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Managing COVID-19: Looking into a Decision Support System for COVID-19

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Abstract

In 2020, the world faced a new threat when SARS-CoV-2 was introduced in Wuhan, China. Immediately, mathematicians, computational scientists, and others began to work on supporting technology to provide medical professionals and others with the assistance and backbone necessary to fight the pandemic. Enterprises rely on business intelligence (BI), which is a combination of sequenced structured, unstructured, and semi-structured data that can be used in business intelligence (BI) from numerous sources that embody a complex and multi-stage process often managed by information technologies. Extensive effort in leadership, technology, and methodology must also be combined to complete these tasks as the massive amounts of data collected most often require the use of advanced data management tools such as big data, machine learning, or artificial intelligence (AI) with advanced neural networks and the Internet of Things (IoT) to formulate a sustainable decision support model for the enterprise. Current data analysis models are simply unable to handle the enormous amounts of data required to process day-to-day data analysis for any enterprise. Regard the data as the raw ingredients necessary to create a decision support system (DSS) to manipulate or create a sustainable DSS or DSS model; however, a reduction in the cost of labor and supplies, decreases the amounts of time involved in performing the decision-making cycle, and speedier responses are generated from the workers. In this paper, we look at all aspects of deep technologies associated with DSS during the Covid pandemic.

Keywords: deep technology, big data, COVID-19, decision support system, business intelligence, artificial intelligence, data warehouse

Introduction

A common data repository data warehouse (DW) is used to store historical data, and other information such as storage of stocks, raw materials, deposits, and other information related to daily business operations (Falih, Jabir, & Rabhi, 2021). While the architecture of such a system should be aimed at data management, the process has been developed for business intelligence—business decision-making using organized, stored historical, and categorized data. A sequence of structured, unstructured, and semi-structured data can be used in business intelligence (BI) from numerous sources that embody a complex and multi-stage process often managed by information technologies. Extensive effort in leadership, technology, and methodology must also be combined to complete these tasks as the massive amounts of data collected most often require the use of advanced data management tools such as big data, machine learning, or artificial intelligence (AI) with advanced neural networks (ANN) and the Internet of Things (IoT) to formulate a sustainable decision support model for the enterprise (Ponomarev & Mustafin, 2021). Current data analysis models are simply unable to handle the enormous amounts of data required to process day-to-day data analysis for any enterprise. Regard the data as the raw ingredients necessary to create a decision support system (DSS) to manipulate or create a sustainable DSS or DSS model; however, a reduction in the cost of labor and supplies, decreases the amounts of time involved in performing the decision-making cycle, and speedier responses are generated from the workers. A DW is not a DSS, but simply the framework by which a DSS is built (Ponomarev & Mustafin, 2021).

DWs use technologies that increase the availability of data from multiple sources so they may be compared and analyzed to ensure that an enterprise can use the consolidated data to make solid decisions about financial matters, manufacturing, supply chain matters, etc. (Simion & Vasile, 2017). This creates a noisy data which is both cluttered and out of sync and requires a great deal of local cleaning of the data so that accurate algorithms and computational data can be gathered from the database, models, etc., to improve the volume and constraints of the system and foster decision-making by corporation executives who can make better decisions related to the development of a business structure or further daily operations and reduce the complexity of the DSS (Mora et al., 2022; Ponomarev & Mustafin, 2021). Furthermore, database applications can increase the reliability and efficiency of the end-user and their decision-making skills; and store, update, and get answers via reports and other tools (Lupei et al, 2022). However, this complex decision support system development process requires significant efforts from other methodologies and technology. Much work is required to highlight the decision support system framework and formulate a DSS configuration. Typically, there are five distinguished DSS frameworks: a) data-driven; b) model-driven; c) document-driven; d) communication and group-driven, and finally, e) knowledge-driven (Aggarwal, Goswami, & Sachdeva, 2021; Ponomarev & Mustafin, 2021).

Decision Support System Models and Decision Making

With the widespread use of DSS in making decisions by corporate executives, the continuous influx of information technology into decision-making models must have some input from educators (Rusliyawati, 2021). Most educational database systems use some form of DSS which can achieve some type of simple analysis and data management. This type of system can, however, collect simple education-related information and perform statistics on the sample data. Most colleges and universities have established a local DSS that works well in that area (Rusliyawati, 2021). Below, Figure 1 (Wang, 2021) explains a conceptual model of a DSS with a decision-maker at the forefront. It is necessary to have a strong configurable and service-oriented conceptual model to build a subsequent strong conceptual model forward (Wang, 2021; Yang et al., 2022). The core of this conceptual model is services. All conceptual models should offer services as the core of their build. There are several types of services to be offered including a) data access services; b) services-applied models; c) solver services (Wang, 2021; Yang et al., 2022).

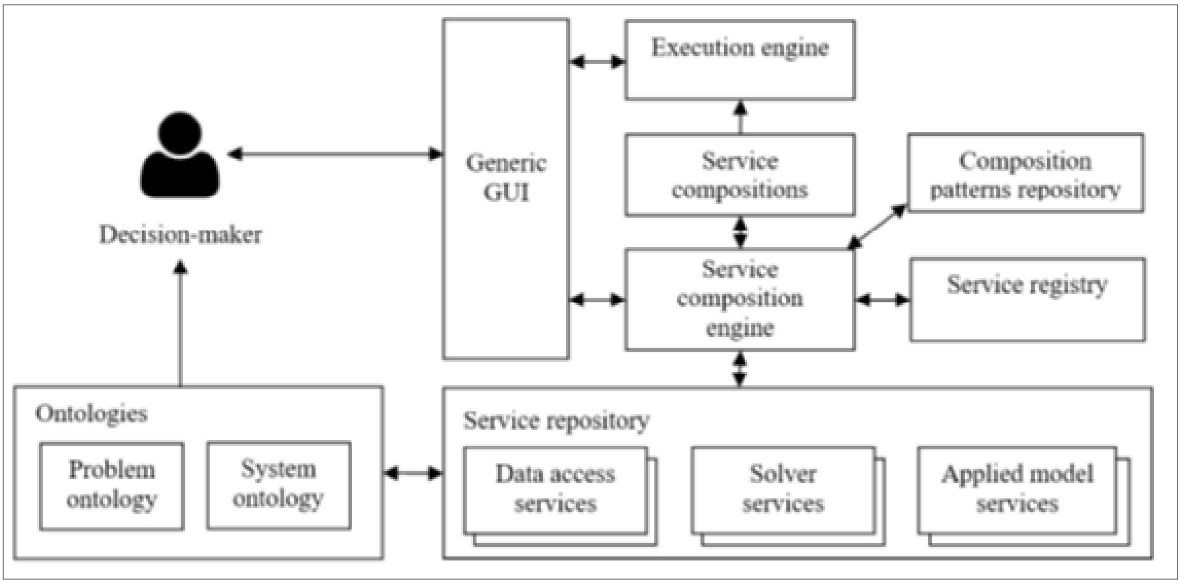

Figure 1: The Conceptual Model of User Services

Consider the DW as the raw components necessary for use in a DSS to manipulate or create a decision-making outcome. For example, in brain-inspired decision-making, recent advances in this technology have nurtured a productive model for brain-inspired decision-making for company executives who take the lead in new advances in neuroscience and psychology (Gupta et al., 2021). Because model-driven and knowledge-driven are the most popular types of DSS Models, researchers typically investigate these two types of models first (Lutz et al., 2022). The analysis highlights the structure between the data analysis and the simplest form of analysis is comparing the data with similar information. Brain science has also been used in other observations requiring techniques using analytical data based on mathematical theories which were developed to make correlations based on mathematical theories using products of a hypothetical nature compared with actual data (Simion & Vasile, 2017). Such situations as judging whether an employee will fit well within the atmosphere of the employer. These new uses of deep technologies used in the context of many employer situations have offered engineers new perspectives (Deng, 2021). The most modern type of DSS includes various types of traditional DSS and newer, innovative DSS that are more indicative of data-driven DSS, and secondly, knowledge-driven DSS that are most often built from several blocks (Deng, 2021; Yang et al., 2022). These blocks include a) user interface and visualization components; b) data management; c) model management, and d) solvers (Wang, 2021; Yang et al., 2022).

The Use of Medical DSS and Smart Decision-Making

In 2020, the global community suffered the beginning of a pandemic that has not only changed the way medical care has been delivered, but also changed the way employees were treated and hired, the working environment, employee training, and most importantly—decision-making by corporations (Palamarchuk & Vaillancourt, 2021; Pirozhkov et al., 2022). Many times, medical providers were brought on board as part of an extended corporate DSS (Suganya et al., 2022). That makes it crucial for the DSS to employ and ascribe to a process that makes decision-making less challenging in unique situations and facilitates medically appropriate decision-making, contributing to various kinds of circumstances (Flisberg et al., 2021).

Decision-making is a central component of management and leadership. A central component of any job is project management where decision-making is a key element. DSS has become more complex, multi-faceted, and characterized by multiple unknown factors which require a significant number of cases, requiring real-time decision-making. The current pandemic has amplified the complexity and novelty of the situation and, at the same time, made an even more critical need for real-time decisions (Visan, Mone, & Filip, 2021). Speed of decision-making is not considered an important factor, however, being able to manipulate an intensely high number of factors for and against the end decision. Making a good decision is ultimately the priority of an effective leader (Chandler, 2022).

The Use of Artificial intelligence in Decision Support Systems

The use of AI and the role it plays in decision-making has been researched and proposed as a more efficient proponent for leadership. However, while AI is not susceptible to the adverse effects of cortisol and the rise and fall of the heart rate, glucose, and other factors surrounding decisions made under stress, AI is formidable in its decision-making capacities (Bokhari & Myeong, 2022). AI and smart decision-making can reinforce decisions made by human leadership and can also use the Internet of Things to positively affect decisions, whether made by human leadership or AI (Afrash et al., 2022). Big data is also used proliferatively in the interaction of smart decision-making so that the massive amount of data can be effectively managed by Big Data analytics tools (Bokhari & Myeong, 2022). In Table 1 (Afrash et al., 2022), a list of important and crucial ideas for making decisions is given with the scores next to them with an express selection of IoT and IoMT.

Improved customer service quality	62
Creation of new digital products and services	59
Creation of new business models and revenue streams	55
Improved decision making through the efficient use of data	53
Reduced operational costs	49

Table 1: Expected benefits of the Internet of Things (IoT) and the Internet of Medical Things (IoMT) investments (select all that apply, %)

Real-time detection and effective prognosis of COVID-19 are eminently imperative to deliver the best possible care for patients diagnosed with COVID-19 (Afrash et al., 2022). However, with the complete abundance of medical information including history and physical, family history, vital signs, etc., this information must be utterly accurate. Table 2 (Unger, 2022) details AI's ability to increase efficiency with automated technologies. This list of ideas improves the ability of AI to automate DSS choices.

Virtual personal assistants	61
Automated data analysts	59
Automated communications like email and chatbots	57
Automated research reports and information aggregation	55
Automated operational and efficiency analysts	52
Predictive analytics	50
Systems used for decision support	49
Robotics	47
Automated sales analysts	45
Machine learning	42

Table 2: Artificial intelligence's potential to increase efficiencies with automated communications (%, relevance)

The Impact of Machine Learning on Decision-Making

With the advent of explosive competition, record-breaking supply chain management issues, disruptive business models, and exponential growth in the complexity of technology and innovation, smart and innovative decision-making has drifted toward the use of multiple technologies in the decision-making process for life as existing capacities do not suit any longer (Higgins & Horak, 2021). Asset-intensive EPC (engineering, procurement, and construction) do not cope with a failure in the systems any longer, therefore, the scarcity of resources available to us must be considered a stressor in the decision-making process (Rane & Narvel. 2021). In the following Table 3 (Higgins & Horak, 2021), the researchers describe the impact of machine learning on organizational operations.

Improving customer experience	95
Automating processes	94
Generating customer insights and intelligence	93
Increasing long-term customer engagement	93
Generating financial insights	91
Acquiring new customers	92
Interacting with customers	91
Increasing customer loyalty	92
Managing logistics	90
Retaining customers	89
Supply chain optimization	87
Building brand awareness	86
Detecting fraud	85
Reducing costs	87
Back office automation	84
Financial planning	85
Recommender systems	86
Managing inventory	84
Reducing customer churn	87

Table 3: The impact of machine learning operations on organizations (%, relevance)

Society's impact by the pandemic has certainly been felt around the globe as prices have soared, costs of living have risen, and predictive healthcare has been necessary for surviving the pandemic. In this situation, predicting whether the patient will need critical care for survival and life support, or whether the patient will continue to survive without life support is essential (Montomoli et al., 2021). In Figure 2 (Yang et al., 2022), the schema represents the DSS of a healthcare decision-making model that will help providers better process data quickly and more urgently, particularly in the situation of a COVID-19 patient.

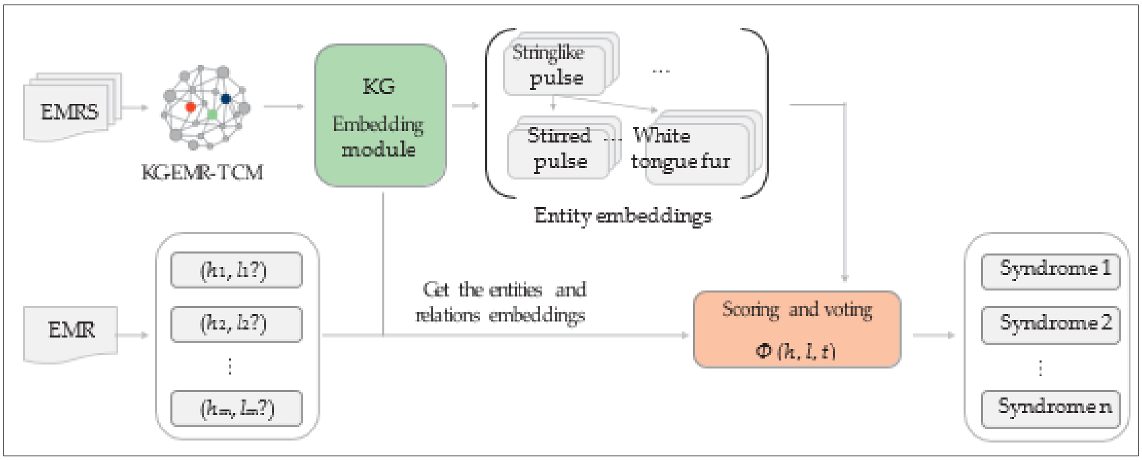

Figure 2: The DSS for Predictive Healthcare

Predictive Healthcare based on a Decision Support System

Industry 4.0 has helped enact a higher quality supply chain, faster, better, and more reliable decision-making for better goods and services at reduced costs; unpredictability and volatility create demand for resources at a lower price, however, an agile and prepared resource management is essential for success (Rane & Narvel. 2021). The business environment continues to be challenged by many spikes in the inability to foster or achieve successful high-quality decision-making. As the business environment continues to face challenges to the supply chain intensely, so does the medical field in staffing, solutions, and ideas for new approaches. With the advent of Industry 4.0, Big Data analytics, and Blockchain, many new ideas for solutions to old problems are now being generated (O'Neill, Morgan, & Burke, 2021).

The new Industry 4.0 is leading organizations to new heights as Big Data and IoT continue to lead enterprises forward and make decision-making easier for managers by offering decision support systems for more complex decisions. Data-driven strategies and potentially difficult decisions in project support are often made easier by supplementing human decision-making with some OR and machine learning technology (Arena et al., 2022). While the stock market has been around for many decades; however, it is the inception of COVID-19 restrictions at the onset of the 2020 pandemic of SARS-CoV-2 which produces the COVID-19 disease that technologies such as AI and machine learning (ML) were activated as viable options for choosing stocks and making solid decisions as far as predicting stock prices, making stock choices, and everyday management of the stock market. Therefore, Mean-Variance Markowitz (MV), Fuzzy Logic based stock options, data mining-based Evolutionary Systems, and others (Patalay & Bandlamudi, 2021). It is due to the inception of COVID-19 restrictions that have shut down many human aspects of DSS and replaced them with computational computerized algorithm programs such as Big Data, data mining, and Machine Learning techniques. Future research should be directed at managing the health of finances, the financial well-being of the DSS, and how well the tools are working for the enterprise (Patalay & Bandlamudi, 2021). It is with those answers and solutions that will help move stock options and financial management further toward the desired Blockchain solutions that many are hoping for to ensure privacy and reduce data access to other peoples' information. In short, privacy and cybersecurity should also be priorities for future research.

Conclusion

The strengths of analytics cannot be understated in this data-driven society where everything written on social media to the demographics and tracings of the victims of the pandemic can be used as input into the computational model makeup for determining who may be future victims of the pandemic. According to the models predicted by JHUCCSE, a high rate of errors was unavoidable at the beginning of the pandemic. However, as the pandemic continued to rage, computerizing the decision-making process or additional automation in the DSS could potentially have increased the accuracy of some of the decisions made by public health leadership. Some decisions by public health officials contributed to high error rates and distorted computational models as data being inputted were skewed. However, as time has shown, knowledge of the factors surrounding the pandemic has contributed to a decrease in the error rates relative to the pandemic. Management would benefit from the installation of some of the simple tools of decision-making. A highly skilled and professionally developed DSS could have been used to assist in tracing victims of the pandemic more efficiently.

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Conflict of interest

Any financial interest or any conflict of interest does not exist.

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