce findings that are applicable to context (Saunders, Sim, Kingstone, Baker, Waterfield, Bartlam & Jinks 2018:286). According to Gehman, Glaser, Eisenhardt, Gioia, Langley and Corley (2018:1894), the qualitative methods allow better understanding of the context within which decisions and actions take place. Thus, making the methods useful in this study.

As the aims of this research lie in the immersion with literature to propose a method that combines interpretive approach and analytics tools, the hermeneutic approach was most useful. In achieving the objectives to: (1) identify some of the gaps that are created by using analytics tools as a single approach for big data analysis; and (2) propose method through which the interpretive approach can be employed with data analytics tools to leverage business objectives, questions were formulated. The questions were: (1) what are some of the gaps created in the single use of analytics tools for analysis. and (2) how can the interpretive approach be combined with analytics tools for big data analysis Section 4 will be dealing with the first question and section 5 with the latter

4. FINDINGS AND DISCUSSION

From a business enhancement perspective, big data analytics enable organisations to analyse an immense volume, variety and velocity of data (Wang *et al*. 2018:1). The analysis from extant studies reveal that the challenges remain in the use of analytics tools (Choi, Chan & Yue 2017:82). Mikalef *et al.* (2018:548) argue that big data analysis is often challenged because of its complexity and multifaceted tasks, which sometimes happen in attempts to enhance business objectives. Iyamu (2018:2) suggests that the challenges are caused by mono-approach of using the analytics tools in the analysis of big data, which could have been done at more than one level.

As mentioned in the methodology section, a total of 46 peer-reviewed articles were reviewed and analysed. Although there are thousands of articles that exists regarding big data, only 46 were considered closely related to this study. Based on the analysis, the answers (findings) to the research questions: what are some of the gaps created by using analytics tools as single approach in the analysis of big data in organisations? and how can the interpretive approach be combined with analytics tools for big data analysis? were divided into two sections, as follows:

Some gaps were identified in the application of big data analytics. This is irrespective of the analytics tools applied in the analysis of the big data. The main factors that create gaps in the application of big data analytics are algorithm adaption and use; facilitate contradiction; filtration of big data; and integration.

4.1 Algorithm adaption and use

Algorithms (newly developed or existing ones) are often required in the analysis of big datasets (Chen & Lin 2014:516). The need for algorithms is primarily because of the high dimension of the datasets, which has large amounts of attributes from various sources that are associated with the big data (Kashyap, Ahmed, Hoque, Roy & Bhattacharyya 2015:1506; Zhou, Pan, Wang & Vasilakos 2017:352). This means that there is a need for solutions that allow defining and formulating the necessary criteria for data representation that will provide valuable meanings (Acharjya & Ahmed 2016:515; Manekar 2017:3). Despite the application of algorithms, challenges remain in the analysis of big data. Najafabadi *et al*. (2015:5) attribute the challenges to the increasing number of data types and data sources that are constantly associated to big data, which affects sustainability and reliability in the results that obtained.

4.2 Hermeneutic Circle Technique

These challenges can be eased if the datasets are decomposed into smaller units through the application of the interpretive approach. A way to achieve this is by applying the principle of the hermeneutic circle technique. Klein and Myers (1999:71) state that the hermeneutic circle advocates that an understanding of complex datasets emanate from the meaning of smaller parts of a dataset and their associations. In the use of the hermeneutic circle, the interpretation process is twofold (Klein & Myers 1999:69). The first step of the process begins from a preliminary understanding of the smaller units to the entire dataset; and the second step involves an overall understanding of the entire dataset back to an enriched understanding of the individual smaller units (Miskon, Bandara & Fielt 2015:7). Essentially, an iterative process considering the symbiotic meaning of the smaller units and the entire dataset it forms a part of

4.3 Facilitate contradiction

On a regular basis, there are incompleteness and inconsistency in big data, which often results in discrepancies and contradictions. This necessitates the use of technologies to facilitate the process of crosschecking contradictory cases introduced by the incompleteness and inconsistency in big data (Jagadish, Gehrke, Labrinidis, Papakonstantinou, Patel, Ramakrishnan & Shahabi 2014:89). The contradictions are also attributed to the diverse sources and wavering reliability in big data analytics. To achieve an organisations' objectives in the use of big data, contradictions need to be facilitated. Even though analytics tools have been applied in the analysis of big data, the contradictions persist.

The contradictory challenge can be attributed to lack of subjective reasoning from interpretive perspective, which does not allow datasets to be unpacked into specific viewpoints. By taking a subjective view and position, datasets can be analysed from the awareness of business goals and objectives (Friedman & Wyatt 2006:251). The interpretation of business data and requirements based on subjectivism has impact on the realisation of transformation and the factors that can lead to addressing the objectives of an organisation (Fuza 2017:546). Such interpretation helps to gain better decomposition of datasets, for gaining comprehensiveness, improved understanding, and to make provisions for the most appropriate solutions.

4.4 Filtration of big data

Big data will continue to be big data in that the datasets will not stop increasing in volume, variety and velocity. The increasing nature of big data does not make it easy for the analytics tools, towards achieving organisational objectives. The increases in big data sometimes results into complexity, which cannot be economically feasible for an organisation. According to Mohamed and Al-Jaroodi (2014:307), there is a need for real-time solutions that will be able to filter and summarise the big data, in leveraging with business goals and objectives.

Datasets can be filtered in the use of descriptive, predictive and prescriptive tools in the analysis of big data. This can only happen through the application of the interpretive approach, which allows data to be viewed from real world perspectives. Thanh and Thanh (2015:26) state that using the interpretive approach an insightful understanding can be gained from the perspectives of the data that was collected. This is because the interpretive approach enables the portrayal of a complex and ever-changing reality that is often found in big data analytics, and leads to a more inclusive understanding of the data (Chen, Shek & Bu 2011:131).

4.5 Integration

Data sources in big data analytics is highly distributed, which brings about challenges such as integration, access and distribution (Wang, Chen, Hong & Kang 2018:3).

Due to this observation by the previous authors the need to create techniques for the purpose to properly prepare distributed data for integration and management of big data towards organisational objectives becomes a necessity. According to Saldžiūnas and Skyrius (2017:112), the results from big data analytics are largely influenced by a complementarity between the logical model of a database system and the analysis effort. The authors further argue that there is a missing middle, which is the integration between database systems and analytical tools, in performance and processing. The analytics tools are major differentiators between high-performing and low-performing organisations, because it allows pro-activeness, which promotes competitiveness and sustainability (Wamba *et al*. 2017:357). This poses a need for the autonomous use of analytical tools from a logical database model, which must be interpretive in nature.

The interpretive approach has been employed in the past where there were integration challenges concerning datasets.. For example, the acceptance of multiple perspectives with differing aspects of big data was used to form and underpin a comprehensive cognisance of datasets through integration approach (Thanh & Thanh 2015:25). The interpretive approach can be employed, to disintegrate or integrate attributes in big data based on the subjective view of the experts. Khanal (2013:117) states that using either sequential (where data is collected and analysed per data type) or concurrent (where data of different types is collected per stage) methodological strategies, integration challenges with data can be addressed. In addition, the use of data conversion and combination strategies in interpretive approach was employed by Henderson (2005:556) to address data integration challenges within context in an environment.

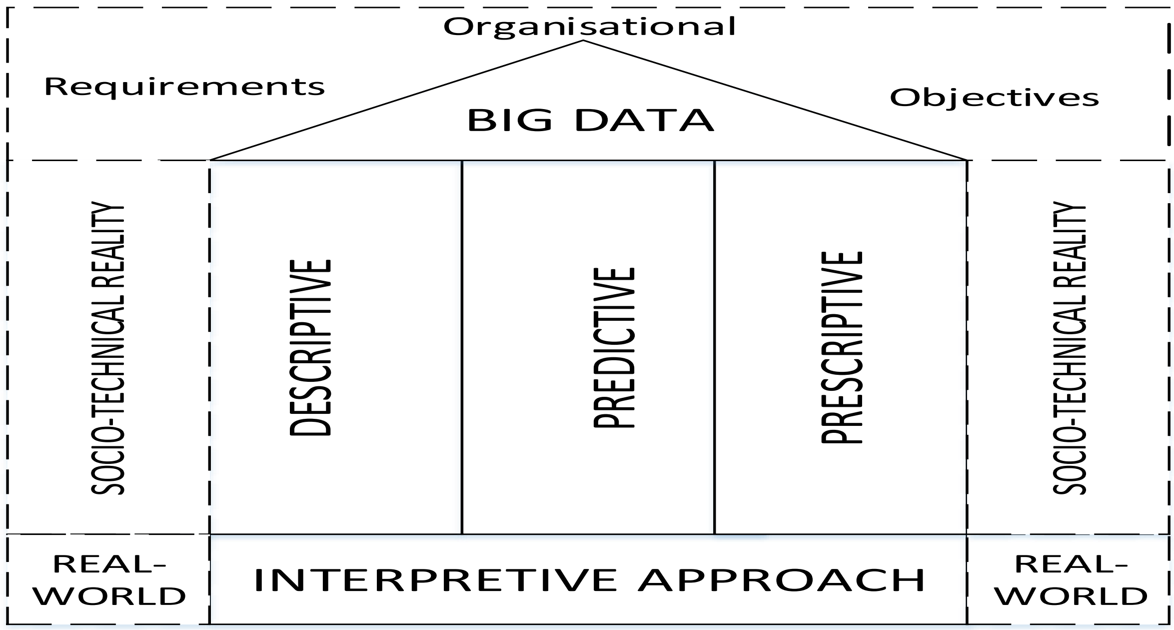
5. BIG DATA ANALYTICS AND THE INTERPRETIVE APPROACH

Analytical tools for big data analysis are the technologies and algorithms used in the analysis of big data for pattern recognition amongst data elements, the identification of risk areas in achieving business objectives and to facilitate decision-making (Bates, Saria, Ohno-Machado, Shah & Escobar 2014:1125; Guleria & Sood 2017:3). In addition, Akter and Wamba (2016:75) argue that in the extraction and interpretation of information from big data analysis analytics tools are used.

Big data analytics encompasses the various analytical techniques, the most common ones, descriptive, predictive and prescriptive analytics as shown in Figure 1 focus on distinct deliverables toward leveraging business objectives.

Employing and managing the tools better to enhance a business will require a better understanding of the challenges faced.

Figure 1: Complementary use of big data analytics and interpretive approach



Source: Developed by the authors

Different types of analytics tools exist that can be grouped as descriptive, prescriptive or predictive (Wang, Zhang, Shi, Duan & Liu 2018:2). The analytics tools make use of algorithmic methods to describe and summarise knowledge patterns (Waller & Fawcett 2013:79). In addition, Hazen, Boone, Ezell and Jones-Farmer (2014:73) state that big data analytics tools are used to probe data and discern patterns, for the purposes of informed business decision-making. The use of analytics tools is also a process of intelligence mining from datasets (Banerjee, Bandyopadhyay & Acharya 2013:3).

Big data analytics tools, such as descriptive, prescriptive and predictive are often viewed from both business and technology perspectives, because of the alignment between business and IT units, which remain a critical aspect of an organisation. This allows the encompassing of the analytics tools into technical and non-technical domain, in assessing their usefulness within context. Watson (2014:1256) distinguishes between the three analytical methods, purposely to understand their impacts on architecture and technology.

The interpretive approach enables the use of hermeneutics technique in the decomposition of datasets into smaller units.

The decomposition is to facilitate better understanding of the smaller units and the associations among the datasets (Miskon *et al*. 2015:9). The use of the interpretive approach from subjectivism stance enhances the analysis of data from various perspectives, which were derived from the business objectives that the data needs to address (Friedman & Wyatt 2006:253).

This approach is intended to ensure that contradictions are avoided within context, in the process of big data analysis. Due to the complex and volatile nature of big data analytics, the solution for achieving business objectives is not as easy as thus claimed. Based on this foreseen challenge, Chen *et al*. (2011:133) state that the interpretive approach can provide in-depth understanding of complex datasets through forming and underpinning multiple interpretations of a specific business context. Iyamu (2018:5) proposes a model in which actor network theory is combined with big data analytics for analysis of big data.

6. IMPLICATIONS OF PRACTICE

The combination of the interpretive approach with the big data analytics for big data analysis, to leverage business objectives has three main implications of practice: cyber security, business transformation, and scientific translation. The implications are tabulated in Table 1.

Table 1: Implications of practice

Implication	Big data analytics	Interpretive approach
Cyber Security	Analytics of big data can be used to prevent and mitigate security threats in the cyber space, by identifying, accessing, and detecting anomalies in system and network data. This include gathering and analysing data generated from computer systems, to gain in-depth understanding, and discovering of patterns which can assist in better detecting and responding to cyber threats.	The process of detecting patterns towards protecting cyber space, is often objective, which does not always cover angles of threat possibilities. The approach needs to include a process that allows patterns of events to be followed and traced. Thus, the analysis cannot always be objective, it does require subjectivism, to understand why certain things happen or did not happen.

Implication	Big data analytics	Interpretive approach
Business transformation	The analytics methods can enable organisation's drivers towards operational efficiency and product innovation, to enhance business capabilities and increase competitiveness.	Allows and enable the researcher to gain a rich understanding of business processes by bridging the gap between business data and decision-making. Through this means, theoretical and practical understanding can be reached, which helps to generate new ideas for the transformation of business initiatives as well as processes.
Scientific translation	In practice, the analytics methods can be used for translation and transformation of data for business enhancement. This includes transfer of data into information and knowledge for the creation of intelligence.	The translation and transformation of data into information and knowledge cannot be one way or through strictly defined pattern. To ensure richness and more purposefulness, it requires interpretation of the data from subjective point of views.

Source: Developed by the Authors

Table 1 provides a summary of the implications of the complementarily use of analytics tools and the interpretive approach. As shown in the table above, it is of fundamental importance for business' aim and objectives, to combine analytics tools with the interpretive approach in the analysis of big data. In practice, the combination analytics tools with the interpretive approach can help to cover a wide spectrum of business logics, from both quantitative and qualitative viewpoints. This is irrespective of size and nature of the organisations' business focus.

7. CONCLUSION

This article makes it possible to gain an understanding of how the interpretive approach can be combined with analytics tools, for big data analysis that can assist in leveraging business objectives. The research is therefore intended to benefit academics as well as organisations and professionals that focus on big data and analytics. For academics, this article provokes discourse on the complementary use of big data analytics and interpretive approach, which does not exist at the time of this study. The discourse can be viewed from both social and scientific perspectives. The research contributes to the academic domain through its addition to the existing literature in the areas of big data analytics, interpretive approach, and information systems. From the business perspective, the benefits come from gaining better understanding of the gaps that in the application of big data analytics as revealed in the study, and its implication of practice. In addition, the research proposes how analytics tools can be combined with the interpretive approach for business purposes.

However, there is more work to be done in this area of big data analytics and interpretive approach. This includes putting in practice the proposed solution from this study. A case study can be conducted to test the theory of combining both analytics tools with the interpretive approach for big data analysis.

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