



# **Harnessing the Power of Big Data: Navigating the Six Vs to Drive Digital Transformation and Innovation**

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## **ABSTRACT**

Big Data refers to the vast and complex datasets generated from numerous digital sources, including social media, sensors, business transactions, and IoT devices. Defined by six Vs Volume, Variety, Velocity, Veracity, Variability, and Value—Big Data is about the volume of data but also the speed and variety of data creation, and the difficulty of processing that data into useful information. Digitalization is advancing rapidly and conventional data management tools are not capable to cope with this complexity. Thus, companies need to apply sophisticated analytics capabilities such as AI and machine learning to make use of Big Data. This knowledge enables more informed decisions, improved operations, and innovation. "But the undoubtedly well-founded, statistical, and constant use of Big Data is the problem. Leveraging Big Data effectively has the potential to lead to a radical reshaping of business and society as it paves the way to data driven strategies that re-define business processes, businesses, industries and markets to create and deliver value in the digital age.

***Keywords:*** *Big Data, Data Analytics, IoT Devices.*

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## **I. INTRODUCTION**

### **DEFINITION AND OVERVIEW OF BIGDATA**

Big Data always cites the enormous amount of data generated from different sources. Conventionally, it is beyond the processing software to interpret and organize. Data comes in all sort of formats (e.g., unstructured, structured, semi-structured) from various sources such as social media, business transactions, sensors and IoT devices. The Big Data is not only the data volume but the velocity and varieties in which the data is received and processed.

The Big Data hype has been driven by the enormity of the digital data that we create, and by the technologies that have allowed us to store, manage, retrieve and interpret that data. This transformation is driving the way organizations are conducting business, not just to be more efficient but to do new things to create value. Big Data is an important aspect of the digital transformation—the place where stuff gets reformed in a new form, and information is produced that could not be obtained before it became available. An important characteristic that sets Big Data apart is the data size/volume. The amount of data that is generated by a diverse range businesses, people and web-enabled devices is enormous and it is still growing at an unprecedented rate. This has become more accessible due to social media, the internet (and mobiles) and the huge amounts of digitization of business bookkeeping and free practices. If variety is the most important aspect of big data, it is the diversity of the types of data that can be acquired and analysed. Data come in many forms, from structured data databases containing names and numbers to unstructured data, like images, texts and videos. This diversity compels an organization to determine their optimal storage, maintenance, processing and subsequent analytics since more than databases and software tools may be required to deal with the complexities of Big Data. Equally determining is data speed defined as the 'speed of data', i.e. the exponentially increasing volume of data that has to be acquired, stored, archived, and analysed on very short time scales. Short-term, or even instant, processing of information is coming to be unmatched in a range of tasks, from detecting online fraud to directing real-time traffic to offering instant personal recommendations on social platforms. The real statement conveys an idea about the genuineness and certainty of the recorded figure. A typical case for Big Data is that data is often imperfect, inconsistent, and unreliable, creating the most difficult analysis task. In this context, strategies providing the trustworthiness and trustiness of analytics information are essential for organizations and companies relying on Big Data as the tool for strategic decision making. This is likely because the values of Big Data emphasize turning Big Data into actionable intelligence, too. Data analytics is all about Big Data Big data is the hottest trend in data analytics, if not all of IT and the Internet, and it's all about volume of data. The promise of big data comes from the ability to use that data to make better decisions, operate more efficiently, create new products, and generate a competitive advantage. Although valuable insights may need to be mined from large and disparate databases, one only needs to use sophisticated instruments to do so. Eventually, inter alia, Big Data will be a complex and multi-sided affair which won't be any less revolutionary than transforming data and the way we operate with it. But its effects are sweeping, representing all that users come to know of social and economic life. As technology advances at a more rapid pace than ever before, understanding and harnessing the power of big data is the thing that sets successful businesses apart from those who simply ride the wave of time in a global market.

### **Big Data Characteristics**

Big Data is always defined with a set of characteristics known as the six Vs: Variety, Value, Variability, Velocity, Volume, and Veracity are the six Vs of big data phenomenon. These dimensions will then help to dissect the complexities of data sets and how they provide the challenges and opportunities with which large scale data environments are tasked. Figure 1 summarises the features succinctly.



**Figure 1: Characteristics of Big Data Phenomenon**

**Variety:** Its toolbox covers a crucial part of the wide range of data content, from structured numeric data previously available in databases to unstructured text, images, videos, and other forms. Because of this diversity, powerful and flexible computational engines which are able to structure and analyse the data are very much desired.

**Value:** It exposes the targets of Big Data analytics, which includes important data processing operations such as fusion of data, data extraction and knowledge discovery from a large amount of data. The true value of Big Data is that it can transform the way managers think, running operations efficiently and it can also show new places where innovation and growth is possible. Since the traffic volume is unstable, large fluctuations exist. The discrepancies can be attributed to different drivers, which include time-sensitive events and viral topics in social media. Optimizing a variety of factors that influence the speed of data processing is one the operating tasks to ensure that system runs efficiently.

**Velocity:** it is the velocity at which data flows in and out of various business and technical sources – Business processes, machinery, network and human interaction. Not only is the speed of data generation and dissemination fast, the whole process of data selection, generation and spread to the internet supposes the filtering & analysis should work immediately to add the value.

**Volume:** The volume has to do with the quantity of data that's being generated by social media, online marketplaces, and the Internet of Things (IoT) at very frequent intervals. This task however occurs in the potential ability to collect, store, and eventually "mine" such large volumes of data, which would contain interesting information and solutions.

**Truthfulness:** It concerns whether the data is true and determinable. Information about Big Data is not necessarily taken from one source, and it is not easy to evaluate reliability and accuracy. Correctly identifying data quality and ownership rights are crucial in data analysis and enhancing the policy process. All these features embody the idea of Big Data, in its difficulties as well as in the infinite opportunities that the use of elaborated awareness could create in each field of the community.

## Sources of Big Data

In medical care, Big Data is revolutionizing medicine through its different sources, especially IoT and transactional data. These sources are a starting point for the betterment of the effective therapies, to the better quality of patient care and to the discovery of the medical field. The IoT in medical devices includes wearable medical monitors, implantable medical devices, and remote patient monitoring systems. These gadgets remain on all the time and can gather important health related data, such as heart rate, blood pressure, glucose, and others, while some advanced gadgets are even able to get ECG or heart electro records. This always-on real-time health data enables direct patient care, timely chronic disease management, individual patient care plans, and the ability to identify under-the-radar health risks. Integration of IoT devices into healthcare systems generates a huge amount of Big Data from which data mining can be employed to reveal significant number of patterns, predict health outcomes and therefore increase the quality in patients` caring process.

Among health care transactions, health insurance transactions are one source for medical data, containing patient histories, treatment history, billing information, insurance claims, pharmacy prescriptions and other information. Back and forth interaction with the patient, both direct and indirect, results in two data points being produced by the healthcare system that only paint a partial picture of the patient's health and the overall efficacy of the treatment protocols. By analysing the data, patterns and correlations can be discovered by healthcare professionals to make diagnostic processes stronger and the care more efficient, which leads to better patient outcomes and more effective care. Equally, this data also indicates that the health care resources are utilized effectively under reduced operational workflows as well as in compliance with regulation criteria. When integrated, IoT and transactional data provide great features of Bigdata in medical field. Not only enable us to see into the well-being of each individual patient, but also the overall health of the community, and are the forceful characters walking ahead of the change in medical treatment, healthcare delivery and disease prevention. The application of Big Data from these sources to practical aspects of health, the administrative operations of healthcare systems, and the science of medicine more generally, and their potential benefit to AM and medicine and health more generally, is potentially transformational.

## Big Data Technologies

In particular, medicine uses Big Data to enhance healthcare outcomes. The need is for exceedingly sophisticated technology to store and handle massive amounts of weighty data. Healthcare data management and analytics is just one example of technologies like Hadoop, Spark, and NoSQL databases that are the foundation of extracting value from data. Big Data forms the foundation of data systems; Hadoop is a model that allows for the distributed processing of large data-sets across clusters of computers using simple programming models. Hadoop-based tools make it possible to record, store and analyse big data from EHRs, genomics and imaging studies in healthcare. It does well on all kinds of data. And it can also deal with the high volume, which makes it even better at identifying patterns and insights to benefit patient care, disease surveillance, and the planning of treatments. Much of this speed comes from its in-memory computing capabilities that allow Apache

Spark to process vast amounts of data at a high velocity. Developing on DNA spark (eg for example for medical) Though there are especially interesting opportunities of DNA spark in medical: It can compute on data in real-time which is necessary in use cases with real-time requirements: ex: monitoring of patient vitals in ICU ex: make predictions about a disease based on health trends etc. Its fast and precise processing speed powers more sophisticated analytical and machine learning models, which can predict patients' risk, create treatment plans of top quality and span myriad research studies to new medical therapies.

Unlike the organized relational database environment, NoSQL databases are designed to handle storage, management, and retrieval operations on unstructured data formats. Thus, in order to accommodate the diversity of data in healthcare such as text, image, and complex data structure, they are suitable types. As JUGs, having the possibility to share our experience managing EHR, genomics data or information from smart-devices and, according to my humble opinion, be the appropriate choice for personalized medicine and scientific research, for bring/discard this information to the data analysts on time. One of the most significant technologies which is leading to a series of breakthroughs in medicine when we talk of Big Data is AI-ML systems. These models are more than adequate to look into complex data-sets, uncover patterns, predict results and automate decision-making. AI and ML in healthcare leverage the exponentially growing data coming from the eHRs, imaging, genomic sequencing, wearable health devices, etc. They are able to build on the basis of a complementary set of predictive models that will be able to anticipate disease progression, to make a treatment plan tailored to the individual and to enhance the diagnostic process. In contrast, such industry AI algorithms are able to “mimic” human capabilities and analyse medical images to very early detect abnormalities, what is not possible with human analysis by itself.

### **Data Analytics and Big Data**

Firstly, big data and data analytics are key operational areas that enable savvy, business-minded people to lead with innovation and make their organizations more effective. Big Data (in the classic sense) is the raw data (a heavily dense, continuously evolved, significantly complex data lake containing information's aggregated from different sources like user interactions, IoT machines, system logs). Data analysis on the other hand is a general term that encompasses the software and/or hardware tools used to process and analyse raw data to aid in decision making. Sorting and counting of data help us to make decision hence if you ask me below is data science not data analysis. Statistical analysis, predictive modelling, or even artificial intelligence - all these tools can be used to analyse big data in order to find trends and patterns and support strategic decisions. This sort of merger (disciplines) offers companies and organizations a way to get deep with complicated questions and get things done (practical) while using data for strategy creation. The domain of software engineering could be employed as an illustration. Analysis of big data assists in developing software according to the user behaviour and will also strengthen the feature of the software. It advocates toward and supports in the cyber-security market the trend finding and data breach discovery. In addition, inside network management, real time analytics and big data handling of network traffic is used for both performance and security. It's an integration of this scale, which not



only relies on strong computational back-end such as existence of cloud computing and specific types of databases (NoSQL, In-Memory databases etc.), the system also need to possess sophisticated analytics and algorithms to be able to deal with the information on the fly. In essence, linking data analysis with big data in the core of technology is not limited to the treatment of large-scale data, but the definition of new ideas as well as the efficiency level of the process to boost global economic and corporate benefits in the era of the emerging digital world.

### **Big Data Storage and Management**

Consequently, regarding vast technological domains such as big data, the issue of adequate storage and management of the data is paramount to capitalizing on smart data cognizance. This is to the fact that as your data becomes larger and larger, traditional storage systems are no longer sufficient and you have a distributed storage like HDFS and NoSQL are needed. HDFS illustrates how it processes vast amounts of data by spreading its pieces across different servers and thereby distributing fault tolerance and availability along with it. In NoSQL databases, on the other side, the different characteristic of Big Data is considered by letting unstructured and semi-structured data coexist with it with respect to relational databases and thanks to their scalability and flexibility presidia. Therefore, huge data storage will be not limited to storage itself when large data is stored effectively. It also requires understanding and formatting large volumes of data correctly. These days the Apache Hadoop, Apache Spark are getting more and more popular. These technologies give the power of high-performance computation and parallelism to accelerate data analytics, thereby enabling businesses to obtain valuable insights in no time. And management bit further inspects data accuracy, quality, security and privacy. Given the sensitive nature of personal data in areas such as healthcare, finance, and government, strong data governance frameworks are required. The data security, integrity and privacy are guaranteed when appropriate structure compliance with data protection laws and ethical rules. Furthermore, as the growth disk size of storage environments, more complex architecture is employed to store and manage data. Such next generation technologies include cloud storage architecture and Data Lake, which means more efficient and data handling and storage at low cost, helping in building the scale and secure computer platforms. Specially, the technical and foremost fields demand with Big Data are based on multidimensional dimensions as it entails to apply modern technological tools with the right type of strategic planning and the empowerment of governance systems to release the transformation power of Big Data.

## **II. REVIEW OF LITERATURE**

Hu et al., outlined a new method through which medical environments, especially healthcare settings, could manage the load-shedding problem of DSMS. The obstruct of the system breakdown and retard of operator's selective way, the unstable method, is the new point of feedback control theory in this system. This is in effort to prevent memory and CPU resource overflow, to let the system running more efficiently and effectively. The DSMS considers the load shedding to maintain high data processing performance even in high data surges. As the traditional method selects the operations manually from those related operations, it usually requires assistance to dynamically adapt to the load bearing changes, causing power deficiency. In contrast to this, the proposed method aims

at memory-resource limitation, as it effectively prevents system overload and guarantees stability. Rapid decision-making is a fundamental principle in medical IoT, in which the fact that the objective of real-time data processing and precision needs to for solving domain problems. This control method has an advantage over the other control algorithms not being the best in these terms, it's that it is possible to match the coming queries to be quick processes. This approach works towards the optimal trade-off degree of accuracy and system per-for Mance or speed under load thus enhancing the overall efficiency of a DSMS in mission critical medicine applications. Testing the reliability and comprehensive assessment of the approach came up to be introduced to enhance the accuracy of queries and the system stability. Tunnelling medical data stream systems in this manner by using a load-shedding approach ensures that such systems can become unusually efficient and that performance is increased which goes to alleviate the problems of coping with large amounts of information and performing detailed timely processing.

Khazaei et al., precluded an innovative platform, Artemis-IC, which can transform HAaaS. To put together a scalable large amount/high throughput database-driven systems for clinical and research retrospective and real-time analyses for NICU's. The work is a novel and highly pressing study at two-fold, which is emerging with the healthcare analytics urgently needed to drive improved patient outcomes in critical care-supervening conditions. The approach emphasizes a master strategy that can be tailored to various health contexts. This flexibility is important to account for differences in health care settings and specific NICU challenges. The Artemis study is the first application of the framework to the NICU at SickKids Hospital. It enables the real-time tracking and retrospective investigation, acting as a live testing ground to demonstrate the performance of the technology. The investigated technology stack and operational settings were described in sufficient detail, making the study one of the major contributions about a successful implementation.

A prominent example is the pilot of Artemis-IC at SickKids Hospital that illustrates the scalability of the ICU management system and sets performance targets that will be beneficial for widespread deployment. The data rates are large and with estimated data capacities of 8.6 TB storage/year, 32 GB memory, and 16 CPU cores for monitoring all 36 beds in the NICU, also highlights the number of resources a real-time health monitoring system can consume and the difficulty they can present. The expansion that will add 90 beds, for example, will need 16 TB of memory, 28 CPU cores and 55 GB of memory per year. Thus, the admissibility of the patient stratification, that leaves room for up to five risk categories, and the parallel processing of over 500 medical algorithms brings out clearly the decision-making logic to be supported by means of big data processing. This is an important issue for NICUs, since the accuracy and the timeliness of the information per se directly interferes with the ability of NICU care. The research also tackles an important problem in healthcare: resource constraints. There's a chance to assist with that problem and make stark reality starker (46 per cent of patients can't get admitted because of restrictions) in the Artemis model, and that's something should be looked into now. Better resource allocation and predicting what will be needed based on incoming patient data could also help make care available to more people. On the other hand, along these lines, while the technical development and Artemis-IC's promise are awesome, perhaps the research may like to look at the integration issues in a current hospital IT environment, the security problems, and

the ethical issues around data in such intimate settings. But the drawbacks of the system are its user adoption and the training period required to become an expert for the medical professionals to work well in with such advanced systems. This is a key aspect that deserves to be considered in order to make the systems successful from concept to feasibility. Finally, this work offers a scalable solution for data analytical systems deployed in the NICU in order to estimate clinical decisions. The Artemis-IC initiative has, for the same reasons, also become a great case study for other companies attempting to roll out massive data analytics in healthcare. This can result in higher outcomes with technology assisting in the care of patients.

Luo et al., developed the DRESS, a new method to address problematic and complex BBD in healthcare. The challenge is how to implement interoperability between healthcare data and legacy systems, and the processing and conversion of the data into standardized patient-centred electronic health records. DRESS addresses this problem providing a modular solution in which ML and human work together to extract and format clinical data from unstructured medical records. The system, heavily based on cloud technologies, leads us into different steps in the treatment of the data: secure capture & storage, transmission, management and the careful transformation of the data into a semi-structured form in the database. A DRESS system in the clinical setting was illustrated and its reliability and reproducibility were validated using 100 Chinese patient cases with surgical treatment for lung cancer. The assessment engine applied Kappa statistics (for discrete variables), correlation coefficients (for continuous variables) and similar statistical methods. The calculation has given a high reproducibility of 98% between different medical data sets modules. The truth demonstrates the ability to return trusted/predictive electronic health from widely varying and disorganized medical information sources. The development of a DRESS protocol coupled with adjudicating every adjudication task by independent adjudication ensures that the DRESS data capture process is highly accurate and reliable. Aside from that, it utilizes distributed computing and data de-identification approaches for further enhancing the security and privacy of data. The cloud-based structure of the integrated medical system will enable multiple sources of data experts to work together on the analysis of huge volume of medical records. In conclusion, the development of the DRESS project is a new scalable and robust solution that is able to handle the complexity of big data in the health domain and more simply address the gap of patient data availability for clinical research and health service delivery by providing higher quality data.

Zhou and Wang., made a novel contribution to medical data signal compression, which is gaining momentum in a while beneath a great deal of data geared towards sensor intelligence. They are developing a power efficient ultralow biomedical signal compression system for use in sensing and health care analytics. The engine uses a window-based turning angle detection approach borrowed from biomedical signs as a feature point extraction method. This leads to a much-simplified compression process. Data-dependent algorithm simplification reduces the power consumption without any significant degradation in the quality of the reconstruction and the computational burden to perform the reconstruction. During this compression, one particular feature of this compressor, its adaptability, becomes apparent. It is adaptable to the angle threshold for compression in correspondence to the difference between the original and reconstituted signals. With this adaptive



property, the engine can cope well with the diverse behaviors of the signal for different people and channels in one person by enhancing the quality of the signal under specific CRs. This architecture uses the circuit level near-threshold technique and an extra method to reduce consumption at the most. This in turn makes the engine extremely efficient. In both in-lab and real life, the processor would showcase its strength by reducing the ECG signals by 71.08% in average, to squeeze out the percentage root-mean-square difference by 5.87%, overshooting the power consumption rate at 39 NW. These represent huge performance gain over our current best of the state-of-the-art ECG compression engines. They're so efficient in fact, while never sacrificing quality or fidelity. The practitioner of this technology for ECG signal compression indicates that it is applicable for the continuous long-term monitoring of (wearable) sensors. These platforms serve as the basis for ongoing health monitoring and data acquisition especially in use cases prioritizing power efficiency and lower power usage. The design by Zhou and Wang, which requires much less power than others, indicates this is an ideal answer to the question because it can operate continuously and does not require costly battery replacement or frequent recharging. The output of the work is a further significant development for the processing of medical data to support sustainable healthcare technology. Apart from the fact that their compression module has helped to solve the instant pressing issue of Big Data processing in healthcare, it does something more. It also creates a new standard for power efficiency, and for adaptability, in biomedical signal analysis. This resolution will become important for creating health-monitoring capabilities out of pathology and upending the way health-care providers collect, interpret and utilize medical information in the course of diagnosis and treatment.

Saheb and Izadi., conducted a deep-focused scientific review of IoT big data analytics in the healthcare sector. Firstly, it presents the converging nature of IoT and big data analytics while describing how the fusion helps copious health data output from telematic and health informatics. This confluence of fields is instrumental in facilitating data collection, storage, and analysis. Notably, it opens the door to more innovations in the healthcare field. The authors detail the adoption of three technological drivers within this paradigm:

- 1) Computing power
- 2) Accessible and low-cost storage
- 3) Processing this information into the abstract form

Each of these trends plays a crucial role in the efficiency of information handling, making them indispensable for real-life health monitoring systems and predictive healthcare analytics. Fog computing provides a solution to the latency and bandwidth problems inherent in centralized clouds, thus it is well-motivated. It offers a decentralized way of processing data in the vicinity of where it is produced. The study explores the application of these emerging technologies in a number of health care contexts, including the neonatal and critical care units, through a case study of the Artemis-IC project. These examples reveal the potential of IoT big data analytics in revolutionizing healthcare procedures and deriving key insights that might contribute to better patient treatment. By examining the answers both from the interviews with the scientists and from the scientific studies, it would be

conceivable to find the overall pattern in which technology is introduced in quest. The report also consider certain factors such as privacy and security of data, which a relevantly important factors which helps in the provision of quality healthcare services. In addition, it provides some pointings that can be investigated to address these problems for IoT big data systems to improve scalability and performance. Anyhow, in overall, this paper presents a complex interaction of IoT and BDA in healthcare. It is a source of a technology status quo for other large-scale R & D studies and designs in the dynamic technological fields and a summary of the current development status, application status and application potential along a point-by-point approach. The results are beautiful evidence of a paradigm shift ushered in by the IoT and deep data analysis in healthcare, opening the door to individualized answers delivered quickly and accurately.

Venkatesh et al., describe an ingenious protocol for disease diagnosis with the BPA-NB method, which uses the merits of the Naive Bayes Classifiers in handling large volumes of data. This particular approach is well-suited in large data settings and in which an application of Bayes' theorem and the fact that feature dependencies do not fail in practice is considered as a desired property. This is because under this assumption we can achieve to decrease the computational burden and still can process large amount of data (common in health care analytics). Hadoop-Spark can be used as computational tools in the handling of the large data, and we might have a sense of how well the model can be leveraged in practice in large-scale data processing that allows for tremendous speed and scalability. The approach for the investigation used heart disease data from the UCI machine learning repository to train BPA-NB model and it has the ability to predict the disease with an accuracy of 97.12%. Such a high accuracy reveals the stability and credibility of the model in predicting health status. Furthermore, as it offers patients with early disease diagnosis, the model efficiently drives the use of timely and effective diagnosis by the doctors to know the possible future medical complexities. Therefore, the approach emphasizes machine learning as a promising tool towards predictive healthcare and also emphasizes the necessity of integrating high performance computing methodologies to analyze the growing amounts of data in health informatics. The results demonstrate the ability of the BPA-NB model to assist in prediction of the disease. But the condition of feature independence and the generalization to other diseases as non-heart diseases is to be further tested.

Syed et al., gave a state-of-the-art innovative healthcare framework built for AAL and targeted at managing the physical activities of older adults. The architecture relies on the combination of IoMT data with state-of-the-art machine learning methodology, which would lead to expedited data processing and decision-making processes and successful treatment outcome. The system consists in bedside wearable sensors, positioned to vital body areas, such as left ankle, right arm and chest. These kinds of devices also demonstrate the growing importance of IoMT in health care, especially in unconventional health care settings in which continuous monitoring is possible. This shows the increasing importance of IoMT in healthcare, particularly in more related to precision help in the ongoing patient continuous monitoring outside the conventional hospital settings. This framework by Syed et al. is distinguished from the others by using the Hadoop MapReduce techniques. These are approaches that need to be applied to process the sensors data in parallel since they are becoming

more and more data plentiful. This makes further processing much more scalable and powerful. It makes it possible to solve one of the most significant problems when it comes to managing big data in healthcare. The use of the Multinomial Bayes classifier on the presented MapReduce is also very novel. This classifier is dedicated to body part movement and classifies 12 types of physical activity, including running, walking, cycling, etc. Such a system, using the case of its adaptation to a parallel processing architecture, utilizes and integrates well-known big data technologies into a complex healthcare setting. As a framework, Module has achieved an acceptable physical activity recognition of 97.1%. Moreover, it also provides very strong remote health monitoring of the elderly. “These are abilities that are important factors in total health, and they can improve the quality of life and independence of a senior, as they monitor for trends in physical activity that may to reveal certain health issues early on. The use of contemporary technological applications of the study and big data analysis provide evidence the VHC systems are verge to bring revolution in health care delivery. This model is in advance in health of others groups and a model to follow for others pathologies. Therefore, the use of smart healthcare will grow. Nevertheless, there are other areas in which the work of researchers is equally needed: issues of privacy, data security, and the feasibility of combining cutting-edge technologies with established healthcare structures and making them accessible, secure, and useful to all that need them.

Yong., examined the vital role of effective load balancing in cloud networks that manage big medical data. It has several sections including an introduction about the problem, methodology, experiments, results and important findings in order to provide an overall introduction to the research process. Introduction The role of big data is booming in the medical industry as a “game-y” to provide personalized healthcare services through better decision making, patient care and medical operative efficiency. Although handling huge amount of data is a big challenge especially in case of delay while processing the data and load balancing in cloud environments there are works done to cope up with that. In this perspective, the researcher claims that the load-balancing methods designed to achieve a proficient use of resources and reduce the latency in the cloud networks became the main subject of research next to be discussed. In section “Methodology,” the development of new load balancing analysis and its application to medical big data on the cloud environment are provided. The low-delay mechanism is the first choice for medical data processing and patient health data delivery. The technical details of the strategy, the architecture, data flow and the criteria used for the traffic load distribution between the nodes of the network are detailed in the paper. The experimental part of this strategy reads out experimentally the strategies. The experiment consists of comparing the new concept with classical load balancing techniques in terms of throughput, utilized resources, and total time under the conditions of the experiment. The experiment design is based on real-world scenarios that simulate the cloud networking systems. According to their particular demands, these experiments process different scales of medical big data. It was shown that the delay constraints in the authors load balancing policy achieve an optimal throughput globally. It did so through the strategies of reducing speed, making efficient use of resources, and eliminating deficiency, which strongly proved that the strategy is available to deal with much medical data in cloud environments. The findings are reported in tables and diagrams to enhance the readability of the outcomes. Finally,

redepicts the importance of the right load balancing position for medical data management in cloud-based health systems. This approach provides efficient healthcare delivery that allows the real time prompt processing of data and improves the patient outcomes.

Zhou et al., proposed a robust structure for a data processing system in healthcare to be implemented and get the proper decision-making pre-eminence. However, although big data is highly effective in solving problems related to healthcare service, the widespread use of such technology, on the other hand, faces a number of problems, such as the handling of the massive amount, velocity, variety, and variability of data. The core of this research work is dedicated to hottest challenges to be overcome in concerning with integration of sophisticated aspects of health and medical big data. Traditional analytical methods need to interpret this distinction, and they generally neglect the connectedness of disparate data sources, the enabler which leads to productive and enlightening results. To bridge the gap of performance, the authors propose a model fed in a data analysis that learns the data and make connection with the human's knowledge establish to create an intelligent system for healthcare management.

The proposed framework is methodically designed to navigate through five pivotal stages:

- 1) Innovative and personalized data cleaning
- 2) Data fusion with consideration targeted at the analysis
- 3) Mapping the insights drawn out
- 4) Exploratory visualizations
- 5) The output of decision-making reports

Such a systematic way guarantees that information goes through a pantheon of quality because it's not only cleaned and amalgamated but also analyzed and visualized to offer the best strategic advice to the healthcare system. This process act as the predomination from unusual and incorrect data and makes it a solid base for the correct analysis. The developed data are trimmed and merged to a data of custom format from these sources in order to be analysed further. The method mapping in analysis is crucial since it allows to select the most appropriate methods for the given data. This way, the method of analysis will be both effective and efficient. Visual exploration makes complex analysis more comprehensible by delivering the results in a clearer form, thereby enabling stakeholders to get insights from the analysis. In effect, it leads to detail, which is part of a direction, which plays a role in a decision. An insight perspective revealed in the document is the intuitive concept of smart big data which expands the definition of big data with the inclusion of topology or rationalization characteristics. This idea emphasizes the importance of the discovery of our dataset-related hidden interrelations and connections and increases the maturity and prediction power of our analytics. But the difficulty of the study should also be taken into account. The authors acknowledge that it may be difficult and confusing to apply exactly the way it was intended when other sources of health care data are used. In addition, while the framework is already very strong for text analysis, this is an area that the application of imaging and non-text data could be further explored.

Tang et al., in particular, highlight the peer review of extensive data application in environmental health and health services research to create a robust difference between the real studies based on comprehensive data methodology and claims made. Supported by plentiful misinterpretations and misunderstandings as regards applications of data in public health research requirements, this study seeks to dispel and exhibit how the classical characteristics of big data are being satisfied or misunderstood. This can, however, make the policy options valid (or invalid) and bias the decisions of research outcomes in to the bargain. The method was planned to fulfil, at least, the PRISMA-P completeness to the research questions through scoping or systematic review. The results will be described according to the PRISMA for Scoping Review or PRISMA 2020 and the synthesis without meta-analysis for ease of use of generally understandable and accepted result generation. We will perform broad-based search on multiple databases (Web of Science, PubMed, Medline, and ProQuest Central) in order to gather as many relevant research papers. Selection process will be critically reviewed by two reviewers. The eligible ones will be included, the data extracted using R statistical software and text documents into NVivo when necessary. This type of work involving publicly available data (not associated with any sensitive personal information) does not require ethical clearance. The conscious investigation and study of big data applications in specific health sectors is the need of an hour when misutilizations are being identified. Conclusion The big data philosophy is being entrenched in environmental health and health services research that informs evidence-based and appropriate decisions on healthcare.

### **III.        SECURING BUSINESS-TO-CUSTOMER DYNAMIC**

The massive run ramping B2C transactions via cloud computing has brought more attention to security issues and reliable computing in the recent industry landscape. This data is not just a promising one indicating expansion potential, featuring a mobile workflow where transactions are completed, but dramatically out-of-control chaos in which there is a very real risk on consumer privacy. This restiveness provides the booting data for launching attacks on the individual users' databases by the bogus marketers who obtain internet connections for market penetration and fabricate markets and demand. Antibusiness interactions among intermediaries are becoming increasingly intricate, and these new technologies are creating a channel leading to targeted and low-cost data leakage. It is now a serious question of how to defend the system against those attacks.

The Blockchain itself is a quite effective way of accidentally solving the security issue in the business-client workflow. Its enhancing security options are helpful when securing information that is so hard to keep private due to complicated digital threats in today's world. There is a growing body of literature supporting the use of Blockchain in B2C record management. Nevertheless, such technology is not yet sufficiently adopted in the business environment, as any other issue on records management application, including document security, the confidentiality of data and the integrity of data.

In order to the deal with these challenges, our study proposes a DDSS based on Blockchain technology that is designed to process secure executed transactions on imprecise in B2C business sectors. For that we use federal encryption, in which users can verify the identities of entities they



have been interacting with and the transactions. Encouraging it to function so transparently and tamper-evidently is one of the responsibilities of the smart contracts (or chain codes) that define how the security measures are implemented. Although the solution of the DDSS is most-effective<sup>32</sup>, it also can safeguard the data much better from current threats that may appear in B2C transactions by regularly improving the data confidentiality and integrity, which is very big progress to the enterprise protection campaign against cybercrime.

#### IV. CONCLUSION

In conclusion, Big Data represents more than just large volumes of information it signifies a technological and analytical shift in how organizations understand and leverage information. The six Vs describe the different dimensions of big data that together define the unique qualities and requirements of modern data environments. As digital information continues to grow at an explosive rate, traditional systems are no longer sufficient and we turn to emerging technologies for storage, analysis and processing of data. Through tackling issues of data verity, variability and velocity, businesses can realise substantial value. It's a battle plan, in other words, that is making for smarter decisions, operational innovations, and sustained competitive advantages in any sector.

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