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Insights on the Costa QDA Technique in Business and Leadership: A Post Covid-19 Outbreak Perspective

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Abstract

Business leaders with aptitude for using data intelligibly will be able to perform better post COVID-19 outbreak era. Literature posits that organisations are required to recognize the prudent role data plays in making crucial decisions about strategic directions and ground-breaking decisions for maximising all stakeholders contribution, organisational growth, environmental, social and governance legitimacy. This is particularly pivotal during the time of catastrophic disasters or events that pose potential threats to business continuity and sustainability. While a lot has been researched in relation to Big Data, not much is available in literature regarding Big Qualitative (Qual) Data, and methods of computational approaches for transforming raw big qual data to information pieces that may produce relevant knowledge required for decision-making. This study proposes that informed decision-making will be beneficial to leaders who need to be at the cutting-edge of knowledge production within the dimension of ideation and innovation. The COSTA Technique provides researchers and organisations with real-time technological enablers, using mix-media applications and web-based approaches that provides business intelligence capabilities with high levels of efficiency and integrity to be utilised in decision making.

The proposed approach to Data-Driven Decision-Making applies the capabilities framework that focuses on five key variables in decision-making, such as data governance, data analytics, insights exploitation, performance management and data integration. The final outcome of utilizing the cloud-based COSTA QDA and technique culminates in presentation of methodologies that demonstrates how large volumes of textual data, also known and referred to as "big qualitative data" may be transformed to structured, coherent, meaningful and timely decision-making enablers.

Keywords: Big data; Big Qual; Business Leaders; COSTA Technique; DDDM; Decision-making

Introduction

Data Driven Decision-Making (DDDM) continues to play a pivotal role for organisations in the 21st century. The outbreak of COVID-19 and the age of the 4th Industrial Revolution compelled different organisation across different sectors (from manufacturing, mining, agriculture, services and education) to adapt to the realm of analytics and use of sophisticated tools to relate to the targeted audiences and customers. This required immediate shift from the normal business practices to swift acquisition of skills and capabilities for adaptation into the realm of analytics. This article addresses five key areas as possible entry portals for provision of such capabilities and further proposes the COSTA QDATechnique and could-based software as a tool to be utilised for attainment of these capabilities (Jia, et al., 2015). Data governance, analytics, insights exploitation and performance helps business leaders and managers to make realistic and efficient use of information. Using the methods derived from BI (Business Intelligence) and AA (Advanced Analytics) components, researchers propound that organisations can further manipulate data for competitive benefits, sustainability and strategic positioning in their chosen markets. Properly utilised, the knowledge will direct management choices and will proactively adapt to market trends and other external variables (Cheong & Chang, 2007). Although companies today capture and store copious amounts of raw data, few are actually harnessing the power of experience to drive demand shifts and improvements. In the real business world, the only real constant is that everything is changing. Business Intelligence and Advanced Analytics offers methodologies and tools for today's business leaders to turn and direct their enterprises efficiently with fact-based decisions and a more strategic understanding of growth opportunities. This article will provide answers to the question, "how can business leaders and managers enhance decision making process through application of data driven decision-making using the COSTA QDA Technique and software? To answer this question, proposed DDDM capabilities will be explored and then later a nexus with proposed tools be articulated.

Methods

A mapping review was used to select, analyse and synthesize data with the sole objective of answering the research question (Grant & Booth, 2009). This is a form of review research approach that fits under the tradition of qualitative research. Mapping Reviews have been used and made popular by the Evidence for Policy and Practice Information Co-ordinating Centre attached to the Institute of Education (EPPI Centre, 2006). The development of this methodology was deliberately intended to map existing data and them atize current literature, define gaps and make suggestions for areas where more study was required (Grant & Booth, 2009). This methodology has 'experienced' steady growth and success as beneficial in establishing a stronger framework to provide sound and rigorous evidence-based studies on published primary research. Mapping review, as an approach to investigative methodology was also described as one of the relevant methods for South Africa's postgraduate study (Academy of Science of South Africa, 2010). Areas that were investigated and further synthesised using mapping review as a method of inquiry were, data governance, big data and big qual, critical relevance skills, data analytics, a case for COSTA QDA.

Data Governance

Data governance may be defined as a cross-functional and vital market asset framework for data collection, analysis and management. The processes of data governance determine decision requirements and accountability for its information for the decision-making of an organization. In addition, compliance with data rules, protocols, and processes is formalized and documented as data management practice (Abraham, vom Brocke & Schneider, 2019). It involves aspects such as management of data, data quality, data storage and security, data standards, policies and procedures, data transformation, data compliance and monitoring mechanisms. Understanding of data size and measurement is critical for proper decision-making about governance of data and what is stored and what is not stored in repositories.

Proper decisions in organisations are made from the quality of data available for making such decisions. The standard of data predicts data quality and may be classified in terms of specificity, type, and domain of data; precision and completeness; uniqueness and reliability; freshness and timeliness, and compliance with market rules (Cheong & Chang, 2007). The logical next question could be the "how" part - how to ensure data quality as a means to proper data governance?

Data governance is not a new concept at all, so is data quality. Many scholars have published on this concept (Davidson, Edwards; Jamieson & Weller, 2019; Jia, et al., 2015; Friedman, 2006; Donaldson & Walker, 2004), so the purpose of this article is to simplify approaches to enhance the subject matter of Data Driven Decision-Making, thereby addressing data governance capabilities. The first requirement is for leaders to understand that data operates in a three-dimensional position as depicted in Figure 1 below. In this model, a number of critical areas are represented in the periphery, while a framework that integrates people, processes and technology as the nexus of sound data governance is located around the centre (Jia, et al., 2015). To enhance data quality, one needs to understand data measurement. Data measurement in this context relates to how much data needs to be retained and processed for decision-making. Analytics technologies and business models do not contribute to the data-driven decision-making of enterprises without data processing which includes data measurement, with consistent data quality practices, data quality management systems, data quality obligations, etc (Buhl, Roglinger, Moser & Heidemann, 2013).

Figure 1: Data Governance Processes; *Source*: Authors.

To be able to function in the area of data governance and make appropriate decisions, organisations need to pay a particular attention on people, technology and processes. People will need to acquire requisite skills that enable them to perform in the era of digital transformation (DX), as clearly explicated in Section 3 below. In this section, critical skills required, particularly in South Africa, are listed in the order of their importance, as part of preparation for DX compliant organisations.

Data Governance Capabilities therefore entail processes involving organisational enablement in providing users with accurate and credible real-time data with high levels of accuracy, confidentiality and security for optimum decision-making (Jia, et al., 2015). Data measurement provides basic understanding of data and its sizes to inform storage decisions.

Big Data

3Vs Paradigm

Whereas the term "big data" is widely used in the science, economics, business and related field's lexicon, the ambiguity of its description and use is practice and scholarship was noted in Frizzo-Barker, et al. (2016). These scholars point to the casual use of the term, which is used to denote different meanings still attached to data. While others use it to describe what is known as 3Vs, (volume, velocity and variability), often used to denote large volumes of data (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012); others use it to denote a cultural thinking and way of deciding in business leadership (Green jr & Chow-White, 3013).

In terms of the 3V paradigm, big data may be characterized as digitally encoded data with voluminous and unparalleled nature or size of a phenomenon that is connected to other networked data. This data has to be processed or measured to be used for analytical work or information. Big data, which is related, traceable, and more difficult to interpret than traditional statistical analysis software permits, has been created by the expanded use of the internet and mobile devices for human communication (Snijders, Matzat & Reips, 2012). As much as the concept or notion of big data has been perceived as a higher form of intelligence or erudition, there are counter claims in literature against this view, as postulated in (Mills, 2018). Impacts of big data across different sectors have been well researched, so the focus of arguments in this article is on business impacts in relation to DDDM.

According to Frizzo-Barker, Chow-White, Mozafari and Ha (2016), techno savvy organisations have used big data to:

- Improve on their operational efficiency.
- Explore new ways of doing business.
- Launch new products or services (doing something completely new).
- co-creation of value with and for customers.
- Monetize data.

Big Qualitative Data ("big qual")

Another interesting aspect of big data refers to big qualitative data and how businesses may derive benefits in terms of real time DDDM. Descriptions of big data have similar connotations with descriptions of big qualitative data in as far as expressions of large data are mentioned as characteristics (Brower, et al., 2019). The emergence of big qual as a discipline related to data has been rapidly growing across different sectors such as education (Eta, Kallo & Rinne, 2018; Brower, Bertrand Jones, Tandberg, Hu & Park, 2017); business (St-Hilaire, Gilbert & Lefebvre, 2018). Big qual has also been used in healthcare and medicine (Jenkins, Slemon, Haines-Saah & Oliffe, 2018; Mayberry, 2016).

Literature further indicates that big qual does not often involve primary data, but mainly secondary data from textual data either in articles, reports, social media platforms such as facebook (Franz, Marsh, Chen & Teo, 2019) and twitter (Brower, et al., 2017). In this context, systematic reviews, which involve review of multiple documents in high volumes, form part of big qual (Calma, 2013). Equally so, sales and marketing reports and related textual business data may be classified under big qual. A lot of businesses are currently struggling on this context as they are used to big data in terms of numbers. It is interesting to note that techniques such as the COSTA QDA does provide insights in the form of quantification of accounts in textual data, providing clear and graphical information for decision-making (Costa, 2020). For big qual to be used effectively for DDDM, organisations need to provide opportunities to shift their focus towards digital transformation (DX) and acquisition of technological skills requisite and relevant for business sustainability during and beyond COVID-19.

Critical skills for data relevance

Frizzo-Barker, et al. (2016) have further noted that many businesses from large and medium sized firms are still struggling with conflation of big data (and big qual) into their corporate strategies. This is a draw-back for these organisations in terms of globalisation and opportunitie offered in a netwoked society (Niemandt, 2013). In the advent of COVID-19, 4IR and fast changing global landscape for business and all other sectors of society, big data epresents a massive shift and preparedness to participate in the new normal and digital world. In South Africa alone, the impacts brought about these changes, particularly COVID-19 has created a massive shift in skills requirements (See Figure 1 above) to enable DDDM in organisations decision value chains. Some of these skills (Figure 2) are in cloud computing, big data, analytics, data science etc. A study conducted by Microsoft on future work skills in 2019, some time before the outbreak of COVID-19 had already predicted national skills requirements for enabling organisationals to combine strategic directions with big data (IDC - Microsoft, 2019).

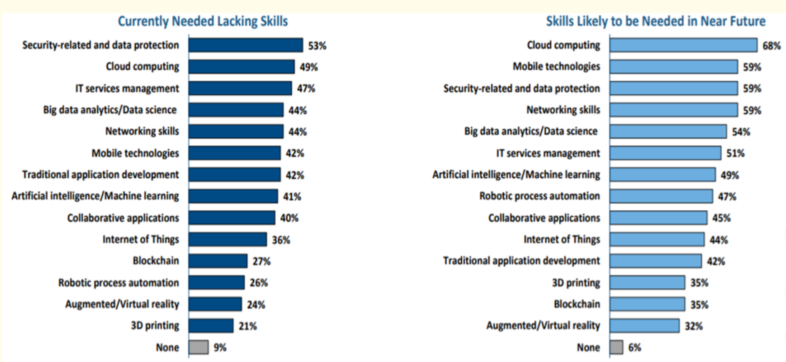

Figure 2: Currently lacking and future skills requirements in South African businesses - source: Future of Work Skills Research (2019).

Data Analytics

Data analytics encapsulate fundamental processes that help turn knowledge into actionable insight for smarter and quicker decision-making (Delen & Ram, 2018). As a discipline that is focused on solving organisational problems and enhancing leadership decision-making, data analytics involves discovery of meaningful and insightful information and new knowledge inherent in data being analysed for this purpose (Sivarajah, Kama, Irani, & Weerakkody, 2017). It may be interpreted in three forms as per Table 1 Below.

	Descriptive Analytics	*Predictive Analytics*	*Prescriptive Analytics*
Purpose	▪ Provide information about what happens in the organisation ▪ Provide understanding	▪ Provide a futuristic perspective ▪ Help understand possible results	▪ Provide information about what can be done ▪ Help decision-making
Key Questions	▪ What happened? ▪ What is happening?	▪ What will happen? ▪ Why should and will it happen?	▪ What should be done? ▪ Why should that be done? ▪ How should it be done?
Characteristic	▪ Data scrutiny ▪ Explication of current state	▪ Forecasting ▪ Concerned with future state ▪ Capacity for pre-cautionary action	▪ Problem solving ▪ Business optimization ▪ Business efficiency ▪ Pre-emptive
Enabling tools	▪ Dashboards ▪ Scorecards ▪ Business Reports	▪ Data mining ▪ Text mining ▪ Web mining ▪ Media mining ▪ Machine Learning	▪ Optimization ▪ Simulation ▪ Decision-Making ▪ Unlocking efficiency ▪ Predicting outcomes
Outcomes	▪ Well defined Business Problem and Opportunities	▪ Well defined projections for future impact	▪ Proactive business decisions and futuristic actions
Fundamental Principles	▪ Retrospective and focused on information and insights.		▪ Prospective, proactive and focused on decision-making.

Table 1: Business Analytics.

Close analysis of Table 1 indicates that core to the concept of data analytics is the creation, generation and adaptation of knowledge and intelligence to support crucial business decisions.

Descriptive Analytics

Descriptive analytics (and analytics of diagnosis) are sometimes referred to as Business Intelligence (BI), and the other two (Predictive and Prescriptive) collectively called Advanced Analytics. Since the beginning of the century, BI has been one of the most common technological developments for information systems designed to help managerial decision-making (Friedman, 2006). BI is defined by analytics as the degree of entry into the analytics world, setting the stage and paving the way for more advanced decision analysis. They produce information about the current state of the organisation and a well-defined business problem or opportunities to be explored. They are an entry level to the realm of analytics in the business world and decision-making process (Bihani & Patil, 2014).

Predictive Analytics

Organizations that have successfully matured in descriptive analytics step into Predictive analytics where the focus is beyond description of what happened to answering the question, "what will happen in the future-near and distant?" Prediction is basically the process of making intelligent/scientific forecasts of the future values of certain variables, such as market demands, consumer behavioural shifts, interest rates, changes in stock prices, etc. (Delen & Ram, 2018). If a categorical variable is what is being expected, the act of prediction is called grouping (or simply called classification), otherwise, if the expected variable is numerical, then it is called regression. If the predicted variable is time-dependent, then the prediction process is often called time-series forecasting (Joseph & Johnson, 2013).

Prescriptive Analytics

The highest layer of the ladder of analytics is prescriptive analytics. It is where action courses are calculated using advanced statistical models, the best option among several, typically created/identified by predictive and/or descriptive analytics. Therefore, this type of analytics attempts to address the question of "What should be done and how should it be done?" in a way. At this level, decision modelling approaches used focus on optimization, simulation, and heuristics. While prescriptive analytics is at the top of the ladder of analytics, the strategies behind it are not new. During and right after World War II in the 1940s, most of the optimization and simulation models that constituted prescriptive analytics were created because there was a desperate need to do the utmost with scarce resources.

Insights Exploitation

Insights that provide visualisations from big qualitative data help business leaders and managers to understand trends, events and behaviours of their customers and product users. Being a product of both BI and AA, at this stage managers need to be able to understand what the data indicates so as to act proactively. Most of this data is available in reports but also on social media as a main point of contact during the COVID-19 era which discourages normative forms of contact.

COSTA QDA Technique

COSTA QDA technique offers a flexible yet rigorous approach to analysis of large qualitative data. The technique is now accessible to teams of researchers across different geographic locations through a cloud-based application that enhances multiple collaboration activities. Built within the C.O.S.T.A. Research Model, (located on Stage 4 - Tact) (Costa: a, 2020), this is an analytic technique that provides a robust and replicable approach to support and legitimize researcher findings and conclusions. It is easy to learn and saves time. Enabled by the online software, business leaders are able to generate visualisations and insights with clarity on precision of accounts and the magnitude of prevailing aspects regarding the phenomena being investigated. The COSTA QDA online software is a user-friendly intuitive application that further enables coherent and structured code creation of qualitative data while at the same time providing a rapid and effective data management and analytic transparency (Machado & Vieira, 2020: Pope, Brandao, Rosario & Costa, 2020; Costa, Breda, Pinho, Bakas & Durão, 2015).

Though this technique, organisations are able to obtain data analytics that can help enterprises make greater use of big data to enhance customer loyalty, control supply chain risk, produce competitive intelligence, offer real-time market analysis to help make important decisions, and maximize pricing if used correctly (Wang & Alexander, 2015; Narayanan, 2014). A study by Xia and Gong (2014) revealed that DDDM through analytics benefited companies with:

- Improved business decision-making processes (78%).
- Faster reporting (81%).
- Improved customer service (56%).
- Increased company revenue (49%).

Another study by Ram, Zhang and Koronios (2016) indicated that DDDM may help organizations

"…increase 60% of operating margins by obtaining market share over its rivals and exploiting the detailed consumer data".

To obtain great results from DDDM, leaders and managers need to avoid the state of being indeterminate and equivocal. Most of information brought by big qual comes from a variety of sources, data scientists need to be consistent of in methods and theories underpinning their findings so as to minimise 'understanding" gaps as postulated by (Kowalczyk & Buxmann, 2014).

Conclusion

As indicated in the introduction of this article, our proposed model is adapted to the work of Jia, et al. (2015), and integrates the COSTA QDA Technique (Costa, 2020) as a method of analysis, using a cloud-based application (Costa, et al., 2015) software.

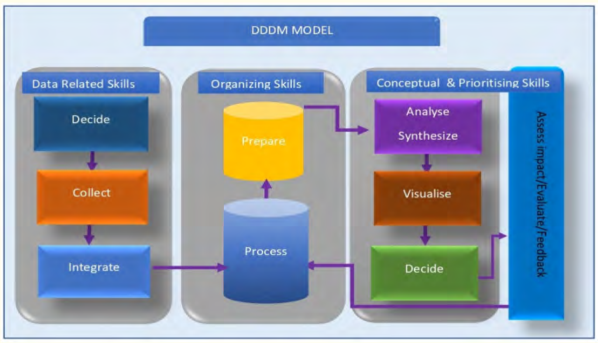

Figure 3: DDDM Model for Business Leaders.

The leader or manager who is dealing with an organisational problem must decide what information is required to solve the issue at hand. The ability to decide requires more than cognitive skills but also essential technical skills related to data are crucial at this stage, e.g. data governance skills such as measurement, storage, regulatory framework etc. At this stage, *decision* could mean collection of new information completely, or working on existing information. It may even be required that existing information is integrated with new information (Mandinach, Honey & Light, 2006).

Second stage of capabilities required focus on the process and preparation requirements of raw data. This stage further involves data transformation so as to attach meaning to it. Attaching meaning to transformed data will point to the information emanating from data itself.

Third capability skills involve rigorous analytic and interpretive skills to make sense of transformed data into information and then into knowledge. Ability to prioritise as a leader is deemed pivotal so as to act upon transformed data (Jia, et al., 2015; Mandinach, et al., 2006). It is at this level that the full data governance definition of the organisation's ability to provide targeted audiences with credible, real-time information with high levels of accuracy, security, confidentiality and connectivity. Furthermore, the organisation demonstrates its ability to package information into knowledge that responds to the changing needs of the business post COVID-19 outbreak (Mithas, Ramasubbu & Sambamurthy, 2011).

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