Information Systems in the 21st Century: Managing Big Data for Easy Decision Making

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ABSTRACT

The confluence of information systems, cloud computing, the internet, mobile devices and the Internet of Things has resulted in massive volumes of data, referred to as big data in Internet of Things (IoT). A combination of structured, semi-structured, and unstructured real-time data is used in data warehouses, Online Analytical Processing (OLAP), Extract, Transform and Load (ETL), and information. Businesses and researchers have developed their own approaches for extracting value from big data, and using enormous datasets as a supplement to decision-making has a lot of promise. The goal of this research is to look into how big data can help people make better decisions in these areas that will bring better performances in business firms. The use of big data to make smart, real-time decisions to improve company performance will be examined. The research goes through literature reviews and secondary data to offer a conceptual overview of potential opportunities for big data especially in decision making. In this research, the concept of big data, its role in decision-making, and the competitive value of big data for various enterprises, particularly in the twenty-first century, are all examined. The paper further discusses a methodology for dealing with data and information systems in decision-making. Businesses must address this issue in order to make better decisions that will lead to higher-quality knowledge and improved performances.

Keywords: Information Systems, Big Data Analytics, Real-time data, Internet of Things (IoT), Data Warehouses

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1. INTRODUCTION

Over time, information systems have progressed from transaction recording systems to assisting business decisions at various levels. For making business choices, traditional information systems relied heavily on internal data sources such as Enterprise Resource Planning systems (ERPs).

These datasets were organized and managed with the help of a Relational Database Management System (RDBMS). These were utilized to support internal business choices including inventory management, pricing, identifying the most valuable consumers, and detecting loss-making products, among other things. In addition, this data was used to create a data warehouse for analysis and mining. Using Enterprise Application Integration (EAI) platforms, these data sources were combined with data from business partners such as suppliers and customers. Business partners were able to seamlessly integrate their information systems thanks to EAI. It improved the speed of business-to-business transactions, improved communication, and lowered the cost of inter-company transactions. The emergence of the internet in the early 1990s, the following wave, substantially facilitated the integration of businesses with their business partners.

Information systems, along with the internet, cloud computing, mobile devices, and the Internet of Things, have resulted in vast volumes of data, generally referred to as big data, in the previous decade. It consists of data warehouse, OLAP, ETL, and information, and comprises structured, semi-structured, and unstructured real-time data. Statistical approaches have enabled computer science to store and process massive volumes of different datasets. Businesses and academics have devised their own methods for extracting value from big data. The goal of this paper is to look at how big data can help you make better judgments and how you can utilize it to make smart, real-time decisions to improve company performance.

The revolution in big data analytics is far more powerful than earlier analytics. When managers use big data, they may make better judgments based on evidence rather than intuition. Businesses are amassing far more data than is required for any one purpose (McAfee et al., 2012); big data aids in generating better predictions and judgments. Big data is being used by executives in a variety of businesses to improve management methods. Various studies have been undertaken in specific domains such as transactional data, social media data, supply chain big data, and so on. However, there is a dearth of a comprehensive examination of the possibilities of big data for decision-makers. We investigate the function of a range of big data in diverse decision-making scenarios in response to this need. This term paper fills in the gaps by accomplishing the following goals:
a) To review the existing literature on big data's underlying concepts and role in decision-making.
b) To investigate the role of big data in strategic, tactical, and operational decision-making.

The research can be used to make vital decisions using large data. Big data is now being employed in a variety of business and educational settings. As a result, better predictions and decisions have been made in such organizations. The next section examines the existing literature on big data and how it is gaining importance in business and society. Different definitions of big data from big data and analytics experts have been studied and various classification systems for analytics applications have been discussed. The third segment delves into the different applications and advantages of big data. In this research paper, a critical look is taken to see how various organizations, such as banks and businesses, have been able to collect, analyze, and use big data to improve their business performance. For some of the world's most successful companies, the role of analytic-based decision making using big data is nothing new. However, there are still many small and medium-sized businesses that can benefit from this new industry. In the fourth section, big data conceptual framework is described that companies can use. This framework could serve as a starting point for them to fine-tune a model that is appropriate for their enterprises. Finally, in the concluding section, findings have been summarized and recommendations made for further research.

2. REVIEW OF RELATED WORKS

In this section, existing literatures are examined to see how companies are employing big data for analysis and decision-making. Identified terms such as "Big Data," "Big Data and Decision Making," and "Big Data Analytics" are discussed after establishing the objectives of this study. We sifted through research papers published in prestigious journals, conference papers, and online sources to find the most relevant publications. Scopus, Science Direct, and Google Scholar databases were used to pick high-quality research papers.

2.1 What is Big Data?

Big data has been defined in a variety of ways by various authors. Boyd and Crawford (2012) characterize big data as a cultural, technological, and intellectual phenomenon, while Fan et al. define it as the ocean of information (2014). According to Kitchin, big data is defined as a high volume of structured and unstructured data (2014). Waller & Fawcett (2013) describe big data as datasets that are too large for traditional data processing methods and so require new technologies to process. Dubey et al. (2015) define it as "standard enterprise machine generated data combined with social data." Big data refers to the massive amount of data – both structured and unstructured – that inundates a company on a regular basis. However, it is not the quantity of data that is important. What matters is how businesses use the information. Big data may be analyzed for insights that can help you make better business decisions and strategic moves.

According to Dyche (2014), big data is simply millions of data that can be analyzed using technology for many people. Big data, in its actual sense, is the proper use of data through technology in any given element. Big data became popular in the first decade of the twenty-first century, with online and startup enterprises being the first to utilize it. Speech, text, log files, photographs, and videos have all become new types of data (Davenport and Dyche, 2013). When handled effectively, big data can be used to enhance decision-making in a variety of ways. Different methods and technologies might assist you in making better selections.

Companies such as Amazon and Netflix have developed algorithms to detect the relationship between user searches and previous purchase history in order to predict what they are likely to buy. Customers are prompted to recall past searches or are given product recommendations based on their purchase history. Customers are more likely to purchase some of the recommended products, which means greater money. As much as a third of their new sales come through this strategy (Artun and Levin, 2015). Telecom companies sift through massive amounts of data to predict which customers will abandon them. This makes it easier to create customer retention policies.

2.2 Five Vs of Big Data

The practice of collecting and storing enormous volumes of data for later analysis has always been in existence but the term "big data" is new. When industry analyst Doug Laney described the now-mainstream definition of big data as the three Vs – Volume, Velocity, and Variety – in the early 2000s, the concept gained traction. Big data is now defined by five V's, as shown in Table 2.1 below, after further refining.

Table 2.1: Five V's of Big Data

Characteristics	Description
Volume	Every forty months, the volume of data in terabytes or petabytes doubles. (Davenport, 2014)
Velocity	In every firm or organization, the rate of data accumulation is rising.
Variety	Examples of data sources include enterprise systems, social media, text, video, audio, email, RFID, web applications, and other digital devices are just a few
Veracity	The need for Quality of Data is very important for effective decision.
Value	Value can be extracted from heterogeneous data, economic and social outcomes can be enhanced.

SAS, a renowned data analytics organization, considers two additional aspects when it comes to massive data: *Variability and Complexity*. In addition to increased velocities and types of data, data flows can be highly irregular, with frequent peaks. Is there a trending topic on social media right now? Peak data loads, whether daily, seasonal, or event-driven, can be challenging to manage, particularly when dealing with unstructured data. Complexity - Today's data comes from a wide range of sources, making data linkage, matching, cleansing, and transformation across systems difficult. Relationships, hierarchies, and various data relationships must all be connected and correlated, or your data will spiral out of control soon. Big Data Can Be Found in a Wide Range of Sources. In addition to traditional information systems, big data comes from a variety of sources, including social networking sites, cloud applications, software, social influencers, Data warehouse appliances, public, network technologies, legacy documents, business applications, meteorological data, and sensor data. Further down, a few sources are discussed.

A. Transactional information

When paired with statistical approaches like Regression Analysis and Decision Trees, transactional data can be used to help construct a model for predicting a certain event, such as sales projections or the success of a new product launch. Based on historical data inputs, the model may be able to forecast dependent variables. These models can be easily created using statistical software such as SPSS or SAS. A 'Transactional Processing System' keeps track of all prior data with independent variables and is referred to as a 'Transactional Processing System.' A Transaction Processing System's main objective is to collect and update data in order to make operational decisions in a business. The two ways for processing transactions are batch processing, which processes data as a single unit over a period of time, and real-time processing, which processes data in real time. Both methodologies are useful for making operational decisions in any firm.

B. Information from Social Media

As social media has grown in popularity in recent years, data has been collected from all corners of the globe. Events are being reported as they happen. In a couple of minutes, netizens can voice their ideas, product or service feedback, and movie reviews on Facebook, Twitter, or WhatsApp. This is a once-in-a-lifetime opportunity for decision-makers to gather market intelligence.

Customers can make purchasing decisions by looking at comments, customer complaints, and other services offered with a product that is shared on social media. Social media also conveys consumer mood, which helps businesses make manufacturing decisions. Competitive intelligence on a company's product and services, as well as those offered by competitors in a certain market category, can be obtained through social media analytics. In order to optimize the company's life cycle, this also fosters new business concepts. As a result, social media analytics play an important role in strategic, operational, and tactical marketing decisions.

C. Web-based Applications

With the advancement of the internet, millions of people are accessing a variety of websites, resulting in massive click streams and web searches for products and services. Millions of individuals log in and use a variety of online ecommerce websites (such as Amazon, Flipkart, Alibaba, eBay, Paytm, bookmyshow.com, and so on), search engines (Google, Yahoo, Bing, and so on), and online banking programs on a regular basis. During their searches or transactions, several click streams and records are generated, which could be beneficial.

D. Information gathered through electronic instruments

Electronic media that generate vast amounts of data include smart phones, Radio Frequency Identification (RFID) tags, GPS sensors, networked equipment, scanners, and cameras, to name a few. Here are a few more big data resources.

2.3 Analytics of Big Data

Big data analytics has emerged as a vital tool for supporting decision-makers. Big data discovery operations, according to Dyché (2014), can uncover previously undiscovered outcomes, resulting in insights that can improve management decision-making. Prior to the emergence of computers, people's ability to store and analyze data was limited. Because enormous volumes of data could not be collected, there used to be professionals who made decisions based on their instincts; nevertheless, these intuitions were not always correct Duan & Xiong (2015).

In this era, big data has resulted in increasing data volume, velocity, and variety. In terms of statistical dependability and model advancement, this has simplified data analysis (Chen et al., 2012). Big data analytics is used to make decisions in e-commerce, e-government, politics, science, technology, health, security, and public safety through database segmentation, graph mining, social network analysis, text analytics, web analytics, and sentiment affect analytics, criminal network analysis, cyber-attack analysis, multilingual text analysis, health analytics, and patient network analysis. The multi criteria decision making tool facilitates in decision making in the health business by giving a decision support tool that helps to grasp the full evaluation process (Venkatesh et al., 2010). In data warehouses, RFID tags are employed and can be integrated into the logic and activities (Zhong et al., 2015).

Big data analytics has a significant impact on company value and firm performance, resulting in cost savings, lower operating costs, better customer interactions, and the creation of new business ideas. The use of advanced analytic techniques to store massive data sets is referred to as big data analytics. Advanced Analytics prepares large amounts of data so that consumers may make educated judgments Russom (2011). The analysts compare past data from the data warehouse, allowing them to draw more accurate judgments. It's not only about data volume when it comes to big data analytics; it's also about data variety.

Only a small percentage of the population is familiar with concepts like predictive analytics, advanced analytics, and big data analytics, according to a survey conducted by Russom (2011). Big data analytics technologies include RDBMS, data warehousing, data mining, clustering, association, OLAP, BPM, ETL, regression, classification, analysis, genetic algorithm, multivariate statistical analysis, and heuristic research. Customers gain from big data in the form of helpful information as well as business analytics and tailored analytic apps. Despite the benefits, employing big data analytics to make judgments has a few drawbacks. The insufficiency of people to handle advanced analytics for decision making, a lack of business support, and frequent database software difficulties are all examples of these drawbacks.

2.3.1 Classification of Analytics

Generally, descriptive, predictive, and prescriptive analytics can be separated into three groups based on their intended use. Descriptive analytics makes use of reports and dashboards to explain a phenomenon based on past data, making it easier to understand what happened. We can use predictive analytics to see what will happen in the future. It allows for historical data-based forecasts, as well as correlations and patterns between variables. Predictive analytics is another useful tool for executive decision-making. It aids in the comprehension of diverse outcomes in various situations. It incorporates a number of techniques, including optimization, simulation, and what-if scenarios using an alternative set of input parameters. Managers may make well-informed decisions if they have a solid awareness of expected outcomes and the ability to plan ahead of time for contingencies. The sources of data have a significant impact on how you can use them for analysis. Analytics can be classified as Text, Audio Video, Web, or Network analytics depending on the data source.

a) Text Analytics

Document representation, enterprise search systems, search engines, user models, relevancy of feedback, query processing', billions of customer searches on Google for a certain product, and searches on Amazon's website provide an indicator of the consumer's intent to purchase the product. Amazon, Jet Airways, and many other ecommerce companies utilize this feature to recommend products or flights to customers the next time they visit their website, increasing the possibility that they will make a purchase.

b) Audio and Video Analytics

Audio analytics is a technology that can track a wide spectrum of sound in the environment and processes audio in seconds for the purpose of safety in any firm. Video analytics is a method of evaluating and processing videos from a variety of industries and businesses. This makes it easier to extract events that can be used to make operational decisions.

c) Web-based analytics

Amazon uses data mining techniques to glean insights from massive amounts of data such as click streams, site searches, order history, and online activity. This intelligence is utilized to make product promotion decisions, which has proven successful for corporations such as Amazon. A correlation is established between previous purchase history and probable future purchases based on comparable historical purchases. This correlation is used to identify and promote to potential buyers via digital media such as emails, Facebook, and Amazon.com flashing messages.

d) Analytical Networks

Network analytics gathers information on the devices connected to a network and how they interact. This information aids in the development of network policies as well as the implementation of actionable decisions that improve company performance and reduce costs.

2.4 Big Data Analytics Technology

As business competitiveness has grown, so has the demand for speedy information and data analysis. Schläfke etal (2012). Rapid data analysis leads to a greater understanding of the situation and, as a result, better decision-making. The application of analytics to forecast the amount of disease and infection risk is being aided by technology. Big data, according to Shein (2012), can be an effective tool for making medical decisions. The hospital collects data from technical equipment that monitors premature births. There is an enormous amount of data that people are unable to analyze. As a result, technology's role may be discerned. Structured data looks for trends that can help predict the onset of diseases and reduce the length of time a patient spends in the hospital. New algorithms may be able to link changes in a patient's behavior to an infection.

3. ROLE OF BIG DATA IN DECISION MAKING

In today's world, business executives face high customer expectations, strong competition, rising labor and material costs, and shorter product lifecycles. As a result of globalization, the borders between countries are becoming increasingly blurred. Market access is no longer restricted by geographic location or distance from the market. Businesses must constantly monitor for dangers and possibilities and make swift business decisions based on current knowledge in such a turbulent environment. Traditional "small data" and "big data" will be looked at and it can help in making better business decisions in this section.

3.1 Traditional Decision Support Systems

Traditional decision support systems (Davenport & Dyché, 2013) helped companies make internal decisions based on data supplied by transaction processing systems like ERPs. Similar systems on both the supply and demand sides were introduced throughout time (SRM and CRM). These technologies aided in the integration of the company's internal operations with their commercial partners, such as suppliers (like Ariba) and customers (e.g. Siebel). All of these systems relied on relational databases to store well-defined structured data.

These decision support systems were used to make operational and tactical decisions within the company (e.g. how to price the products for optimizing sales, status inquiry of orders, inventory planning, cost analysis, outstanding balance payments according to their due dates). As a result of this knowledge, internal decisions were more precise and faster. Traditional data sources were employed as inputs in data warehousing and data mining procedures. A main transaction database, a data warehouse that saves extracted data and separates it into smaller databases, and a data warehouse that stores and categorizes that data were all part of the overall architecture. Additional data mining tools can be used to these datasets in order to extract business intelligence. In a significant amount of data, data mining was utilized to assess and find patterns, correlations, and association rules (Han et al., 2011).

3.2 Advantages of Using Big Data in Easy Decision Making

As a result of the arrival of big data, CEOs' information requirements have transformed in recent years. Huge datasets in organized, semi-structured, and unstructured formats are available from a variety of sources in addition to the standard datasets discussed above. Companies can use these datasets in a variety of ways to make strategic, tactical, and operational decisions. When business transaction data is mined for association rules, it can provide decision makers with useful information about products bought together or forecast demand for specific things. Understanding trends allows retailers like Wal-Mart to rethink their isles and product positioning, which leads to higher sales (Shaw et al., 2001). Predicting demand for specific commodities allows for better planning ahead of major natural disasters like hurricanes (Shaw et al., 2001). The analysis of terabytes of data from aircraft engines gives part failure warnings, enabling for improved maintenance and safety (Dyche, 2014). Big data insights lead to knowledge, prediction, and actionable decisions, as seen in the table below.

Table 3.1: Big Data's Role in Decision-Making

Sources of Big data	Big data driven Insights	Actionable Decisions	Reference(s)
Google search for a product or brand	• Determine customer desire to purchase a specific product. • Determine customer preference for a specific brand.	Predicting demand for product	
Google search by specific key words	What exact information are citizens looking for or concerned about	Predict spread of flu by geography or by regions	Mayer-Schönberger & Cukier, 2013
Amazon search	Intention of Customer to buy a specific product	Setting a reminder for the customer the next time he or she visits the site, increasing the likelihood of a transaction	Amazon.com website
Sales' history of Amazon	Identification of different products bought by customers using association rules derived from billions of records.	Advice on a product (customer who bought this also bought some other items).	Amazon.com website
Sources of Big	Big data driven Insights	Actionable	Reference(s)

data		Decisions	
POS data (Walmart)	• Identifying products customers buy together (market basket analysis) using association rules mined from billions of records. • During disasters like hurricanes, individuals buy certain strange items such as pop-tarts, in addition to the normal water, batteries, shovels, and so on.	• Stock planning based on purchase trends prior to calamities such as hurricanes • Redesigning store layouts to place such products together	• Waller & Fawcett, 2013. • Dyché, 2014
Social media provides competitive intelligence.	Analysis between competing products.	Plan product strategy	Vries et al.,2016
Data from UPS Vehicles' telematics sensors.	Speed, route, direction, braking, and drive train performance data.	Route redesigns have resulted in millions of gallons of gasoline being saved.	Davenport & Dyché, 2013
Logs from call centers and account usage on the internet.	Create complete profile for customer journey	Strategies used for customer service for the future.	Davenport & Dyché, 2013

3.3 Understanding Customer Journeys

As shown in Figure 3.1, leading banks such as Wells Fargo, Bank of America, and Discover leverage big data from a variety of sources to better understand their customer connections. Structured, semi-structured, and unstructured data are combined from call center logs, website clicks, transaction records, ATM transactions, and clickstreams, among other sources, to provide a complete profile of a customer's trip. By connecting client journeys with opportunities and concerns, this profile assists them in discovering the causes of customer attrition. (Davenport & Dyché, 2013).

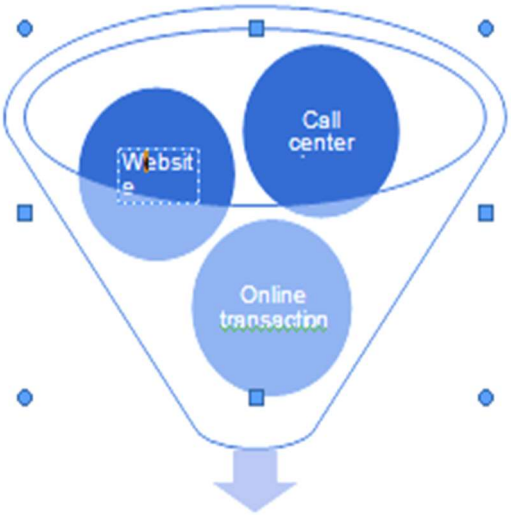

Figure 3.1: Profile of Customer journey

(i) **Competitive Intelligence**
Several studies have been conducted using social networking platforms to better understand customer moods, attitudes, and opinions. In addition to what customers think about their own products, Business Executives need to know what customers think about their competitors' products. This data will aid in the development of future product enhancements as well as the establishment of a product marketing plan. Mining social media data can provide a comparative analysis of customer sentiments and sales performance of a company and its competitors. Similarly, Google's trends analysis can be used to compare product searches for two or more competing products. These stats show how different products, services, and individuals are searched for on the internet in different parts of the world. This data can aid in product awareness as well as the formulation of future marketing strategies or new product launches. There are websites like sentiment 140.com that provide you a sense of how this data can be used.

ii) **Cost and Time Savings**
There are numerous opportunities to save money and time by utilizing big data. Big data technologies, such as Hadoop clusters, are proving to be significantly less expensive than traditional databases. It can assist with making real-time decisions about which products and services to promote to customers based on their current locations. UPS saves millions of dollars on gasoline by collecting, assessing, and adjusting its vehicle routes based on data from telematics sensors installed in its 46,000 vehicles Davenport & Dyché, (2013).

iii) **Supply Chain Optimization and Simulations**
Supply chains are becoming increasingly complicated as a result of the large number of suppliers and business partners. Members of the supply chain have put in place enterprise systems that keep track of every transaction over the last two decades. As EAI progresses, information is shared among business partners such as suppliers and customers. The efficient transportation of goods across supply networks relies heavily on technology.

With inventory movement, scanning equipment like sensors and RFID, position tracking devices like GPS, video recordings, and other technologies generate massive amounts of data. By providing an integrated picture of data across the supply chain, supply chain analytics increases decision-making capabilities. We can extract, convert, and analyze data, as well as conduct analytics to derive information, within the supply chain system. Dashboards, pattern and trend analysis, dig down views, predictions, knowledge base, scenario and what-if analysis, simulations, and optimization capabilities are all available with supply chain analytics. These aid firms in making better decisions and analyzing circumstances, both of which are essential in today's competitive business world. (Nair, 2012).

iv) **Forecasting Future Results**
Datasets can be used to forecast future outcomes in a variety of ways. Analytics frameworks can be created to evaluate various datasets and produce predictions:

a) Future sales can be forecasted for a firm's product or service using forecasting models such as regression based on historical transactional data.

b) Identification of products that are purchased jointly by customers based on past purchase correlations. Predict which product a consumer is most likely to buy based on these connections and their purchasing history, and provide online recommendations. (Artun & Levin, 2015; Artun & Levin, 2015; Artun & Levin, 2015

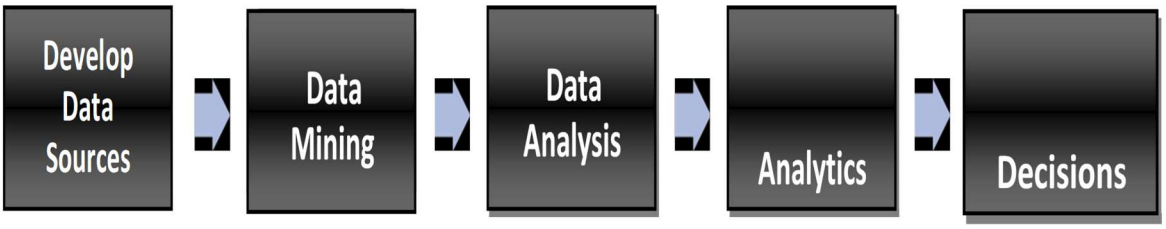

Figure 3.2: Conceptual Framework on Big data and Decision Making
Source: Jeble, S., Kumari, S., & Patil, Y. (2017)

Analyze historical data, look for patterns in customer attrition, and figure out which variables lead to customer attrition. Predict which clients are most likely to abandon ship and take aggressive measures to keep them. (Artun & Levin, 2015; Artun & Levin, 2015; Artun & Levin, 2015 Predictive analytics can be used in a variety of ways, including projecting which customers are most likely to buy particular products based on their previous purchases. In addition, illness outbreaks in specific geographic places can be anticipated using Google searches.

Decision Making in Real time

Numerous foresighted businesses have developed capabilities for real-time decision-making based on supply and demand data. They have online real-time decision-making capabilities that traditional business models cannot match thanks to analytics. For instance, Uber leverages big data to optimize real-time vehicle routing and enhance the client experience throughout a journey (Woodie, 2015). Ola and Uber rely on Google Maps to provide customers and cab drivers with real-time information. They receive a continuous stream of data on high-volume cab demand as well as cab availability in various locations. They provide demand management strategies that are informed by real-time data on demand. Beeline, a demand-driven, shared private transportation concept powered by data analytics and mobile technologies, has been unveiled by the City of Singapore. This technology identifies potential travel routes based on crowd-sourced travel patterns and transportation data and dynamically allocates buses to routes based on demand patterns. This significantly reduces commuter travel time and encourages the use of shared transportation (Askari, 2015).

4. BIG DATA VS DECISION MAKING:

Conceptual Framework

The conceptual framework for organizations who want to establish analytics practices for their business to assist business choices in many areas is presented in this section. Several top companies, as mentioned in the previous section, use analytics in one or more elements of their business. Several small and medium-sized businesses are yet to implement analytics to obtain a competitive advantage. We've created a platform to help these companies integrate analytics into their daily operations. Once the company's analytics practice is established, we recommend that this function be led by a senior executive. This will ensure that essential data analysis insights are leveraged in decision-making. Analytics can also be used in Performance Measurement Systems such as balanced scorecards, real-time dashboards, and Key Performance Indicators (KPIs). Many authors have investigated various ways in which big data plays a crucial role in analytics, which in turn provides insights for decision making, based on literature reviews. The road from big data to decision-making is depicted in Figure 3.2. The constructions are covered in depth further down. Figure 3.2 displays a link between five constructs; develop data sources, data mining, data analysis, analytics and decisions between “big data and decision making in business firms” in a conceptual framework.

Establish Data Sources

Business systems, customer data, supplier data, social media data, and logistics trajectories, are examples of traditional data sources. It is pertinent that a company must establish an information systems architecture and processes to collect data from a range of sources in accordance with its business strategy. A Corporation that focuses on designing and constructing new items, for example, will collect data on supply, distribution, and logistics. A logistics company will gather information about its fleet's movements, packages, and routes, among other things.

Data Exploration

Data mining is a technique for identifying patterns in huge datasets by combining statistical approaches, computer algorithms, and database systems. It aids in the extraction of useful information from data. Following the establishment of data sources, a data warehouse will be built to store multi-dimensional data for query and analysis purposes, based on analytics requirements from various departments. Finding previously unknown patterns, correlations, and associations between distinct variables can be aided by mining these datasets.

Analyze the data

Having a large number of different datasets is important, but it is not enough. To gain insights from data, the company must establish analytic capabilities.

The firm must build an analytic team with various interdisciplinary skills, such as:

a) knowledge and experience with statistical tools such as R software, SPSS, SAS, and others.
b) programming capabilities
c) domain understanding of business processes
d) SQL data management skills
e) data analysis experience Using domain expertise and data analysis, many analytics project opportunities can be identified.

Analytics

As previously stated, businesses can use three sorts of analytics: descriptive, predictive, and prescriptive. Businesses may adapt their needs in order to improve their chances of recruiting new consumers, maintaining existing customers, or identifying business concerns. Business analytics is a collection of concepts, statistical techniques, and computer algorithms used to derive meaning from data. All of the major software companies, including IBM, SAP, Oracle, SAS, SPSS, and R, have produced data analysis and model development tools. Hadoop is a platform for developing models using data from a variety of sources.

Making a Decision

Business analytics is gaining appeal as a tool for businesses seeking to enhance their customer service, retention, and acquisition success. Predictive analytics enables us to estimate future events using available data. This provides a competitive advantage to a business by allowing it to prepare ahead. Data patterns, correlations, and linkages can aid in increasing sales performance, locating the right clientele for products, and segmenting the market. Every domain in which data may be collected has an analytics application. Supply chain analytics are provided for inventory optimization, procurement planning, demand forecasting, fleet and route sizing and optimization (Nair, 2012). Social media data provides competitive intelligence, new product ideas, and reviews of existing items, all of which are critical for defining future strategy (Bell, 2012).

The discovery of large amounts of data can produce unexpected and actionable findings (Dyche, 2014). The primary goal of data science is to empower managers to make more informed business decisions (Provost and Fawcett, 2013). Leading firms such as Amazon, Wal-Mart, Google, and Netflix have perfected the discipline of forecasting, simulating situations, and gaining insights through data and analytics. Amazon and Wal-Mart use analytics to make judgments across several parts of their businesses, from demand generation to effective supply chain management.

5. CONCLUSION AND FUTURE RESEARCH DIRECTION

Information revolution has longed changed the way businesses work. Big data is supporting organizations in achieving a competitive advantage by using various analytical approaches. These methods aid us in gaining insights, patterns, relationships, and interconnections that would otherwise be impossible to comprehend with traditional data. Corporate leaders may make more informed decisions by leveraging social media data, competitive intelligence, cost-cutting strategies, supply chain analytics, and web analytics, among other tools. Companies who recognize the value of big data and develop solutions around it have received major benefits in recent years. Many firms employ analytics in almost every aspect of their operations to reap the benefits of analytics-based decision making. In this paper, we suggest a conceptual framework for developing analytics capabilities, as well as how this rising knowledge might help small and medium firms compete with fewer resources. It can be applied by such businesses with minor modifications based on their industry and business style. This framework can be used as a foundation for additional research, development, and analysis.

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