The impact of big data analytics on malaria prediction in humanitarian organizations in Harare, Zimbabwe

By

Robson Mutuva

(C18135843G)

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Supervisor

Mr Engineer N. Thusabantu

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DECLARATION

I Robson Mutuva, declare that this MSc study is my own effort and is a true reflection of research executed by me. This research in full or part thereof has not been submitted for examination for any degree at any other university/institution.

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Robson Mutuva

Name of Student

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DEDICATION

I dedicate this research to my wife Monica Chimanzi and my daughter Kunaishe Mutuva who helped me quite lot in order to come up with this well researched dissertation. You have all inspired me in so many ways that I cannot explain. Thank you for all your support and having confidence in me.

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ABSTRACT

This research, the impact of big data analytics on malaria prediction in humanitarian organizations in Harare, Zimbabwe was undertaken because of the contemporary developments in malaria prediction technology globally that is posing challenges to malaria prediction practices in humanitarian organizations in Zimbabwe. The study sought to gain an understanding of the application of data science by humanitarian organizations in Zimbabwe, establish the impact of data science on malaria prediction in humanitarian organizations in Zimbabwe, identify factors which influence the use of data science on malaria prediction by humanitarian organizations and establish the improvements on malaria prediction arising from adoption of data science by humanitarian organizations in Zimbabwe. A mixed research strategy was adopted for this study. Questionnaires were circulated to 292 employees at humanitarian organizations through a technique of convenience sampling. Based on the analysis of responses through these questionnaires, it emerged that humanitarian organizations in Zimbabwe associate the meaning of data science with the processes of data assessment and analysis that enable us to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups of organizations, and or entire industries; humanitarian organizations in Zimbabwe do not deliberately adopt data science to improve malaria prediction; lack of skills and expertise influence the use of data science on malaria prediction by humanitarian organizations and that organizations should invest in malaria prediction technologies such as such as statistical sampling and malaria prediction approaches. Humanitarian organizations in Zimbabwe can make use of this study to enhance and fully embrace data science in malaria prediction to malaria prediction time, efficiency and reliability thus contributing to their profitability and overall success of their work. This will ultimately give value to Zimbabwe's humanitarian sector considering the data science in malaria prediction is the direction in which the world is going. It will also provide insights into how data science can be incorporated in their malaria prediction practices. Insights given show that for data science to be effective in humanitarian organizations there is need to adopt a strategic approach to data science on malaria prediction. This is possible when humanitarian organizations create separate data science departments that handle strategic data science plans.

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LIST OF ABBREVIATIONS

IC50: Inhibitory Concentration

STEM: Spatio Temporal Epidemiological Modeller

UM: Uncomplicated Malaria

nMI: non-Malaria Infections

RTDs: Rapid Diagnostic Tests

ML: Machine Learning

WHO: World Health Organisation

DHIS2: District Health Information System

TAM: Technology Acceptance Model

CEO: Chief Executive Officer

MoHCC: Ministry of Health and Child

MoICT: Ministry of Information Communication and Technology

CHAPTER 1
INTRODUCTION

1.0 Introduction

Ever since the beginning of the 21st century the data obtained from public surveillance has amplified due to technological innovation and the use of data systems. According to (Moolman C, Sluis RV, Beteck RM, Legoabe & LJ, 2020) transcription profiles of experimentally tested isolates, machine learning models have been developed to predict the IC50 of malaria parasites. The half greatest inhibitory concentration (IC50) is also known as the drug concentration at which 50% of parasites die. This research is on the impact of big data analytics on malaria prediction in humanitarian organizations in Harare, Zimbabwe. This chapter covers the background to the study, statement of the problem, research objectives, research questions, hypothesis of the study, assumptions of the study, significance of the study, limitations of the study, delimitations of the study, definition of crucial terms and structure of the study.

1.1 Background of the study

Many organizations nowadays are teaming up with researchers to use big data to predict the outbreak of various diseases such as malaria and fever. IBM (2021) defined data analytics as the usage of advanced analytic practices against very large, varied big data sets that embrace structured, semi-structured and unstructured data, from diverse sources, and in dissimilar sizes from terabytes to zettabytes. Big data analytics can be viewed as a complex process of exploratory big data to understand more information such as correlations, hidden patterns, trends and preferences that can help organizations to make well-versed business decisions. Organizations can embrace big data analytics to make data-driven decisions that can help them monitor their key performance indicators results.

Big data analytics benefits may be seen in different ways, and this include new revenue opportunities, customer personalization and improved operational efficiency. According to Kaufman (2021) in the United States of America, IBM Company teamed up with Harvard University, Johns Hopkins University and the University of California researchers to use big data and analytics to forecast the outbreak of deadly conditions, including dengue fever and malaria. The main objective of the research was to know more about the transmission of illnesses in real-time so that public health resources be properly channelled and deployed. The researchers use big data sets to see the effects of rainfall variations, temperature, and even ground acidity on the populations of wildlife that carry the diseases.

According to Kaufman (2021) companies are merging information with other data sources such as airport and highway traffic to further understand various outbreaks. Moreover, IBM Company in the United States of America has developed a Spatiotemporal Epidemiological Modeler (STEM) open-source modelling program which allows any data to be quickly linked to associated illness data. Research has shown considerable evidence of mosquito propagation in indulgent dengue, which is noticeable in areas like Texas and Florida.

The disease was formerly considered to be found in the tropics or impoverished nations after being tested worldwide. These diseases have spread to more than 100 countries, and malaria is still accountable for a million deaths a year (Kaufman, 2021). Electronic health records have been adopted across the United States of America, making it easier to evaluate data in real-time. Data can be processed and analyzed fast on the cloud or in data centers connected to the internet. Scientists used STEM to develop realistic and available models of these infectious illnesses, including demographic analysis, diseases algorithms.

In the United Kingdom, Morang’a et al., (2020) conducted a study on machine learning techniques in classifying malaria data based on haematological parameters. They noted that Malaria is a major global health problem which gives countries headaches. According to Morang’a et al., (2020) more than 3.2 billion people in 100 countries are at risk of the disease.

Malaria was then differentiated from other diseases, such as uncomplicated malaria (UM) from non-malaria infections (nMI), which continues to be a challenge. Morang'a et al., (2020) have shown that Pfhrp2/3 removals and lowered sensitivities of low-slung parasitemia threaten the effectiveness of rapid diagnostic tests (RTDs).

A hematologic indices examination was implemented to identify potential instances of malaria, such as in travellers from endemic areas, for further diagnosis as a new request for precision medicine. Morang'a et al., (2020) aimed to evaluate machine learning (ML) approaches that can precisely categorize uncomplicated malaria, non-malaria infections and severe malaria by means of haematological parameters. The research provides proof of concept methods that categories uncomplicated malaria and severe malaria from non-malaria infections, proving that the machine learning approach is a viable tool to use in clinical decision support. According to Morang'a et al., (2020) machine learning and big data analytics can be fused into clinical decision-support algorithms for the diagnosis of acute febrile illness and monitoring response to acute severe malaria treatment particularly in endemic settings.

In Sub-Saharan Africa resistance in malaria is a growing concern (Ford & Janiels, 2021). According to Ford & Janiels (2021) malaria has left organizations and countries with various options of developing computational models that address crucial problems in advancing and predicting malaria. The objective of the research by Ford & Janiels (2021) was to correctly estimate Plasmodium falciparum isolates' artemisinin drug resistance levels, assessed by IC50. They also intended to estimate the malaria parasite clearance rate based on vitro transcriptional patterns. Ford & Janiels (2021) observed that malaria is a serious disease caused by the genus Plasmodium parasites transmitted in the genus by Anopheles mosquitoes. The World Health Organization (2018) reports that there were 219 million cases of malaria in 2017 across 87 countries.

In Zimbabwe, the country has made considerable development in predicting malaria occurrence compared to levels recorded a period ago (WHO, 2019). Nevertheless, in more recent years, the annual sum of described malaria cases has wavered between about 250,000 and 500,000 cases, with no continual downward trend (Global health, 2020). Figure 1.1 below shows cases which were recorded.

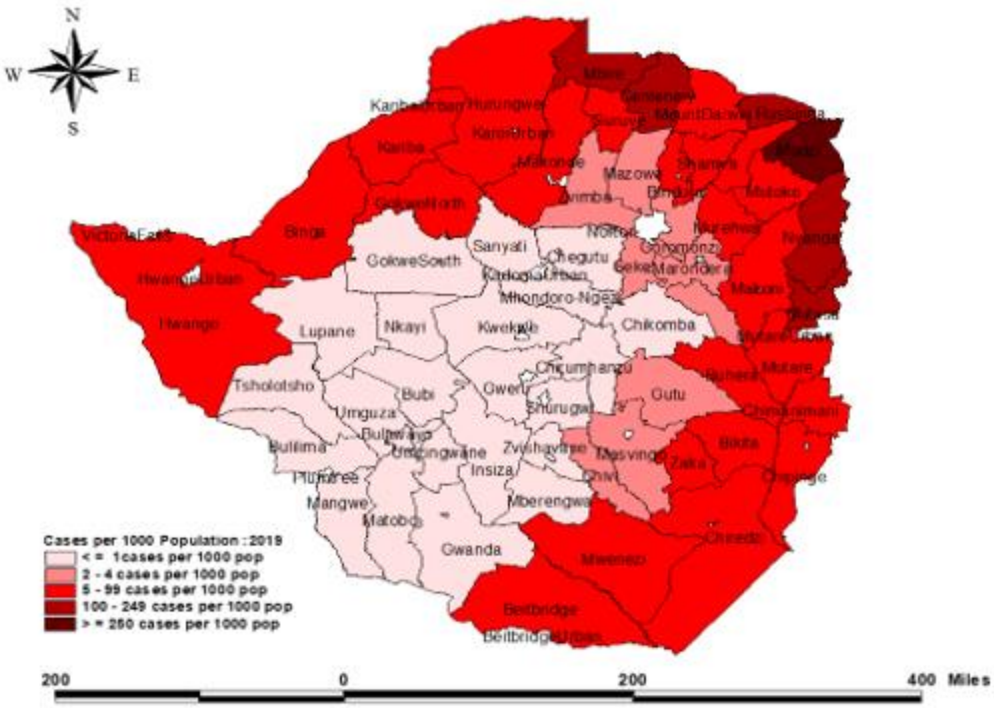

Figure 1.1: Cases recorded in Zimbabwe (Source: https://www.cdc.gov/globalhealth/countries/zimbabwe/annual-report/pmi.html)

In 2019, DHIS2 data shows about 310,000 malaria cases, which equates to a rate of 22 per 1000 populace, this signified a 19% rise in the number of cases recorded in 2018 (about 260,000). Malaria fatalities have also increased from 236 in 2018 to 266 in 2019. This has left humanitarian organizations in Zimbabwe more worried. The main objectives of humanitarian organizations are to save lives, reduce suffering, and maintain human dignity during and after the human-induced crisis and natural catastrophes to strengthen preparedness for the occurrence of such situations.

In Zimbabwe organizations such as Catholic Relief Services, Adventist Development and Relief, Mecy Corps, Zimbabwe Redcross Society, Cordaid and World Vision are worried whenever there is a threat of infectious disease. There has been a need to adopt big data analytics in dealing with infectious diseases where data of medical records of individuals can be collected using the healthcare system's channels which can also be used for insights (Garattini et al, 2019).

Big data allows more to be gained from the various sources of data through integration of information giving better results and better decision making (Wu et al, 2020). The use of big data in health care involves its implementation at national level.

This means there is a lot of data sharing that will take place and the need for privacy for patient's data is also very important. Humanitarian organizations have not been adopting big data analytics well, over the years' humanitarian organizations in Zimbabwe have been encountering challenges concerning malaria prediction (Mambondiani, 2018). Jenkins (2019) denotes that the approaches used by humanitarian organizations to adopt and implement big data analytics in malaria prediction are poor, in that many organizations do not have any clear knowledge about the strategies that can be used to enhance big data analytics to improve malaria prediction (Cao, Chychyla & Stewart, 2015).

Although big data analytics in malaria prediction has become important in the world of humanitarian business, very little research has been done to support the development of big data analytics in humanitarian organizations in developing countries (Ruhnke & Schmidt, 2017). It is also reported that humanitarian organizations in developing countries (including Zimbabwe) engage in some form of big data analytics although their activities are not officially documented in either the print or the electronic media (Ruhnke & Schmidt, 2017). It is against this background that this research wishes to gain an in-depth insight into the impact of big data analytics on malaria prediction in humanitarian organizations in Harare, Zimbabwe.

1.2 Statement of the problem

The relationship between big data analytics and malaria prediction has been extensively researched in a variety of fields. This study has been examined by many researchers (Bender, 2017; Nasser & Tariq, 2015; Manson, McCartney & Sherer, 2017). Despite the plethora of studies on big data analytics in the last few decades, there is no widely accepted causal relationship between big data analytics and malaria prediction.

The empirical evidence on the impact of big data analytics on malaria prediction in humanitarian organizations has produced inconclusive and contradictory findings. Because of these contradictory findings, the question of whether big data analytics improves or worsens malaria prediction warrants further investigation. This study aimed to fill this gap by investigating the situation in Zimbabwean humanitarian organizations with respect to the impact of big data analytics on malaria prediction.

1.3 Research objectives

The broad objective of this research is to analyze the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe. The specific objectives are:

- To gain an understanding of the application of big data analytics by humanitarian organizations in Zimbabwe.
- To establish the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe.
- To identify factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe.
- To establish the improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe.

1.4 Research questions

- What is the meaning attached to big data analytics by humanitarian organizations in Zimbabwe?
- What is the impact of big data analytics on malaria prediction efficiency in humanitarian organizations in Zimbabwe?
- Which factors influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe?
- Are there any improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe?

1.5 Research hypothesis

The following are the study's hypotheses.
H1: The use of big data analytics has a positive effect on malaria prediction in humanitarian organizations
H2: Organization size has a positive effect on the use of big data analytics
H3: Nature of assets has a negative effect on the use of big data analytics

1.6 Significance of the Study

Control of malaria is essential as it is one of the main causes of mortality especially during mosquito breeding seasons like summer. The study will add empirical literature to the knowledge on application of data analytics insights in health care. It will also assist policy makers on how to respond timeously to outbreaks. The study is important to different stakeholders for the purpose of improving empirical literature and assisting in decision making to some. It will be valuable in the following manner.

1.6.1 To the researcher or student

The research would help the student to advance on communication skills, critical thinking and be analytical in the academic field. Also, the study would help the student to bridge the gaps of the literature which was reviewed by previous scholars.

1.6.2 To the University

Faculty mentors, students, lecturers can benefit from the study because they can use the research for academic purposes and the literature help them for further research. Also, it is hoped that this study provided collected data to future academics considering the fact that it covers an extensive period and there are few studies which have been done on the area.

1.6.3 To the field of Health

The study would enlighten the role of data insights in improving decision making on control of malaria. The study will provide a framework on how the health sector can benefit from implementation of data analytics and big data in analysis of trends for historical data and improve on preparedness to deal with disease control. The study will give policy recommendations of control of malaria from study findings.

1.6.4 To policy makers

The study would help the responsible authority on policy formulation. The study envisages coming up viable intervention strategies in order to develop a vibrant capital market that satisfies the nation's goal of being a developed economy by 2030. The study will also come up with variables that can be used for model building. Investors and investment practitioners might use the results to determine the risk and return properties associated with investing on the Zimbabwe stock exchange.

1.7 Research assumptions

This research on the impact of big data analytics on malaria prediction in humanitarian organizations in Harare was guided by the following assumptions:

- Employees from humanitarian organizations attach various meanings to the concept of big data analytics.
- Given that the study used a mixed research approach, the results of this study could be generalized to other populations in Zimbabwe.
- The respondents provide accurate and unbiased information collected by the researcher to sum up valid and reliable information.
- The researcher assumed that the information provided by the informants is correct and up to date.

1.8 Study delimitation

The researcher was restricted to humanitarian organizations such as Catholic Relief Services, Adventist Development and Relief, Mecy Corps, Zimbabwe Redcross Society, Cordaid and World Vision in Zimbabwe. The study confined itself to the period 2017 to date because this assisted in evaluating the trend of malaria prediction, opinions that have been given over the stated period and also this was the period where humanitarian organizations started adopting big data analytics. More so, the choice of this period was to assist in the use of recent data analytics in organization results of prior studies.

1.9 Study limitations

This section presents limitations of the study. These limitations were grouped into methodological, financial and theoretical limitations. Due to the sensitive nature of the topic, some respondents felt obliged to divulge information due to fear of organization retribution. The researcher assured respondents of privacy of interviews, their responses were going to be regarded as classified information, and the researcher elaborated to the respondents that their responses were going to be used for academic purposes only. Lack of adequate knowledge by respondents to respond fully to questions affected this research study. Meanwhile the researcher explained the questions to respondents. There was lack of proper finance; therefore, researcher had little or no data bundles to conclude the research, because the rates by the network operators had been increased. The researcher also decided to plan his time well so as to complete the research at the required time period. Then the researcher sacrificed his time to keep the research as the priority and finally he went well with the deadline, and he finally met the deadline. However, the researcher asked for financial assistance from his friends and workmates.

1.10 Definition of key terms

This section presents definition of terms which has been used in relation to this research study

- ***Big data***: In this study, big data refers to large amounts of unstructured data generated by people, transactions, and machines. The four Vs of Big Data are commonly used to describe it: volume, velocity, variety, and veracity. (Kessel, 2017).

- ***Volume***: The term volume refers to the amount of data generated. The rate at which data is created and analyzed is referred to as velocity. Because new data is generated so quickly, information becomes obsolete more quickly. (Coyne, et al., 2017).

- ***Big data analytics:*** Big data analytics is defined in this research study as the process of inspecting, cleaning, transforming, and modelling big data in order to discover and communicate useful information and patterns, suggest conclusions, and support decision making (Alles, 2015). IBM (2021) defined data analytics as the application of advanced analytic practices to very large, diverse big data sets that include structured, semi-structured, and unstructured data.

- IC50: In this study IC50 is also identified as the half greatest inhibitory concentration which is a drug concentration at which 50 percent of parasites die.

1.11 Structure of the study

Chapter 1 was composed of the background of the study, statement of the problem, research objectives, research questions, and assumptions of the study, significance of the study, limitations of the study and definitions of key terms, scope of the study and structure of the study.

Chapter 2 presented the literature review of the study guided by objectives of the study such as to gain an understanding of big data analytics by humanitarian organizations in Zimbabwe, to have an insight into the impact of big data analytics on malaria prediction efficiency in humanitarian organizations in Zimbabwe, to identify factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe and to establish the improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe. Chapter 2 will also present the theoretical framework of the study.

Chapter 3 focused on presenting the methodology of the study. The research design was introduced in this chapter. More precisely, the processes of both data collection and its refinement stand out clearly, as different phases of the research were described. Chapter 3 of this study concentrated much on main phases of the research study. The research philosophy, the research strategy, research design, targeted population, sample size, sampling method, research instrument, data collection procedure, data analysis and presentation methods, reliability and validity, ethical considerations were laid out.

Chapter 4 presented and analysed data collected in line with this research study on the impact of big data analytics on malaria prediction in humanitarian organizations in Harare. Chapter 4 presented and analysed the data collected.

Lastly, chapter 5 of this dissertation presented the conclusions and recommendations of the research study.

1.12 Chapter summary

This research is on the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe. This chapter discussed the background of the study, statement of the problem, research objectives, and research questions, scope of the study, significance of the study and limitations of the study. The following chapter 2 will present the literature review of the study which will be guided by research objectives of the study.

CHAPTER 2
LITERATURE REVIEW

2.0 Introduction

This chapter presents literature related to this study guided by objectives of the study. The objectives are to gain an understanding of big data analytics by humanitarian organizations in Zimbabwe, to have an understanding of the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe, to identify factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe and to establish the improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe. Chapter 2 also presents the theoretical framework of the study.

2.1 Data analytics

According to Cao *et al.* (2015) big data analytics can be defined "*as the process of inspecting, cleaning, transforming and modelling large and unstructured data produced by people, transactions, and machines to discover and communicate useful information and patterns, suggesting conclusions, and support decision making*". It is possible to identify patterns and anomalies in large and unstructured data sets using computerized tools, which can aid in the discovery of hidden information. Big data analytics is already being used in many business areas, such as malaria prediction by humanitarian organizations. Firms can determine the best course of action to reduce costs or increase revenues for a specific company by analysing trends and other patterns.

However, the use of big data analytics in malaria prediction is still uncommon. Big data analytics adds value in malaria prediction by trying to improve the efficiency and effectiveness of malaria reduction rather than providing innovative and competitive insights (Earley, 2015). Therefore, big data analytics has to be applied differently in the malaria prediction practice.

According to Byrnes et al. (2016), big data analytics in malaria prediction is the science and art of discovering and analysing patterns, identifying anomalies, and extracting other useful information from data underlying or related to the subject matter of a malaria prediction through analysis, modelling, and visualization for the purpose of planning or performing the malaria prediction.

Moreover, Byrnes' et al. (2016) argues that there are two types of big data analytics: exploratory and confirmatory. Exploratory big data analytics is inductive and is typically used during the planning stage of malaria prediction. It is used to gain a better understanding of the company, identify, and assess risks, and design additional malaria prediction procedures. Confirmatory big data analytics is deductive in nature and is used in the final two phases. To provide assurance, the malaria predictioner must carry out substantive procedures to ensure that the items in the plans are correct. According to Patil (2012) there is no widely accepted definition of what is big data analytics is, Patil (2012), Patil (2011), and Loukides (2012) defined a data scientist as someone who asks unique, interesting questions of data based on formal or informal theory, to generate rigorous and useful insights. It is likely to be a person with multi-disciplinary training in computer science, business, economics, statistics, and domain knowledge relevant to the question at hand.

The field's potential is enormous, with just a few well-trained data scientists armed with big data having the ability to transform organizations and societies. In the narrower domain of business life, the role of the data scientist is to generate applicable business intelligence (Culotta, 2010). According to Kaufman (2021) companies are merging information with other data such as airport and highway traffic data to further understand various outbreaks. Furthermore, the IBM Company in the United States of America developed an open-source modeling application known as the Spatio Temporal Epidemiological Modeler (STEM) that allows any type of data to be quickly combined and linked with disease data. The studies were significant in indulgent dengue fever, which is striking areas such as Texas and Florida, as well as recognitions to the spread of the disease.

Businesses can also foster leadership development by tracking performance, success rate, and other important metrics with data analytics. Industries can use workforce analytics to determine what works best for their employees. The most important aspect of business is predictive analytics (Loukides, 2012). Companies' ability to deal with various types of data has grown as a result of the introduction of advanced predictive tools and technologies. Predictive analytics is the statistical analysis of data that uses several machine learning algorithms to predict future outcomes based on historical data. There are several predictive analytics tools like SAS, IBM SPSS and SAP HANA (Dean, & Sanjay, 2018).

There are various applications of predictive analytics in businesses such as patient segmentation, risk assessment, sales forecasting, and market analysis (Dean, & Sanjay, 2018). Businesses gain an advantage over competitors by using predictive analytics to predict future events and take appropriate measures in respect to it. Predictive analytics has different implementations depending on the industry. Regardless, it plays a similar role in forecasting future events. Figure 2.1 below shows the predictive analytics process.

Figure 2.1: Predictive analytics process **(**Source: Cullota (2010)

Advances in big data analytics can be applied to perform more effective malaria predictions and provide new forms of malaria prediction evidence (Cullota,2010). Many organizations nowadays are teaming up with researchers in adopting the use of big data to forecast the spread of diseases such as fever and malaria. IBM (2021) defined data analytics as the usage of advanced analytic practices against very large, varied big data sets that embrace structured, semi-structured and unstructured data, from diverse sources, and in dissimilar sizes from terabytes to zettabytes.

Big data analytics is the complex process of exploring big data to discover information such as hidden patterns, correlations, trends, and preferences that can assist organizations in making well-informed business decisions. Organizations can use big data analytics systems and software to make data-driven decisions that will help them achieve better business outcomes. Big data analytics may provide advantages such as more effective marketing, new revenue opportunities, patient personalization, and increased operational efficiency. According to Ford & Janiels (2021) malaria has left organizations and countries with various options of developing computational models that address crucial problems in advancing and predicting malaria.

2.2 The four malaria prediction phases

In general malaria prediction is performed in four stages (Hayes, Gortemaker & Wallage, 2017). The first one is planning and risk identification (Ramlukan, 2015). During this stage, the malaria predictioner must learn about the company, identify the risk, and decide what steps must be taken to provide reasonable assurance. The second step is to develop a strategy and assess the risks (Hayes, Gortemaker & Wallage, 2017). The malaria predictioner must determine the company's strategy and assess the magnitude of the risks at the humanitarian organization. The malaria predictioner performs substantive procedures in the third stage, execution. These are tests to see if the information presented in the organization is accurate and free of material errors. The final stage is known as conclusion and reporting.

According to Hay, Knechel & Wong (2016) big data analytics can be applied in several stages. Especially in the first two stages big data analytics is expected to be beneficial (Cao, et al., 2015). Big data sets contain a large amount of unstructured data. Such information is regarded as sloppy and untrustworthy leading to big data analytics results which are less reliable. Therefore, it is easier to focus on causation instead of correlation (Alles, 2015). Patterns and trends can be identified in the first two stages, which rely on correlation rather than causation. In reference to the terms used by Byrnes et al. (2015) big data analytics applied in the first two stages can be regarded as exploratory data analytics. When data becomes less reliable it becomes more difficult to implement big data analytics in the third and fourth stage (Cao, et al., 2015). Substantive or analytical procedures are data sensitive, so untrustworthy data yields untrustworthy results.

2.3 Technology acceptance model

Since big data analytics is defined as the process of inspecting, cleaning, transforming, and modelling large amounts of data in order to discover and communicate useful information and patterns, as well as to suggest conclusions and support decision making, the technology acceptance model speaks of using new technologies such as computers and systems by firms and this is more relevant to malaria prediction improvement. Chung, Animesh, Han & Pinsonneault (2015) noted that the technology acceptance model is one of the extensions of Fishbein and Azjen's Theory of Reasonable Action. According to Chung, Animesh (2015) the technology acceptance model was introduced by Davis in 1986 to explain and predict users' adoption, acceptance or rejection of new technologies.

Curty & Zhang (2011) noted that the theoretical basis of the technology acceptance model is built on the foundation that when users are presented with a new technology three major factors influence their decision on how and when they will use it. The technology acceptance model consists of six related constructs namely external variables, perceived ease of use, perceived usefulness, attitude towards using, behavioural intention to use and actual use (Ko et al., 2010). Curty (2011) denotes that perceived usefulness is defined as the degree to which a person believes that using a particular system would be free of effort.

According to Pinson (2015) the technology acceptance model talked of perceived ease of use and perceived usefulness to determine an individual’s information system acceptance by determining their attitude toward using and subsequent behavioural intention to use which has an effect on actual use. Chetuparambil (2019) denotes that the technology acceptance model is a perfect model which shows how users accept and use technology. According to Dennison (2019) in the technology acceptance model the main determinants of user’s acceptance of new technology are perceived usefulness and perceived ease of use.

2.4 Agency Theory

Since, big data analytics is the application of software tools which analyses data from and about the patient to gain insights into the patient’s reactions and numbers this theory is relevant in this research study in the sense that humanitarian organizations always target to provide the necessary information to directors and shareholders who wants to correct enhanced malaria prediction information for decision making. Erle and Means (2017) discuss issues surrounding the separation between ownership and control in large firms and became widely accepted when Jensen and Meckling (2007) formulated the agency problem in the governance of firms.

The theory is defined as the relationship between the shareholders, who are the principals, and the agents, who are the CEOs and managers. According to the agency theory, shareholder wealth maximization may not work due to moral hazard, that is the agents, who are managers, to whom shareholders have entrusted the reactions of their firm, will act opportunistically to achieve their own interests rather than the principals', who are shareholders, resulting in agency conflict. According to Abdoullah and Valentine (2016) “*the agency theory holds that most businesses operate under conditions of incomplete information and uncertainty. Such conditions expose businesses to two agency problems, namely adverse selection and moral hazard. Adverse selection occurs when a principal cannot ascertain whether an agent accurately represents his or her ability to do the work for which he or she is paid. On the other hand, moral hazard is a condition under which a principal cannot be sure if an agent has put forth maximal effort.*”

2.5 Attribution Theory

According to this theory, the expected level of future performance in a specific task is primarily determined by the specific causes to which prior success or failure in the same task is attributed. Jaffar et al (2017) explains that attribution theory is used to suggest the effect of malaria predictioner's ability to assess the risk.

2.6 The information theory

As noted in the 'agency theory' by Eisenhardt (2010) reporting is central to monitoring purposes. Donaldson and Davis (2013) noted that an alternative or complement to the monitoring principle is the information principle, focusing on the provision of information to enable users to make economic decisions. Donaldson and Davis (2013) went on to say that investors require malaria prediction information on behalf of their decision-making and assessing of risks. Malaria prediction is valued by investors as a means of improving information. Malaria prediction is also valued as a way to improve the data used in internal decision-making. More accurate data will improve internal decision-making.

2.7 Gaining an understanding of big data analytics by humanitarian firms

It is important to investigate whether humanitarian organizations understand big data analytics and if big data analytics is effective and efficient or whether big data analytics in malaria prediction needs improvement (Nasser & Tariq, 2015). Humanitarian organizations are cautious about their data and find possibilities to ensure the challenges are overcome when implementing big data analytics (Coyne, Coyne & Walker, 2017). Although many humanitarian organizations believe big data analytics is the future because the opportunities weigh out the threats, it is important to investigate where big data analytics in the malaria prediction currently stands (Coyne, Coyne & Walker, 2017).

It is possible to identify patterns and anomalies in large and unstructured data sets using computerized tools, which can aid in the discovery of hidden information. Big data analytics is already widely used in many business and humanitarian organizations. Firms can determine the best course of action to solve various challenges by analysing consumer trends and other patterns. However, in malaria prediction the use of big data analytics is not very common yet. A problem for the use of big data analytics in malaria predictions is that malaria predictioner's are no longer allowed to do malaria prediction for a firm and give advice about the business activities of a company as noted by European laws. (PWC, 2015).

According to Byrnes et al. (2015), technological advances in malaria prediction can be used to either increase efficiency or provide greater assurance. However, most of the time, technology is used solely to improve efficiency. To put it another way, the same level of assurance is provided at a lower cost. This development makes it likely that big data analytics in malaria prediction will mostly be applied to increase the efficiency and quality of the malaria prediction (Adrian, 2018).

2.8 The impact of big data analytics on malaria prediction in humanitarian organizations

According to Kessel (2017) the true effect of big data analytics on malaria prediction in humanitarian organizations has not been looked upon because it is probably because researchers have no access to data which can help tackle the question. External stakeholders are unable to determine whether a public humanitarian organization employs big data analytics during the malaria prediction process. There exist no rules or regulations which state that anyone who uses big data analytics in humanitarian organizations has to provide such information (Alles, 2015). The only way to find out if big data analytics is being used is to obtain data from public humanitarian organizations themselves. Because big data analytics is relatively new and anyone who uses big data analytics in humanitarian organizations do not fully know the effects of data analytics, they are not keen on providing such data to the public (Manson, McCartney & Sherer, 2017).

Anyone who use big data analytics in humanitarian organization have been under a lot of pressure lately and disclosing such data could lead to more criticism of the profession (Crawford & Boyd, 2016). Despite the fact that there has been little research into the use of big data analytics in malaria prediction, it is important to understand how big data analytics affects malaria prediction. Big data analytics is a growing market (Gershkoff, 2015). Other professions, like consulting, have already widely adopted the use of big data analytics for their current daily business (Cao, et al., 2015). Hay, Knechel & Wong (2016) and Liddy (2015) describes how big data analytics can improve insights and risk assessment. Byrnes, Criste, Stewart & Vasarhelyi (2016) expect malaria predictions to become more efficient with the help of data analytics. Earley (2015) believes malaria predictioner benefit by allowing more transactions to be tested.

This explains why a couple of years ago public humanitarian organizations started to invest and implement big data analytics in their malaria predictions (NBA, 2015). Furthermore, stakeholders of public humanitarian organizations will require their information to be malaria predictioned on a larger scale due to the large increase in data generation, which is not possible with the current way of malaria prediction (Alles, 2015).As big data analytics in malaria prediction will become more prevalent in the coming years, it is critical to have reliable answers on the effects of big data analytics in malaria prediction rather than theories based on expectations.

The planning of the big data analytics team is also required to determine the hours spent on malaria prediction assignments by the big data analytics team members (Gershkoff, 2015). By measuring the number of hours of the big data analytics team this research study determines whether big data analytics is applied during the malaria prediction or not. According to Bender (2017) big data analytics does not affect efficiency during the malaria prediction. Bender (2017) conducted a study on the effect of big data analytics on malaria prediction and noted that big data analytics is the application of certain software tools which analyses data from and about the patient to gain insights into the patient’s reactions and numbers.

According to Bender (2017) dependent variables such as malaria prediction hours, malaria prediction costs and billed costs do not change when big data analytics is implemented. There are several reasons why malaria prediction is unaffected by data analytics. For starters, big data analytics takes a long time to implement. In order to apply big data analytics, the malaria predictioner must constantly consult with the patient and the big data analytics team. Additionally, the big data analytics team develops the big data analytics tool which is used during the malaria prediction (Manson, McCartney & Sherer, 2017). As the big data analytics team has no experience with malaria prediction, the tool may not be useful to someone who uses big data analytics to meet the needs of humanitarian organizations. Moreover, someone who uses big data analytics in humanitarian organizations have to get used to the new way of malaria predestining.

2.9 Factors which influence the use of big data analytics on malaria prediction by humanitarian organizations

According to Manson, McCartney & Sherer (2017) past experiences show that malaria predictioners consistently fail to advance in the current technological developments. With regard to big data analytics one of the reasons malaria predictioners are lagging behind is because they do not have the required skills to apply big data analytics (Earley, 2015).

According to Ruhnke & Schmidt (2017) anyone who uses big data analytics in humanitarian organizations understands how risks related to the organization can be minimized. When applying data analytics, a different skill set needs to be used (Manson, McCartney & Sherer, 2017). Big data analytics identifies patterns and correlations which have to be analysed by the malaria predictioner (Whitehouse, 2017), this necessitates a different approach to using data to draw conclusions.

Malaria predictioners need to become used and more familiar with this new way of analysing data in order to provide a more efficient and effective malaria prediction (Cao, Chychyla & Stewart, 2015). In addition, there is also a need for big data analytics specialists (Business.com, 2017). Developing big data analytics tools is not a requirement for anyone who uses big data analytics in humanitarian organizations (Earley, 2015).

At this moment with the current increase in data analytics, the new and rising demand for such specialists is growing faster than the amount of people who are schooled to become such specialists (Gershkoff, 2015). This implies that public humanitarian organizations will have difficulty finding staff capable of developing big data analytics tools.

Furthermore, a high demand will almost certainly result in a high price for big data analytics specialists. Besides the fact that big data analytics specialists are scarce, big data analytics specialists are often not familiar with malaria prediction (Alles, 2015). Because they create the tool, it may be difficult for them to create one that can be used effectively and efficiently during malaria prediction.

2.10 The improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations

Big data analytics makes it possible to test 100% of the transactions (Byrnes, et al., 2014). It gives the malaria predictioner the opportunity to detect anomalies which helps malaria predictioners to assess risks and identify trends (Adrian, 2015). This will improve malaria predictions year after year because malaria predictioners will learn which areas to focus on during the malaria prediction. Furthermore, better understanding of the patient's system allows malaria predictioners to forecast estimates or going concern issues more easily.

Non-data evaluation becomes easier with the help of specially developed tools. Such data can provide extra insights in business risks and other areas (Earley, 2015). Table 2.1 below shows that big data analytics can be used to enhance detections. Issues can be detected more easily now that there are more data available and computerized tools that use mathematical principles.

Table 2.0: Types of data and their role in malaria prediction

Type of data	Current practice	Potential future practice
data	Malaria predictioners collect and test a sample of transactions and rely on their judgment in areas that are difficult to test.	Big data analytics tests 100% of the transactions. Anomalies and patterns in the provided data will be identified using big data analytics. This will help with future testing and may reveal disorganizations. In assessing anomalies that are discovered, the malaria predictioner must use his or her discretion.
Non- data	Unless the malaria predictioner has specific knowledge of the patient or industry, this is rarely used during malaria predictions	Big data analytics was developed to run models or predictive analyses to assist malaria predictioners in identifying business risks and areas of focus during planning, assisting in issue detection, and assisting in the evaluation and assessment of ongoing concerns.

(Source: Bender, 2017)

Besides the fact that malaria predictioners can improve their malaria prediction, another reason for the enthusiasm of the public is that anyone who uses big data analytics in humanitarian organizations for big data analytics expects that malaria predictions will become more efficient (Alles, 2015). More insights not only provide the malaria predictioner with a better overview of the patient's position, but they can also assist the malaria predictioner in determining which areas require more or less attention.

Statistical programs can reduce the workload of malaria predictioners by determining whether transactions are abnormal because they do not meet certain standard criteria. If there are any inconsistencies, the malaria predictioner can immediately focus on them. This is more efficient than checking a random sample. This is an important reason for malaria predictioners to improve their data analytics skills. In a competitive market, public humanitarian organizations are active. If malaria predictioners do not invest in data analytics, they might fall behind their competitors who are able to provide better services (Alles, 2015). Public humanitarian organizations that provide malaria forecasts that are less effective and more expensive are unlikely to survive for long.

However, the survival of public humanitarian organizations is not solely dependent on the accuracy of their malaria forecasts. There exists the necessity to invest in big data analytics because big data becomes more important for customers (Earley, 2015). Once big data becomes a necessity for the strategic business of the entity, customers, regulators, and other stakeholders will want malaria predictioners to check whether their big data is indeed correct and reliable (Alles, 2015).
Estimates based on big data information, for example, must be checked and confirmed by the malaria predictioner once these estimations have a material impact on the organization. To provide reasonable assurance, the malaria predictioner should use big data analytics to check whether the information presented by the company is correct. Although malaria predictioners might not be trained for the usage of data analytics, the growing market for big data analytics also leads to an increase in developing user-friendly software (Alles, 2015). It is likely that such software will be a facilitating factor in malaria predictioners' willingness to adopt big data analytics, which can explain why we are seeing an increase in the use of big data analytics in malaria prediction engagement.

2.11 Empirical Evidence

Sijpesteijn (2011) conducted a study on organization users' understanding of the messages in the malaria prediction report. Sijpesteijn (2011) noted that in the public debate on the causes, the accountability, and the solutions concerning the global crisis, the role of the malaria predictioner has been widely discussed and criticized: '*Where were the malaria predictioners*?' Sijpesteijn (2011) noted that the global crisis was not prompted by malaria prediction failure, however the malaria predictioner was at the centre of the meltdown, and failed to fulfil its social responsibility to provide a clear and adequate clarification on the organizations, especially on the uncertainties concerning malaria.

Sijpesteijn (2011) also noted that the value of the malaria prediction report, and the demand for malaria prediction services depend on confidence in the independence and integrity of malaria predictioners. The purpose of this study was to determine the effectiveness of malaria predictioners' communications, or the "value relevance" of the malaria prediction report. The study evaluated the effectiveness of the malaria prediction report in communicating about the malaria prediction process, the responsibilities of the malaria predictioner, and the nature of the assurances provided. The main goal of developing the research was to learn how to complete such a long-term process, with all of its difficulties: coming up with an idea and translating it into a research proposal, developing a theoretical framework, conducting empirical research, analysing the research results, and formulating an answer to the main research question.

Alexeyeva (2017) conducted a study on malaria prediction fees and the joint provision of malaria prediction and non-malaria prediction services. The research examined the factors affecting malaria prediction Alexeyeva (2017) focused on environmental factors. The study examined whether changing economic conditions affect the level of fees paid for malaria prediction services over a six-year period, including pre-crisis, crisis, and post-crisis periods, using data from Swedish listed companies. The findings of the study suggested that malaria predictioners increase their risk premium for malaria prediction during a crisis.

A significant decrease in non-malaria prediction fees, on the other hand, suggests that companies are less willing to invest in consulting services during the crisis and post-crisis periods. The study also looked into the effects of environmental factors on malaria forecasting. The study examined whether the level of effort spent on evaluating fair values is higher for more uncertain fair values using data from institutions in 24 European countries.

The findings also suggested that an increasing level of complexity and risk necessitates a greater level of malaria prediction effort. Furthermore, the findings revealed that the strength of a country's institutional framework is positively related to the effort expended on evaluating high uncertainty fair value estimates. The study's findings suggested that malaria predictioners expend more effort in more regulated countries, possibly due to higher potential litigation costs. According to Kaufman (2021), IBM Company collaborated with researchers from Harvard University, Johns Hopkins University, and the University of California to use big data and analytics to predict the outbreak of deadly diseases such as dengue fever and malaria. The study aimed to gain a better understanding of disease spread in real time in order to better deploy and channel public health resources.

The researchers are using big data analytics to see how changes in rainfall, temperature, and even soil acidity can have a big impact on the populations of wildlife and insects that carry the diseases. According to Kaufman (2021) companies are merging information with other data such as airport and highway traffic to further understand various outbreaks. Moreover, The IBM Company in the United States of America developed the Spatio Temporal Epidemiological Modeler (STEM), an open-source modelling application that allows any type of data to be quickly combined and linked with disease data.

The studies were significant in indulgent dengue fever, which is affecting areas such as Texas and Florida due to the spread of mosquitoes. The disease was previously thought to be limited to the tropics or developing countries, but it is now being detected all over the world. These diseases have spread to more than 100 countries, and malaria is still accountable for a million deaths a year (Kaufman, 2021).

In the United States of America, electronic health records have been implemented across the country, making it easier to assess data in real time. That data can be crunched and analyzed quickly in the cloud or web-connected data centres. Scientists used STEM to build realistic and accessible models of these infectious diseases by using population analytics, disease path algorithms, and powerful computing.

Morang'a et al., (2020) conducted a study in the United Kingdom on machine learning approaches for classifying clinical malaria outcomes based on haematological parameters. They noted that Malaria is a major global health problem which gives countries headaches. According to Morang’a et al., (2020) more than 3.2 billion people in 100 countries are at risk of the disease. They distinguished malaria from other diseases, such as uncomplicated malaria (UM) and non-malaria infections (nMI), which is still a challenge. Morang'a et al., (2020) stated that Pfhrp2/3 deletions and reduced sensitivity at low-slung parasitaemia endanger the success of rapid diagnostic tests (RTDs).

An examination of haematological indices has been implemented to aid in the identification of potential malaria cases for further diagnosis, such as in travellers returning from endemic areas. Morang'a et al., (2020) sought to evaluate machine learning (ML) approaches that can precisely classify uncomplicated malaria, non-malaria infections, and severe malaria using haematological parameters as a new request for precision medicine. Their study provided proof-of-concept methods for distinguishing uncomplicated malaria and severe malaria infections from non-malaria infections, demonstrating that the machine learning approach is a useful tool for clinical decision support. According to Morang’a et al., (2020) machine learning and big data analytics can be fused into clinical decision-support algorithms for the diagnosis of acute febrile illness and monitoring response to acute severe malaria treatment particularly in endemic settings.

In Sub-Sahara Africa resistance in malaria is a growing concern (Ford & Janiels, 2021). According to Ford & Janiels (2021) malaria has left organizations and countries with various options of developing computational models that address crucial problems in advancing and predicting malaria. The goal of Ford and Janiels' (2021) study was to accurately predict artemisinin drug resistance levels in Plasmodium falciparum isolates, as measured by the IC50. They also wanted to predict the parasite clearance rate of malaria parasite isolates using in vitro transcriptional profiles. According to Ford and Janiels (2021), malaria is a severe disease caused by parasites of the genus Plasmodium, which are transmitted by Anopheles mosquitoes of the genus. The World Health Organization (2018) reports that there were 219 million cases of malaria in 2017 across 87 countries.

2.12 Chapter summary

This chapter discussed the literature that was relevant to this study. This chapter presented the study's literature review, which was guided by the study's objectives, such as gaining an understanding of big data analytics by humanitarian organizations in Zimbabwe and understanding the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe, to identify factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe and to establish the improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe. The methodology of the study is presented in the following chapter.

CHAPTER 3
RESEARCH METHODOLOGY

3.0 Introduction

The section on research methodology includes a detailed description of the research process and methods. Each subheading starts with a research technique, followed by a thorough explanation of the technique and rationale for its selection. The researcher went into greater detail about the research strategy, research method, research methodology, data collection techniques, sample selection, research procedure, data analysis style, and ethical considerations in this study. The chapter concludes with a review of research validity and reliability, as well as how these two criteria were met in the current study.

3.1 Research Philosophy

The novel nature of this research required the researcher to adopt the pragmatism research philosophy. Pragmatism is a research philosophy that believes concepts are only relevant if they support action. According to this philosophy, the most important determinant of the research philosophy is the research question (John, 2017). According to the nature of the research question, pragmatics can combine both positivist and interpretivism positions within the scope of a single study. The philosophy can incorporate multiple research approaches and research strategies. In social science research, this is frequently a combination of quantitative and qualitative methods used to assess various aspects of a research problem.

This research philosophy is appropriate for the research because of the following factors: the research included both quantitative and qualitative data. Qualitative data can concentrate on the motivation, views, and motives for big data analytics on malaria prediction. Quantitative data will be collected to determine the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe. Pragmatism provided the researcher with versatility in terms of the type of data and knowledge he or she might use. In contrast to other rigid paradigms, pragmatism advocates that no particular point of view is right, allowing one to exercise control over the data to be used.

3.2 Research Strategy

The researcher employed an inductive approach. This allowed the researcher to make broad generalizations from specific observations. The inductive approach starts with the observations and theories are proposed towards the end of the research process because of observations (John, 2017). Inductive research involves the search for patterns from observation and the development of explanations, theories for those patterns through a series of hypotheses (Raimo, 2019). In inductive studies, no theories or hypotheses would be applied at the start of the research, and the researcher was free to change the direction of the study after it had begun.

This approach assisted the researcher in generating meanings from the data set collected in order to identify patterns and relationships in order to build a theory; however, the inductive approach does not preclude the researcher from using existing theory to formulate the research question to be investigated. Inductive reasoning is based on experience-based learning, and it employs a bottom approach. The researcher used the approach depicted in figure 2.1 below, which shows where the inductive process begins (bottom) and how it progresses to theory formulation and generalizations.

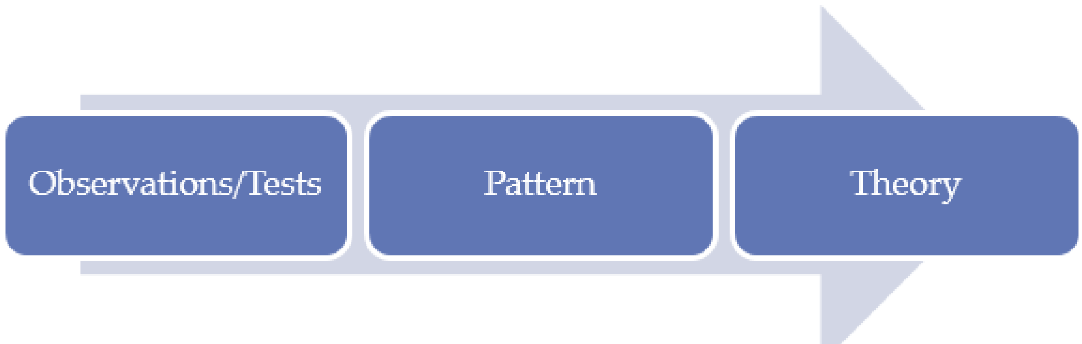

Figure 2.1: inductive approach process (Source: (John, 2017))

3.3 Research Design

The mixed method research design was used by the researcher. This is a technique for gathering, compiling, analysing, and interpreting both qualitative and quantitative data. Data is combined, related, and mixed during the research process. The sequential explanatory design was chosen among the various types of mixed research designs by the researcher. This method entails gathering and analysing quantitative data first, then gathering and analysing qualitative data. The underlying logic to choosing the overall mixed method design is that neither qualitative nor quantitative methods are sufficient in themselves to capture the trends and details of the research area.

When combined, qualitative and quantitative data provide a more complete analysis, and they complement one another. This is consistent with triangulation, which results in more reliable conclusions. The quantitative component of my research focused on putting theories to the test, determining facts, demonstrating, and predicting outcomes. The qualitative component of the study sought to investigate the impact of big data analytics on malaria prediction in humanitarian organizations in Harare, Zimbabwe, in their natural settings. This section focused on process and meaning qualities that cannot be tested or measured experimentally.

3.4 Population

The population under study is defined as an aggregate or totality of all the objects, subjects, or members that meet a set of criteria. This study's population is drawn from humanitarian organizations such as Catholic Relief Services, Adventist Development and Relief, Mecy Corps, Zimbabwe Redcross Society, Cordaid and World Vision in Zimbabwe. The researcher focused on the branches within Harare Central Business District. The targeted population was 1200 respondents.

3.5 Sample size

A sample is typically a representative subset of a target population selected to represent the remainder of the population. It is ideally synonymous with studying the entire population while conveniently scaling down the study elements where this is not possible. (Cresswell, 2016) defined a sample as a smaller set of data that a researcher chooses or selects from a larger population by using a predefined selection method.

The participants in this study were drawn from the staff of humanitarian organizations such as Catholic Relief Services, Adventist Development and Relief, Mecy Corps, Zimbabwe Redcross Society, Cordaid and World Vision in Zimbabwe. Raosoft's online sample size calculator was used in this study. Raosoft Tool is a robust collection of over 15 utilities for database and file management of research survey data collected using Raosoft online survey software (http://www.raosoft.com). The researcher typed the URL http://www.raosoft.com and 1200 as the population size, and the site automatically calculated a sample size of 292 that was used in this study.

3.6 Sampling Methods

The researcher used a non-probability sampling method for this research. Non-probability sampling method represents a group of sampling techniques that help researchers to select units from a population that they are interested in studying (Borg & Gall, 2016). When compared to probability sampling, the researcher chose the sampling method because the procedures for selecting units for inclusion in a sample are much easier, faster, and less expensive.

The researcher used convenience, purposive, and random sampling methods for non-probability sampling. Convenience sampling is simply one in which the units chosen for inclusion in the sample are the most easily accessible. Convenience sampling refers to the practice of recruiting study participants based on their availability. It is by far the most commonly used sampling procedure. This sampling technique was used to select branches of humanitarian organizations such as Catholic Relief Services, Adventist Development and Relief, Mecy Corps, Zimbabwe Redcross Society, Cordaid and World Vision that are near to avoid transport costs. These branches the researcher could easily access them without any problems.

Purposive sampling this is when the researcher chooses the sample based on who they think would be appropriate for the study (Kothari, 2015). This is typically used when there are a limited number of people with expertise in the area being researched. The relevant department will be chosen using purposive sampling. It is useful because it enables the researcher to acquire specific information from the members of the selected departments who have knowledge about specific areas under study and helps to gather large amounts of relevant information. The researcher was able to select departments who have more information. Then employees were randomly selected from the departments. In addition, purposive sampling was used to select clients who can participate.

3.7 Research instruments

The main media of data collection for primary data were questionnaires. Interviews were also conducted to get clarifications on certain areas whenever there was need. The questionnaire was crafted in a manner, which allowed collection of both qualitative and quantitative data. As an overview, the questionnaire had the following sections: the first section was a demographic section that addressed issues to do with age, sex and occupation. The second section provided dual responsibilities that were yes or no answers. The questionnaire also had a Likert scale, which gave the respondent the choice to respond from strongly, agree up to strongly disagree. The last section had a free response and a semi-structured question, providing unlimited response and a chance for the respondents to give their views.

3.8 Data collection procedure

These are the basic steps taken by the researcher in administering instruments and collecting data from respondents. The researcher gave the respondents 292 questionnaires in which they had to fill in their desired responses. The self-administered questionnaires were used by the researcher. The questionnaires were hand-delivered to the respondents and were collected later; this was done as a way of avoiding loss or any inconveniences caused by postage systems. The researcher made regular follow-ups on the respondents, which were selected to try to make sure that all questionnaires were completed. This was done mainly through the use of telephone.

3.9 Data presentation and analysis procedures

Data analysis enabled the researcher to judge and assess outcomes in order to reach a legal, significant, and important decision. The retrieved questionnaires were thoroughly reviewed to ensure consistency in responses. To facilitate easy analysis, the questionnaires were coded so that similar responses were coded as one. To aid analysis, responses from interviewees were also coded.

The data was presented using statistical tools such as a frequency table and percentages. The responses were presented using tables and figures. Some responses, however, were only discussed without the use of tables. The frequency table summarized the data for easy comprehension and comparison. The percentages addressed the data's relative frequencies, and the table and figures displayed a diagrammatic representation of the responses.

3.10 Validity

The results of the empirical data collected were measured for reliability. Validity refers to the extent to which an empirical measure adequately reflects the real meaning of the concept under consideration (Leard, 2021). The questionnaire was tested before it was distributed to the remaining respondents. In the pilot test, the project supervisor reviewed the questionnaire. In order to improve the quality of the questionnaire, the supervisor was asked about clarity of questions in the questionnaire, as was their ambiguity. This exercise provided reliable answers since interviewees should fully understand the questions and correctly respond.

3.11 Reliability

Reliability tests whether a particular method yields the same results if applied repeatedly to the same object each time. However, it does not measure accuracy. The researcher needed to make sure the questionnaire was of a manageable length. The fact that the scales to be used were frequently used scales of prominent researchers with a professional purpose was the strongest indicator of this study's high reliability. Furthermore, the researcher had to use a sufficient sample size to ensure that the results were representative of the entire population (Kotter, 2017).

3.12 Ethical Consideration

The research adhered to all ethical implications of research and ensured that the participants' rights, safety, and well-being were a top priority throughout the study. The following pillars guided the researcher in observing research ethics in light of the ethical boundaries that should be observed.

To begin, there was voluntary and informed consent, which meant that participation in this study was solely based on the participant's consent after all relevant information had been relayed to them. By avoiding identifying respondents' ethnic or cultural backgrounds, the researcher ensured anonymity, confidentiality, and privacy. The study also avoided using their names or disclosing any other sensitive information about a participant. In terms of advocacy and safety, the overall research project was designed in such a way that it did not violate the interviewees' or respondents' rights or safety.

3.13 Summary

This chapter discussed sampling issues, the types of data obtained, and the data collection and analysis procedures used in this study. Also, evaluate the validity and dependability of the instrument used to collect data for the study. The fourth chapter examines data analysis and presentation. The data that is collected from the 292 participants using the questionnaire is analysed and presented in an understandable manner in the next chapter.

CHAPTER 4
DATA PRESENTATION AND ANALYSIS

4.0 Introduction

This research focused on the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe. The data for analysis was collected using qualitative and quantitative analysis methods. Qualitative data is presented in a descriptive manner, and on the other hand, the researcher has used graphs, tables and charts to present quantitative data. The use of graphs, tables and charts was chosen to enable easy interpretation of the data collected. Data collected was analyzed and interpreted as a means to provide answers to the research objectives and questions.

4.1 Response rate analysis

A total of 292 respondents were considered for contribution in this study. The participants in this study were drawn from the staff of humanitarian organizations such as Catholic Relief Services, Adventist Development and Relief, Mecy Corps, Zimbabwe Redcross Society, Cordaid and World Vision in Zimbabwe. Out of the 292 questionnaires, 250 valid questionnaires were returned and 42 were not returned. The response rate was 85%, with a 15% non-response rate consisting of questionnaires, which were not returned. The response rate is considered excellent by Makanyeza (2018) who noted that a response rate of 50% or above is deemed adequate for analysis and reporting; a rate of 65% is very good and a response rate of 70% and over 70% is excellent.

4.2 Demographic data

4.2.1 Level of respondents and Position held

Table 4.1 below shows the level of respondents and the positions they hold in the humanitarian organization that is being targeted.

Table 4.1: Level of respondents and position held

	Frequency	Percent %	Cumulative Percent %
Program coordinator	88	35	25
Directors	50	20	45
Senior managers	38	15	60
Other	100	40	100.0
Total	250	100.0	

According to Table 4.1, 88 (35%) of the respondents were partners of humanitarian organizations, 50 (20%) cited that they were directors, 38 (15%) indicated they were senior managers whilst 100 (40%) cited others, possibly they were caretakers. The humanitarian organization partners have much influence to make decisions for their humanitarian organizations pertaining to the use of big data analytics. According to the data in Table 4.1 above, humanitarian organizations' partners are well-versed in big data analytics issues. Figure 4.1 shows the level of respondents as well as their position in the organization.

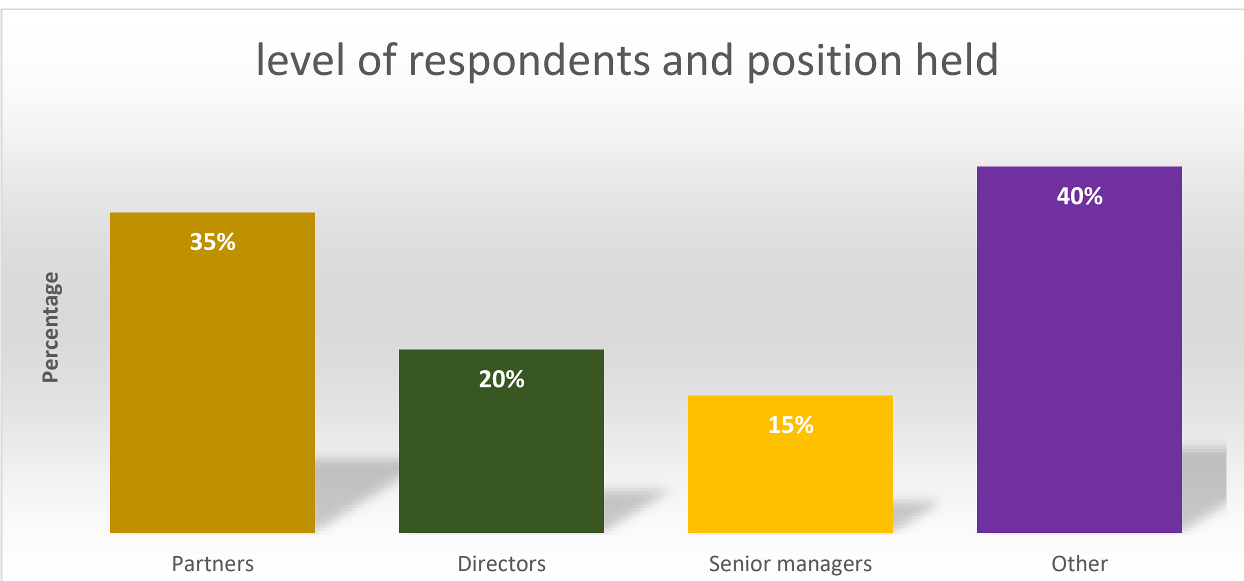

Figure 4.1: Types of respondents and position held (Source: Survey conducted for this study)

Figure 4.1 shows that the majority of respondents from humanitarian organizations in Zimbabwe who completed the questionnaire on the impact of big data analytics on malaria prediction, such as Catholic Relief Services, Adventist Development and Relief, Mecy Corps, Zimbabwe Red Cross Society, Cordaid, and World Vision, indicated that they were partners. In a similar study conducted by Koreff (2018) on three studies examining malaria predictionors' use of data analytics in Florida, United states of America, he noted that the majority of partners in humanitarian organizations constituted 80% of respondents of his study hence the results attained in this research were highly expected.

Table 4.2: Demographics of respondents

Variable	Category	Number	Percentage (%)
Age	Below 20	25	10
	20-30	45	18
	31-40	55	22
	41-50	45	18
	51-60	50	20
	61+	30	12

Source: Survey

4.2.2: Age of respondents

Figure 4.2 shows the distribution of respondents by age in Zimbabwean humanitarian organizations.

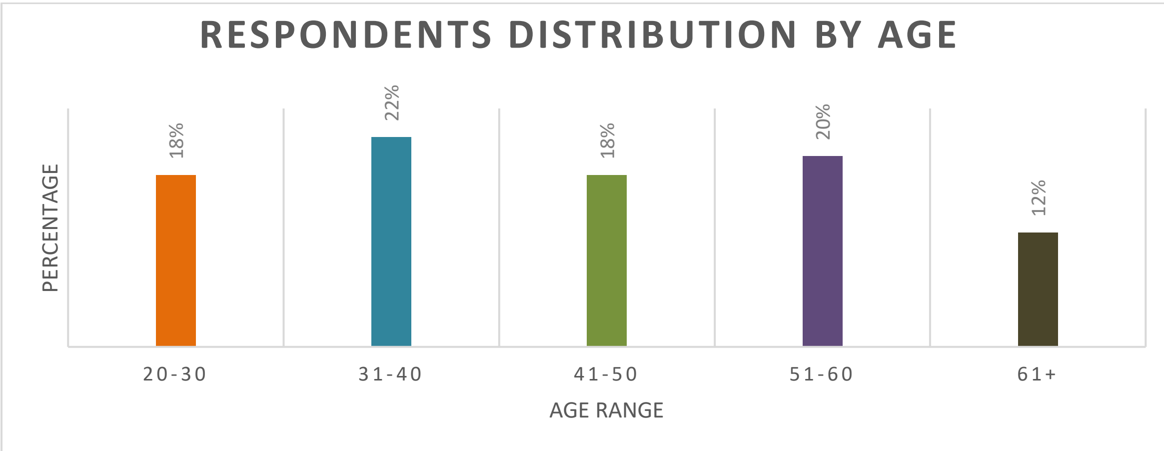

Figure 4.2: Respondents distribution by age (Source: Survey conducted for this study)

According to Figure 4.2, 10% of the respondents were under the age of 20, while 18% were between the ages of 20 and 30. 22 percent of respondents were between the ages of 31 and 40, 18 percent were between the ages of 41 and 50, 20 percent were between the ages of 51 and 60, and 12 percent were 61 and older. As a result, the data in Figure 4.2 above show that the majority of the respondents were between the ages of 31 and 40, and they were able to analyze and provide reliable information on the impact of big data analytics on malaria prediction in Zimbabwe humanitarian organizations.

Based on the data in Figure 4.2 above, it can be concluded that the questionnaire responses were reliable based on experience. Bieger (2015) also conducted a study on the acceptance and adoption of data analytics by external malaria predictionors: A quick view on the graph noted that the majority of employees in organizations are aged between 25 and 40 hence the results attained in this study were highly expected.

4.3 The meaning of big data analytics by humanitarian organizations in Zimbabwe

The first research question sought to investigate the meanings associated with big data analytics by Zimbabwean humanitarian organizations.

Table 4.3: Meaning of big data analytics by humanitarian organizations in Zimbabwe.

Meaning of Big data analytics					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	**Big data analytics refers to qualitative and quantitative techniques used to enhance productivity**	**88**	**35**	**35**	**35**
	Big data analytics involves studying past historical data to research potential trends,	**37**	**15**	**15**	**50**
	Big data analytics is the processes of data assessment and analysis that enable us to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups of organizations	**125**	**50**	**50**	**100**
	Total	**250**	**100.0**	**100.0**	

According to Table 4.3, 35% of respondents defined big data analytics as qualitative and quantitative techniques and processes used to improve productivity and business gain; 15% defined big data analytics as studying past historical data to research potential trends, analyze the impact of certain decisions or events, or evaluate the performance of a given system. whereas 50% defined big data analytics as the processes of data assessment and analysis that allow us to measure, improve, and compare the performance of individuals, programs, departments, institutions, or enterprises, groups.

According to the findings, the most frequently cited definition of big data analytics is the processes of data assessment and analysis that enable us to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups of organizations, and or entire industries. The responses gathered in this research show that the respondents of the study attach different meanings to the concept of big data analytics. All the definitions given refer to big data analytics, perhaps something that humanitarian organizations do most of the time.

According to De Kroon and Karp (2018), big data analytics is defined as an analytical process that extracts insights from operational and other forms of electronic data that are internal or external to the organization. Ernst and Young (2018) use the following definition of big data analytics as an analytical and problem-solving process to identify and interpret relationships amongst variables. Norris and colleagues (2019) defined big data analytics as the processes of data assessment and analysis that enable people to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups of organizations, and or entire industries hence the results attained in this study were highly expected.

According to Cao *et al.* (2015) big data analytics can be defined "*as the process of inspecting, cleaning, transforming and modelling large and unstructured data produced by people, transactions, and machines to discover and communicate useful information and patterns, suggesting conclusions, and support decision making*". It is possible to identify patterns and anomalies in large and unstructured data sets using computerized tools, which can aid in the discovery of hidden information.

Big data analytics is already widely used in many business areas, such as by humanitarian organizations in malaria prediction. By analysing consumer trends and other patterns, consulting firms can determine the best course of action to reduce costs or increase revenues for a specific company. However, the use of big data analytics in malaria prediction is still uncommon. A problem for the use of big data analytics in malaria predictions is that malaria predictionors are no longer allowed to do malaria prediction of an organization and give advice about the business activities of a company according to European laws (PWC, 2015).

Table 4.4: Level of understanding big data analytics

Level of understanding big data analytics			
	Frequency	**Percent**	**Cumulative Percent**
Very good	**83**	**33**	**33**
Good	**60**	**24**	**57**
Fairly good	**33**	**13**	**70**
Poor	**58**	**23**	**93**
Very poor	**18**	**7**	**100.0**
Total	**250**	**100.0**	

Source: Survey conducted for this study

Respondents of this research on the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe were asked about their level of understanding of big data analytics and their responses were captured in table 4.4 above. According to table 4.4 above, the majority of respondents 60 (24%) indicated that they had a good understanding of big data analytics. Idil, Halit & Koray (2018) conducted a study on big data analytics in malaria prediction. Idil, Halit & Koray (2018) noted that humanitarian organizations have a good understanding of big data analytics.

The research aimed to analyze the role and effects of big data analytics on malaria prediction. To achieve this aim, Idil, Halit & Koray (2018) attempted to define big data analytics and its impact on malaria prediction. As a course of nature of the malaria prediction, analytical review procedures are embedded in control models and malaria detection techniques (Idil, Halit & Koray, 2018). According to Idil, Halit & Koray (2018) the results were similar with the literature that organizations that have a good understanding of data analytics increase the effectiveness of malaria prediction.

4.4 Does the humanitarian organization use big data analytics in malaria prediction practices?

Research question two sought to find out if the humanitarian organization uses big data analytics practices in their malaria prediction practices.

Table 4.5: The humanitarian organization use big data analytics in malaria prediction practices

The humanitarian organization use big data analytics in malaria prediction practices			
	Frequency	**Percent**	**Cumulative Percent**
Very much	**78**	**31**	**31**
much	**100**	**40**	**71.0**
I am not sure	**23**	**9**	**80.0**
Not much	**50**	**20**	**100.0**
Total	**250**	**100.0**	

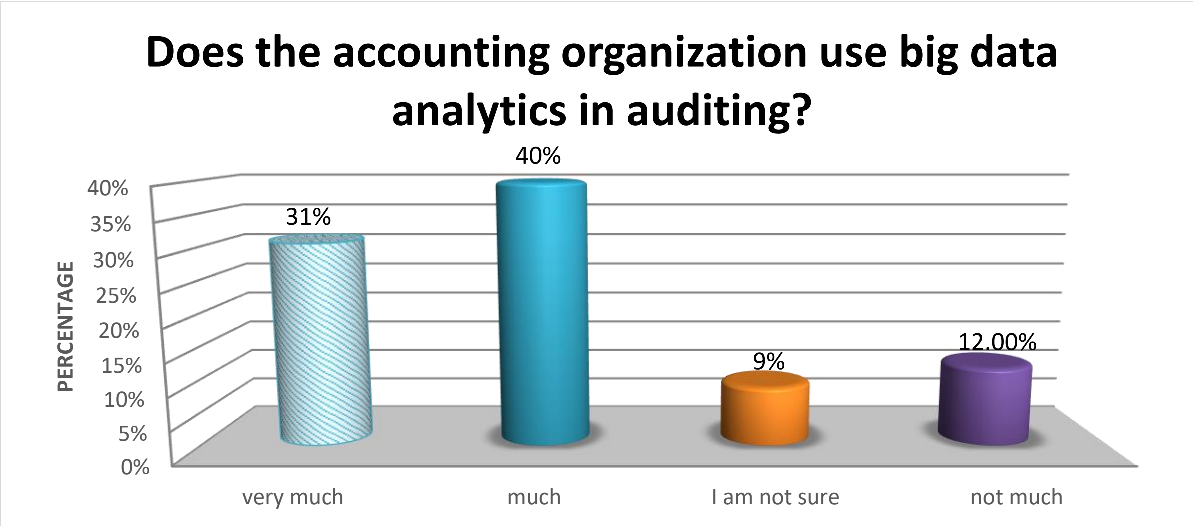

Figure 4.3: Does the humanitarian organization use big data analytics in malaria prediction practices? Source: Survey

Figure 4.3 above shows that the majority of respondents 100 (40%) who completed the questionnaire on the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe indicated that their humanitarian organizations undertake significant big data analytics in their malaria prediction activities. From the findings obtained above 78 (31%) cited very much the humanitarian organization use big data analytics in malaria prediction practices, 100 (40%) cited much, 23 (9%) cited they were not sure whilst 50 (20%) cited not much. Pepping & Nooitgedagt (2019) in Sweden conducted a study on big data analytics in humanitarian organizations malaria prediction: Does big data analytics improve the efficiency of malaria prediction?

According to Pepping & Nooitgedagt (2019) we experience regularly that malaria predictioners are reluctant to use big data analytics. For this reason, Pepping & Nooitgedagt (2019) set out to investigate the benefit of big data analytics in malaria prediction. Pepping & Nooitgedagt (2019) quickly came to the conclusion that the added value should be visible in two areas. Big data analytics should contribute to either the efficiency or the effectiveness of the malaria prediction, or both. According to Pepping & Nooitgedagt (2019) in our daily work, we perform data analytics for humanitarian organizations malaria predictioners. In our experience, it is challenging to gain added value from applying big data analytics during malaria prediction.

Chabert & Jeppesen (2019) in Dernmark conducted a study on data analysis in revision processes and noted that the focus of the study was on the use of data. According to Chabert & Jeppesen (2019) data analysis tools have increased significantly during the recent years, which in addition to an increase in the amount of available data, suggested that there is a possible potential waiting to be exploited by the malaria prediction business. The purpose of the research was to investigate how big data analytics can be implemented in the malaria prediction process in practice and to what extent this will affect the efficiency of a malaria prediction. To answer this question, the legislation that malaria predictionors are subject to, was examined to identify in which way big data analytics can be implemented in theory. For example, a company was involved in malaria prediction with the use of big data analytics to determine how this affects the efficiency of the malaria prediction process, compared to the actual malaria prediction without the use of big data analytics.

An interview with a key expert on the subject was conducted, in addition to relevant external material to apply relevant perspectives to the research. Based on the examination of the regulation and standards, it was concluded that the international standards on malaria prediction, despite lacking suggestions on how to use big data analytics in the malaria prediction process, are not to be seen as an obstacle towards its use.

4.5 Descriptive statistics

The descriptive statistics (mean and standard deviation) of the study constructs are presented in this section. On each of the four constructs, a five-point Likert scale was used. The response points were 1=strongly disagree, 2= disagree, 3= neutral, 4=agree, 5= strongly agree.

4.5.1 To gain an understanding of the application of big data analytics by humanitarian organizations in Zimbabwe

Table 4.6 below shows descriptive statistics for gaining an understanding of the application of big data analytics by humanitarian organizations in Zimbabwe.

Table 4.6: Mean and standard deviation for gaining an understanding of the application of big data analytics by humanitarian organizations in Zimbabwe.

Item	**Mean**	**Std. Deviation**	**N**
Big data analytics is used to uncover hidden trends and patterns that provide decision-makers with useful information.	4.13	.963	250
Using big data analytics in malaria prediction could improve the quality accuracy of malaria prediction, allowing malaria information users to make more informed decisions.	4.17	.933	250
Big data analytics enables malaria prediction to focus efforts on things that are likely to be problematic rather than testing a large number of previous false positives that do not improve understanding.	4.03	.941	250
The ability to use technology throughout the malaria prediction process could lead to a more robust malaria prediction by allowing malaria predictions to look at larger volumes of data than previously available through non-data analytics methods.	4.16	1.033	250

Overall mean =4.1225; Standard deviation= 0.9675

The results in Table 4.6 above show that the lowest mean rating is 4.03 with a standard deviation of 0.941, while the highest mean rating is 4.17 with a standard deviation of 0.933. Descriptive statistics of humanitarian organizations in Zimbabwe gaining an understanding of the application of big data analytics revealed an average mean of 4.1225 with a standard deviation of 0.9675. On average, respondents agreed that using big data analytics in a malaria prediction could improve the quality of malaria prediction, resulting in malaria information users making more informed decisions.

The results are similar to Warren et al. (2015) who stated that using big data analytics in malaria prediction could enhance the quality of a malaria prediction, which, in turn, ultimately leads to users of malaria information making more informed decisions. By incorporating big data analytics using analytical tools or big data analytics software such as CaseWare's IDEA and Tableau into malaria prediction, both the efficiency and the effectiveness of malaria prediction could be improved (Cao, et al., 2015; Brown-Liburd, Issa & Lombardi, 2015).

Improving the efficiency and effectiveness of malaria prediction and serving the needs of the public through the use of data analytic tools is a key reason for the use of big data analytics in malaria prediction. Furthermore, Littley (2012) stated that incorporating big data in malaria prediction could result in a more accurate assessment of ongoing concern and malaria. Smith (2018) investigated the use of big data analytics in malaria prediction by examining malaria risk and prediction quality. This study included two papers that investigated, through interviews and an experiment, the current practices of big data analytics in CPA organizations, whether and how malaria risk influences the use of big data analytics in malaria prediction, and the effect big data analytics has on the efficiency and effectiveness of malaria prediction.

According to Smith (2018) the implementation of big data analytics in malaria prediction is relatively new, and there is no good understanding of how it is currently being used in practice. Although historically the malaria prediction profession has been slow to adopt new technologies, the need for malaria predictions to embrace new technologies is critical to keep pace with their clients (Smith, 2018).

4.5.2 To establish the impact of big data analytics on malaria prediction efficiency in humanitarian organizations in Zimbabwe

Table 4.7 below shows descriptive statistics for the impact of big data analytics on malaria prediction efficiency in humanitarian organizations in Zimbabwe.

Table 4.7: Mean and standard deviation for the impact of big data analytics on malaria prediction efficiency in humanitarian organizations in Zimbabwe

Item	**Mean**	**Std. Deviation**	**N**
Big data analytics helps to identify potential risks easier, and it helps to test those risks as well	4.00	.878	250
Big data analytics allows more transactions to be tested	4.04	.893	250
Organizations can use the big data analytics, after they have identified the potential issue, to test it and be able to identify the transactions they need to look at	3.92	.979	250
Humanitarian organizations can use data analytics to identify that you might have a potential issue that is a risk of humanitarian organizations misstatement	3.99	.975	250

Overall mean =3.9875; Standard deviation= 0.93125

The results in Table 4.7 show that the lowest mean rating is 3.92 with a standard deviation of 0.979, while the highest mean rating is 4.04 with a standard deviation of 0.893. The descriptive statistics of the impact of big data analytics on the efficiency of malaria prediction in humanitarian organizations in Zimbabwe revealed an average mean of 3.9875 with a standard deviation of 0.93125.

Respondents generally agreed that big data analytics enables more transactions to be tested. Byrnes, Criste, Stewart & Vasarhelyi (2016) expect malaria predictions to become more efficient with the help of big data analytics. Earley (2015) believes malaria prediction or benefit by allowing more transactions to be tested.

This explains why a couple of years ago public humanitarian organizations started to invest and implement big data analytics in their malaria predictions (NBA, 2015). Furthermore, clients of public humanitarian organizations will require their malaria information to be predicted on a larger scale due to the large increase in data generation, which is not possible with the current way of malaria prediction (Alles, 2015).

4.5.3 To identify factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe

Table 4.8 below shows descriptive statistics for factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe.

Table 4.8: Mean and standard deviation for factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe

Item	**Mean**	**Std. Deviation**	**N**
Lack of specialist	3.83	.886	250
Organizational culture	3.76	1.068	250
Organization size	3.92	.934	250
Limited skills to use big data analytics	3.96	1.031	250

Overall mean =3.8675; Standard deviation= 0.97975

The results in Table 4.8 show that the lowest mean rating is 3.76 with a standard deviation of 1.068, while the highest mean rating is 3.96 with a standard deviation of 1.031. Descriptive statistics for factors influencing humanitarian organizations' use of big data analytics on malaria prediction in Zimbabwe revealed an average mean of 3.8675 with a standard deviation of 0.97975.

On average, respondents agreed that their organization's ability to use big data analytics is limited. According to Manson, McCartney & Sherer (2017) past experiences show that malaria predictions consistently fail to advance in the current technological developments. With regard to big data analytics, one of the reasons malaria predictors are lagging behind is because they do not have the required skills to apply big data analytics (Earley, 2015).

Ruhnke & Schmidt (2017) denotes that accountant learn how debits and credits affect the balance sheet or income statement. According to Ruhnke & Schmidt (2017) accountants understand the consequences of overstating or understating accounts and how risks related to humanitarian organizations can be minimized. When applying big data analytics, a different skill set needs to be used (Manson, McCartney & Sherer, 2017).

Big data analytics identifies patterns and correlations which have to be analysed by the malaria prediction (Whitehouse, 2017). This necessitates a different approach to drawing conclusions from data. Malaria predictions need to become used and more familiar with this new way of analysing malaria data in order to provide a more efficient and effective malaria prediction (Cao, Chychyla & Stewart, 2015). Developing big data analytics tools is not a requirement for an accountant (Earley, 2015). At this moment with the current increase in big data analytics, the new and rising demand for such specialists is growing faster than the amount of people who are schooled to become such specialists (Gershkoff, 2015). This implies that public humanitarian organizations will have difficulty finding staff capable of developing big data analytics tools. Furthermore, low demand will almost certainly result in a high price for big data analytics specialists. Besides the fact that big data analytics specialists are scarce, big data analytics specialists are often not familiar with a malaria prediction (Alles, 2015).

4.5.4 The improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations

Table 4.9 below shows descriptive statistics for improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations.

Table 4.9: Mean and standard deviation for improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations

Item	**Mean**	**Std. Deviation**	**N**
Organizations with no existing advanced big data analytics capabilities may effectively build their big data analytics capabilities	3.48	1.175	250
Involving every worker	3.49	1.199	250
Training employees	3.74	.996	250
Organizations should invest in malaria prediction technologies such as such as statistical sampling	3.90	1.037	250

Overall mean =3.6275; Standard deviation= 1.101

The lowest mean rating was 3.48 with a standard deviation of 1.175, while the highest mean rating was 3.90 with a standard deviation of 1.037, as shown in Table 4.9 above. Descriptive statistics for malaria prediction improvements resulting from humanitarian organizations' adoption of big data analytics revealed an average mean of 3.6275 with a standard deviation of 1.101.

On average, respondents were agreeing that organizations should invest in malaria prediction technologies such as statistical sampling and business risk malaria prediction approaches. The propensity to invest in malaria prediction technologies is not new among malaria prediction organizations; historically, they have also made investments in malaria prediction technologies such as statistical sampling and business risk malaria prediction approaches. The corollary to this is the claim that malaria prediction technologies change the way malaria predictions are approached in the field, in particular the issue of malaria prediction evidence (Matthews, 2016).

For instance, Power (2012) and Lee (2013) indicated that the malaria prediction profession has for a long time struggled with addressing the notion of what constitutes appropriate and sufficient malaria prediction evidence. Therefore, the developments in malaria prediction technologies, despite others suggesting that they are meant to address political and economic dimensions of the malaria prediction profession (Lemon *et al.*, 2010; Robson *et al*., 2017), have been portrayed as a quest to address the issue of malaria prediction evidence for establishing malaria prediction opinions (Matthews, 2016).

As a result, the emphasis should shift to assessing the strength of the client's internal control system, a method known as system-based malaria prediction. In order to provide justification for the reduction in malaria prediction evidence, malaria prediction organizations introduced statistical sampling to determine the amount of malaria prediction evidence (Power, 2017).

Tables 4.10 below shows there is an association between ways of adopting big data analytics and organization performance and malaria prediction quality. Gamma -.683 indicates a very strong negative relationship. The findings indicate that as methods of implementing big data analytics in Zimbabwe become more and more formal Adoption of big data analytics in humanitarian organizations has an effect on malaria prediction and malaria resources. In empirical research which has been conducted by Mushipe et al. (2015) on the adoption of big data analytics and its impact on the malaria performance of humanitarian organizations, they concluded that there is an association between the methods of adopting big data analytics and company performance as measured by sales revenue per year.

They noted that humanitarian organizations who adopt big data analytics can improve in terms of performance, and this seems patently unfit to explain why humanitarian organizations adopt big data analytics in a desirable outcome.

Table 4.10 Direction of the relationship between ways of adopting big data analytics and humanitarian organization performance.

Chi-Square Tests	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	78.079[a]	4	.000
N of Valid Cases	250		
a. 2 cells (20.0%) have expected count less than 5. The minimum expected count is 3.45.			

		Value	Approx. Sig.
Ordinal by Ordinal	Gamma	-.683	.000
N of Valid Cases		250	
a. Not assuming the null hypothesis.			
b. Using the asymptotic standard error assuming the null hypothesis.			

4.6 Testing hypotheses (H1 to H6)

This section aims to demonstrate whether differences in the use of big data analytics have a positive effect on malaria prediction quality, malaria prediction efficiency and whether the use of big data analytics is based on organization size, the leverage, nature of assets and malaria prediction or tenure. The study sought to test the following hypothesis:

H_1: The use of big data analytics has a positive effect on malaria prediction in humanitarian organizations.

H_2: The use of big data analytics has a positive effect on malaria prediction efficiency in humanitarian organizations.

H_3: Organization size has a positive effect on the use of big data analytics.

H_4: The greater the leverage the higher the intention to use big data analytics.

H_5: Nature of assets has a negative effect on the use of big data analytics.

H6: Malaria prediction or tenure has a positive effect on the use of big data analytics

4.6.1 Big data analytics has a positive effect on malaria prediction quality

The one-way ANOVA results in Table 4.11 show whether big data analytics has a positive effect on malaria prediction quality.

Table 4.11: Positive effect on malaria prediction quality

Big data analytics components	**N**	**Mean**	**Std. Deviation**	**Std. Error**
Data strategy	70	13.2000	1.84252	.29133
Data engineering	56	13.0000	2.01990	.39614
Data analysis and models	57	13.0000	1.79505	.29511
Data visualization	61	13.0968	1.46867	.26378
Data operationalization	3	12.3333	1.15470	.66667
Total	247	13.0657	1.75819	.15021

F=0.208; p= 0.934

The results in Table 4.11 above indicate that the model is not statistically significant (F= 0.203; p=0.934). Because the p-value of 0.934 exceeds the significance level of 0.05. This demonstrates that there is insufficient evidence to support the hypothesis. As a result, H1 is not supported. This means that big data analytics has no discernible effect on malaria prediction quality. The findings are similar to those of Chung et al. (2010) and Matikiti (2018) which show that big data analytics does not have an effect on malaria prediction quality. Matikiti (2018) noted that big data analytics only enables improvements in customer service and identification of customer dissatisfaction areas.

4.6.2 The use of big data analytics has a positive effect on malaria prediction efficiency in humanitarian organizations

This section aims to see if big data analytics improves malaria prediction efficiency in humanitarian organizations. H2 was tested using one-way ANOVA. Table 4.12 displays the results.

Table 4.12 the use of big data analytics has a positive effect on malaria prediction efficiency.

Big data analytics used	**N**	**Mean**	**Std. Deviation**	**Std. Error**
Robots	30	12.1500	1.92696	.43088
Technologies	217	13.2222	1.68723	.15598
Total	247	13.0657	1.75819	.15021

F= 6.615; p= 0.011

Table 4.12 shows that the model is statistically significant (F= 6.615, p= 0.011). As a result, H2 is supported. These findings imply that the use of big data analytics in humanitarian organizations is linked to the accuracy of malaria prediction. The results are similar to those of Rogers (2003) and Agarwal and Prasas (1999) who found that the use of big data analytics has a positive effect on malaria prediction efficiency in humanitarian organizations. They noted that real-time reporting enabled by big data analytics has improved business efficiency for organizations with a high customer service component. Bender (2017) conducted a study on the effect of big data analytics in Netherlands on malaria prediction efficiency and concluded that big data analytics is the application of certain software tools which analyses data from which results in increased efficiency.

4.6.3 Organization size has a positive effect on the use of big data analytics

This section aims to determine whether the size of an organization has a positive impact on the use of big data analytics. H3 was tested using one-way ANOVA. Table 4.13 displays the results.

Table 4.13: Organization size has a positive effect on the use of big data analytics.

Organization size	N	Mean	Std. Deviation	Std. Error
Small	60	12.4000	1.42984	.45216
Medium	98	12.8676	1.62907	.19755
large	88	13.3793	1.90868	.25062
Total	246	13.0515	1.75676	.15064

F= 2.104; p= 0.126

Table 4.13 shows that the model is not statistically significant (F= 2.104, p= 0.126) because the p-value (.126) exceeds the significance level of 0.05. As a result, H3 is not supported. These findings imply that the size of a humanitarian organization has little bearing on its use of big data analytics. The results differ from those of Rahayu and Day (2015) who advocate that size does not influence the use of big data analytics in organizations as long as organizations have resources whether small or large, big data analytics can be adopted. Also, the findings contradict those of Awa et al. (2015) who established that organization size has a positive influence on the adoption of big data analytics.

4.6.4 The leverage

Table 4.14 displays the results of a one-way ANOVA to see if there is a significant difference in the intention to use big data analytics due to leverage.

Table 4.14 One-way ANOVA: The greater the leverage the higher the intention to use big data analytics

The leverage	N	Mean	Std. Deviation	Std. Error
debt	50	12.6000	2.09762	.33166
equity	89	12.8980	1.32673	.18953
assets	53	13.6087	2.08325	.43439
expenses	43	13.5652	1.37597	.28691
Total	235	13.0444	1.76139	.15160

F= 2.500; p= 0.062

Table 4.14 shows that the model is not statistically significant (F= 2.500, p= 0.062). As a result, H4 is not supported. This means that the greater the leverage, the less likely that big data analytics will be used. According to Agwu and Murray (2015) companies often leverage big data analytics techniques to analyse their supply chains and determine the optimal way to meet customer requirements.

4.6.5 Nature of assets has a negative effect on the use of big data analytics

The purpose of this section is to test if the nature of assets has a negative impact on the use of big data analytics. H5 was tested using one-way ANOVA. Table 4.15 displays the results.

Table 4.15 Nature of assets has a negative effect on the use of big data analytics

Nature of assets	**N**	**Mean**	**Std. Deviation**	**Std. Error**
Current assets	92	12.7885	1.81860	.25219
Fixed assets	93	13.2264	1.82548	.25075
Non-operating assets	52	13.2500	1.52400	.26941
Total	237	13.0657	1.75819	.15021

F=1.355; p= 0.355

Table 4.15 shows that the model is not statistically significant (F= 1.044, p= 0.355) because its p-value (0.355) is greater than the significance level of 0.05. As a result, H5 is not supported. This means that the nature of assets has a negligible impact on the intention to use big data analytics. The results are similar to that of Rahayu and Day (2015) who found that assets have a significant effect on the adoption of big data analytics among organizations in Indonesia. However, the findings contradict Aguila-Obra and Melendez (2006), who argue that the nature of an organization's assets has a significant impact on managerial resources, implying that the smaller the organization, the less likely it is to use expert advice to implement big data analytics.

4.7 Testing hypothesis H6

This section presents the findings on whether the tenure of a malaria prediction has a positive effect on the use of big data analytics.

The study sought to test the following hypothesis:

H6: Malaria prediction or tenure has a positive effect on the use of big data analytics.

The hypothesis was tested using regression. The results are shown in Tables 4.18, 4.19, and 4.16 below.

4.7.1 Testing H6

Table 4.16 below shows the model summary.

Table 4.16: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.401[a]	.161	.154	7.69116
a. Predictioners: (Constant), malaria prediction or tenure				

According to the findings in Table 4.16, malaria prediction or tenure accounts for approximately 16.1 percent of changes in big data analytics use (R square= 0.161). This implies that there are additional factors influencing the use of big data analytics in humanitarian organizations.

Table 4.17 below shows the ANOVA test results.

Table 4.17: ANOVA

ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	1373.162	1	1373.162	23.213	.000[b]
	Residual	7157.635	121	59.154		
	Total	8530.797	122			
a. Dependent Variable: Use of big data analytics						
b. Predictioners: (Constant), Malaria prediction or tenure						

The model is statistically significant (F= 23.213; p=0.000), according to the results in Table 4.17 above. These findings indicate that the regression model provides a good fit to the data.

Table 4.18 below presents coefficients for the regression model.

Table 4.18: Coefficients

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.325	5.637		-.235	.815
	Malaria prediction or tenure	2.053	.426	.401	4.818	.000
a. Dependent Variable: Big data analytics use						

According to the findings in Table 4.18, malaria prediction or tenure has a positive effect on the use of big data analytics (Beta= 0.401, t= 4.818, p= 0.00). As a result, H6 is supported. This implies that the use of big data analytics is influenced by malaria prediction or tenure.

These results are similar to those by Venkatesh et al. (2003) and Masa'deh et al. (2015) who found a significant effect of malaria prediction or tenure on big data analytics. Also, there is vast literature supporting the malaria prediction or tenure and big data analytics use (Davis et al., 2000; Taylor & Todd, 1995; Venkatesh & Davis, 2000; Venkatesh et al., 2003).

Table 4.19: Results of quantitative research

Research Question	Results
1.What meaning is attached to big data analytics by humanitarian organizations in Zimbabwe?	1. Humanitarian organizations in Zimbabwe attach many meanings to big data analytics. 2. Big data analytics is defined in relation to the malaria prediction practices specialized by humanitarian organizations in Zimbabwe.
2.What is the impact of data practices on malaria prediction efficiency of Humanitarian organizations in Zimbabwe?	1. Humanitarian organizations in Zimbabwe consider big data analytics as an expense. 2. Big data analytics practices have an influence on malaria prediction efficiency of humanitarian organizations in Zimbabwe. 3. In Zimbabwe, humanitarian organizations do not have separate budgets for big data analytics. 4.Managers are excluded from big data analytics programs. 5.In Zimbabwe, humanitarian organizations lack specialized departments for big data analytics. 6. Big data analytics practices in malaria prediction for humanitarian organizations are not formalised. 7. Humanitarian organizations in Zimbabwe do not have strategic policy options for big data analytics use.
3.What are the factors that motivate humanitarian organizations to engage in big data analytics?	1. The need to make profits is a major factor that motivates humanitarian organizations to engage in big data analytics. 2. The need to improve on malaria prediction efficiency 3. The need to improve malaria prediction quality
4.What are the barriers to big data analytics practices in Zimbabwe?	1.In Zimbabwe, a major impediment to big data analytics practices by humanitarian organizations is a lack of funds. 2. Lack of experienced and skilled personnel 3. Managerial attitudes are a major impediment to the use of big data analytics by humanitarian organizations in Zimbabwe.

Source: Prepared for this study

Table 4.20: The Interview Guide Questions

	Research Question	**Interview questions**	**Results expected**
•	What meaning is attached to big data analytics by humanitarian organizations in Zimbabwe?	• What do you understand about the concept of big data analytics? • Who in your organization is involved in big data analytics?	Meaning attached to big data analytics by humanitarian organizations
•	What is the impact of data practices on malaria prediction efficiency in humanitarian organizations in Humanitarian organizations in Zimbabwe?	• What are the advantages of big data analytics to your organization? • How much does big data analytics cost your organization? • How does the practice of big data analytics influence your organization?	The negative and positive effects of big data analytics on the accuracy of malaria prediction in humanitarian organizations.
•	What are factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe?	• What are the legal implications of using or not using big data analytics in your organization? • What are the economic implications of using or not using big data analytics in your organization?	Drivers of big data analytics used in humanitarian organizations.
•	What are the barriers to big data analytics practices by humanitarian organizations in Zimbabwe?	• What challenges does your organization experience in adopting big data analytics requirements?	Barriers to big data analytics use in humanitarian organizations.
•	Are there any improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe?	• Has your organization improved anything on big data analytics?	Improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizationsin Zimbabwe

4.8 Chapter summary

This chapter presented both quantitative and qualitative data. To present qualitative data, frequency tables, bar graphs, and pie charts were used. To analyse qualitative data, the tabular form and the reduction method were used. To collect both qualitative and quantitative data, this study used a mixed research approach. The quantitative data was then displayed in the order in which the research questions from the questionnaire were asked. The response rate for this study was 85 percent, with a 15 percent non-response rate made up of unusable questionnaires. The study's findings will be presented in Chapter 5.

CHAPTER 5
CONCLUSIONS AND IMPLICATIONS

5.0 Introduction

This research focused on the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe. The previous chapter looked at results and discussion. The conclusions and implications are the focus of this chapter.

5.1 Conclusions of the study

5.1.1 Conclusion: Research objective 1: To gain an understanding of the application of big data analytics by humanitarian organizations in Zimbabwe

According to the findings of this study, humanitarian organizations in Zimbabwe associate the concept of big data analytics with a variety of meanings. Most humanitarian organizations associate big data analytics with data assessment and analysis processes that allow us to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups of organizations, and or entire industries.

Other definitions of big data Analytics refers to the current process of analysing structured and unstructured data using a variety of techniques and processes, as well as the process of inspecting, cleaning, transforming, and modelling big data in order to discover and communicate useful information and patterns, suggest conclusions, and support decision making, and data analysis, underlying malaria statements, together with related malaria or non-malaria information for the purpose of identifying potential misstatements or risks of material misstatement.

The lack of a clear definition of big data analytics, humanitarian organizations in Zimbabwe do not engage in strategic big data analytics adoption in malaria prediction quality. Policy does not govern big data analytics. Because the concept of big data analytics is known in a variety of contexts, big data analytics activities and practices cannot be expected to be consistent across companies. The nature of the industry and the culture of the country housing the company affect the way big data analytics practices are understood and practiced (Karin Stahl, 2019).

5.1.2 Conclusion Research Objective 2: To establish the impact of big data analytics on malaria prediction efficiency in humanitarian organizations in Zimbabwe

Humanitarian organizations that took part in this study see big data analytics as an unnecessary expense in their operations. Big data analytics is viewed as having no quantifiable benefits to the organization. It was also mentioned that humanitarian organizations in Zimbabwe do not deliberately adopt big data analytics to improve malaria prediction and boost their performance. Big data analytics is adopted because it allows more transactions to be tested and sometimes it is adopted for survival purposes.

As a result, an improvement in malaria prediction by humanitarian organizations can be explained by factors other than big data analytics. Humanitarian organizations in Zimbabwe face challenges in formalizing their big data analytics initiatives because formalizing big data analytics necessitates the expenditure of ever-increasing resources to implement big data analytics programs and initiatives. Due to a lack of funds, humanitarian organizations in Zimbabwe do not have separate budgets for big data analytics. Humanitarian organizations in Zimbabwe do not have specialised departments to implement big data analytics.

Some managers are not involved in decisions pertaining to big data analytics in malaria prediction and the methods that humanitarian organizations use to manage and implement big data analytics The leader-dominated approach, the priming approach, and the facilitation approach are among the approaches used. The leader-dominated approach is the most popular, and the priming approach is the second most popular.

These two approaches do not include workers in the decision-making processes for big data analytics. The facilitation approach, which involves workers in big data analytics decision making, is the least used.

5.1.3 Conclusion Research objective 3: To identify factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe

This study noted that humanitarian organizations in Zimbabwe are forced by customer expectations to embark on big data analytics programmes. The most cited factors include the need to improve malaria prediction quality. The implication of this to management in humanitarian organizations is that humanitarian organizations who neglect big data analytics suffer loss of customers and stakeholder support. Big data analytics practices by humanitarian organizations in Zimbabwe are formalised.

This study established that there are limited skills in their organization to use big data analytics. In terms of big data analytics, one of the reasons malaria predictions are lagging is that they lack the necessary skills to apply big data analytics. When applying big data analytics, a different skill set needs to be used. In this study it was also noted that there are other factors such as technological factors, organizational factors and environmental factors which influence the use of big data analytics. This objective was achieved.

5.1.4 Conclusion Research Objective 4: To establish the improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe

The last objective of the study sought to establish the improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe. According to the findings of the study, businesses should invest in malaria prediction technologies such as statistical sampling and business risk malaria prediction approaches.

Malaria prediction organizations' proclivity to invest in malaria prediction technologies is not new; historically, they have also invested in malaria prediction technologies such as statistical sampling and business risk malaria prediction approaches. Therefore, the research objective was achieved.

5.2 Recommendations

The researcher makes the following recommendations as a direct outcome of this study.

5.2.1 Recommendation 1

Humanitarian organizations in Zimbabwe are encouraged to take a strategic approach to big data analytics for malaria prediction. This is possible if humanitarian organizations establish a big data analytics department that develops and executes strategic big data analytics plans. Adopting a big data analytics policy and reporting all big data analytics on malaria prediction practices in the media is what strategic big data analytics entails. This arrangement would assist humanitarian organizations in gathering more information on global big data analytics practices and in clearly understanding the meanings attached to big data analytics by other business partners.

5.2.2 Recommendation 2

Humanitarian organizations in Zimbabwe should adopt big data analytics practices on purpose in order to improve malaria prediction and organizational performance. This means that Zimbabwean humanitarian organizations should formalize their big data analytics practices in order to take a professional approach to big data analytics. Formalisation of big data analytics entails the incorporation of big data analytics objectives in mission statements, creating separate budgets for big data analytics, involving managers in big data analytics, having a specialised department that deals with big data analytics issues and making meaningful corporate plans. Big data analytics should be treated as a serious matter of humanity.

5.2.3 Recommendation 3

Humanitarian organizations in Zimbabwe should shift their big data analytics activities from general to specialized. The activities should concentrate on issues that are unique to Zimbabwe. Malaria forecasting and transparency issues are affecting Zimbabwe. These necessitate specialized big data analytics activities aimed at addressing the aforementioned issues. Since the main impediments to humanitarian organizations' use of big data analytics in Zimbabwe are lack of specialised and skilled workforce and managerial attitude, there should be an environment that encourages humanitarian organization managers and partners to consider big data analytics as critical to their survival and malaria prediction as well.

In Zimbabwe, big data analytics is a relatively new practice. The Western World was the birthplace of big data analytics. Humanitarian organizations require education and information sharing about the importance of big data analytics and how it can be implemented in a country like Zimbabwe.

5.3 Implications of the study

The first objective of the study sought to gain an understanding of the application of big data analytics by humanitarian organizations in Zimbabwe. The study established those big data analytics is mostly used by humanitarian organizations in Zimbabwe. Therefore, the study creates new knowledge in the big data analytics field since some research indicated that there is a low usage. According to the findings of this study, expertise is a significant factor influencing the adoption of big data analytics. On the other hand, this study discovered that humanitarian organizations can use this research to improve and fully embrace big data analytics in malaria prediction in order to profitably manage their business, business models, and overall success. Given the big data analytics in malaria prediction direction in which the world is heading, this will ultimately add value to Zimbabwe's humanitarian sector.

It will also shed light on the types of big data analytics that they can pursue, as well as how to effectively implement them in their organization. As a result, the findings both strengthen existing knowledge and generate new knowledge. This research will benefit users of malaria statements such as humanitarian organizations management and Ministry of Health and Child (MoHCC). The knowledge they gain could alter their strategies.

The study's third objective was to identify factors that influence the use of big data analytics. on malaria prediction by humanitarian organizations in Zimbabwe. This study established that there are limited skills in their organization to use big data analytics. The research findings support the existing researcher, indicating that there is a significant influence on the use of big data analytics on the quality of malaria prediction.

The study established that humanitarian organizations in Zimbabwe occasionally use big data analytics. As a result, it is recommended that the management of humanitarian organizations encourage the use of big data analytics for malaria prediction so that their employees have a more positive attitude toward big data analytics. It is also suggested that they hire Big data specialists who are well-versed in how big data analytics can be applied.

Furthermore, the Ministry of Health and Child Care (MoHCC) can play a critical role in raising awareness and assisting these organizations in using big data analytics to improve malaria prediction quality.The Ministry Of Health And Child Care (MoHCC) in collaboration with the Ministry Of Information Communication And Technology (MoICT) can conduct workshops on big data analytics and their benefits so that the managers and employees in the industry will appreciate the benefits of using this technology.

5.4 Further suggestions for future research

The purpose of this study was to examine the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe. According to the study, the following areas should be researched in order to generate more knowledge on the impact of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe:

- The attitude of humanitarian organization managers, partners, and directors as a barrier to the adoption of big data analytics.
- The contribution of big data analytics programmes to the malaria well-being of humanitarian organizations in Zimbabwe.
- The effect of formalising big data analytics in humanitarian organizations

5.5 Limitations of the study

This study was carried out in the Harare region of Zimbabwe. The study sought to investigate the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe. Humanitarian organization managers in some cases participated in this study. It was noted that all big data analytics decisions were made by program directors. This means that data gathered from managers may not have accurately reflected the wishes of the board of directors regarding big data analytics practices.

Four objectives guided this study on big data analytics in Zimbabwean humanitarian organizations. The objectives covered areas such as, an understanding of the application of big data analytics by humanitarian organizations in Zimbabwe, the impact of big data analytics on malaria prediction efficiency in humanitarian organizations in Zimbabwe, factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe and the improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe.

These objectives may not have been sufficient to provide insights into all of the big data analytics practices of humanitarian organizations in developing countries in general, and Zimbabwe in particular. As a result, more research studies on the big data analytics practices of humanitarian organizations are required, and the studies must include different objectives in order to capture other aspects of humanitarian organizations' big data analytics practices that were not captured by this study. Despite the limitations mentioned, the findings of this study can be used to accurately represent the big data analytics practices of humanitarian organizations around the world.

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Appendix 1: CUT Approval Letter

CHINHOYI UNIVERSITY OF TECHNOLOGY

PERMISSION LETTER

Student Name: Robson Mutuva

Student number: C18135843G

Programme: Master of Science in Data Analytics

Approved research topic:

THE IMPACT OF BIG DATA ANALYTICS ON MALARIA PREDICTION IN HUMANITARIAN ORGANIZATION IN HARARE, ZIMBABWE

TO WHOM IT MAY CONCERN

I hereby confirm that the above-mentioned student is registered at Chinhoyi University of Technology for the programme indicated. The proposed study met all the requirements as stipulated in Chinhoyi University of Technology policies and guidelines and has been approved by the Graduate Business School.

The proposal adheres to ethical principles as outlined by the Research Ethics Committee of the University. Permission is hereby granted to carry out the research as described in the approved proposal. May you please assist the student in any way possible.

The main objective of the study is to

i. To gain an understanding of the application of big data analytics by humanitarian organizations in Zimbabwe.

ii. To establish the impact of big data analytics on malaria prediction in humanitarian organizations in Zimbabwe.

iii. To identify factors which influence the use of big data analytics on malaria prediction by humanitarian organizations in Zimbabwe.

iv. To establish the improvements on malaria prediction arising from adoption of big data analytics by humanitarian organizations in Zimbabwe.

Best Regards

CHINHOYI UNIVERSITY OF TECHNOLOGY
GRADUATE BUSINESS SCHOOL
DIRECTOR'S OFFICE
23 JUL 2021
PRIVATE BAG 7724
CHINHOYI

Prof D Chavunduka

Director, Graduate Business School

Tel: +263 267 2129447

E-mail: directorgbs@cut.ac.zw

Appendix 2: MoHCC Approval

CHINHOYI UNIVERSITY OF TECHNOLOGY

PERMISSION LETTER

Student Name: Robson Mutuva

Student number: C18135843G

Programme: Master of Science in Data Analytics

Approved research topic:

THE IMPACT OF BIG DATA ANALYTICS ON MALARIA PREDICTION IN HUMANITARIAN ORGANIZATION IN HARARE, ZIMBABWE

TO WHOM IT MAY CONCERN

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MINISTRY OF HEALTH AND CHILD CARE
DIRECTOR POLICY & PLANNING
ZIMBABWE

Best Regards

Stephen Banda

....

Signature and Date Stamp

....

Name of Director, Graduate Business School

Tel: +263 267 2129447

E-mail: directorgbs@cut.ac.zw