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Review Article

Trends in Decision-making: Looking at Decision Support Systems and Brain-inspired Decision-making

Cheryl Ann Alexander[1]* and Lidong Wang[2]

[1]Institute for IT Innovation and Smart Health, Mississippi, USA

[2]Institute for Systems Engineering Research, Mississippi State University, Vicksburg, USA

***Corresponding Author:** Cheryl Ann Alexander, Institute for IT Innovation and Smart Health, Mississippi, USA.

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Abstract

This original review paper will map out strong support for machine learning technologies for use in a brain-inspired decision-making tool that can be applied to a range of engineering management problems, including a decision support system (DSS). Studies have shown that machine learning is a solid foundation for a DSS. Big data analytics can lead to a stronger organization as decision-making skills are less dependent upon stress-related situations that can skew data. The Naïve Bayes algorithm could be an effective conclusion. In this paper, I introduced several areas of decision-making and decision support systems, including brain-inspired machine learning, smart decision-making, stress and smart decision-making, the impact of machine learning on decision-making, big data and decision support systems, COVID-19, and emerging diseases and deep technologies. In conclusion, a DSS with a data-driven strategy and machine learning methods can offer valuable experience and decision-making skills. Artificial intelligence such as machine learning facilities brain-inspired decision-making.

Keywords: Machine Learning; Decision Support Systems; Brain-inspired Decision-making; Decision Making; Naïve Bayes Algorithm; Big Data; COVID-19

Introduction

A data warehouse (DW) is a common data repository used for enterprise data storage; this data storage includes historical data, other information such as storage of stocks, raw materials, deposits, and other such information related to daily business operations. While the architecture of such a system should be aimed at data management, the process was developed for business intelligence—business decision-making using organized, stored historical, and categorized data. A combination of structured, unstructured, and semi-structured data can be used in business intelligence (BI) from a collection of various sources [1]. The massive amounts of data collected most often require the use of advanced data management tools such as Big Data analytics, machine learning, or artificial intelligence (AI) with advanced neural networks (ANN) to formulate a sustainable decision support model for the enterprise. Current models of data analysis are simply unable to handle the enormous amounts of data that are required to process day-to-day data analysis for any enterprise. Consider the data as the raw ingredients that are required to create a decision support system (DSS) by the engineering manager to manipulate or create a sustainable DSS. It is important to remember that a DW is not a DSS, but simply the framework by which a DSS can be built [1].

DWs use technologies that allow available data from multiple sources to be compared and analyzed so that an enterprise can use the consolidated data to make solid decisions about financial matters, manufacturing, supply chain matters, etc. [2]. However, in a DW, the data is often noisy and out of sync, which requires a great deal of local cleaning of the data so that accurate algorithms and computational data can be gathered from the database is built to enhance the volume and requirements of the system and foster decision-making by enterprise managers who can make decisions related to the development of a business structure or further daily operations [3]. Furthermore, database applications may improve the reliability and efficiency of the end-user and their decision-making skills; and store, update, and get answers through reports and other similar tools [4].

Consider the DW as the raw ingredients that an engineering manager can use in a DSS to manipulate or create a decision-making outcome. In brain-inspired decision-making, recent advances in technology have nurtured a fruitful opportunity for brain-inspired decision-making for enterprise administrators who can take the lead in new advances in neuroscience and psychology [5]. Leaders have been scrutinized in crisis management; the application of brain-inspired technologies has been shown to work well in studies on management functioning in improving skills of decision-making under stress, while compromised emotionally, and while physically challenged. The component dialog facilitates communication with crucial departments of the organization, making the decision-making process much easier and facilitating a more reliable decision [5]. 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 [2]. 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.

Over the last two years, the global community has suffered a pandemic that has not only changed the way medical care has been delivered, but also changed the way employees were treated, hired, the working environment, employee training, and most importantly—decision-making by engineering managers. Therefore, it is a crucial factor for the DSS to employ and ascribe to a process that makes decision-making less challenging in unique situations and facilitates decision-making medically, contributing to various types of medical and non-medical situations [6].

This original review paper will map out strong support for machine learning technologies, particularly Naïve Bayesian, for use in a brain-inspired decision-making tool that can be applied to a range of engineering management problems. A powerful literature review is underlying support for this review paper which is wrapped up with a culmination of discussion and completed with a prediction of future technology development and a conclusion.

Brain-inspired machine learning technologies

Over the last few decades, society has become overtly more data-driven; however, with the onset of the SARS-CoV-2 pandemic, the reliance upon data and technology has reached an all-time high. From telemedicine and work-at-home to online school and recreation, people began to utilize social media, Zoom, FaceTime, etc. as ports of access to socialize with others and conduct business. In-store enterprise sales also fell as online sales soared, changing social sales structure possibly forever. Operations research (OR) has been the synergistic basis of all decision-making for the last 75 years; however, with this new sales platform, much has changed also about decision-making. For the enterprise to have a sustainable vision and mission for its business, it must have a viable decision-making process at each stage. Therefore, a DSS based on an applicable DW is a critical need for every enterprise today. In addition, the OR must have a relevant technological basis such as Big Data, AI, or ANN because most enterprise data have surpassed traditional technology and can no longer effectively manage or analyze the current and massive amounts of data produced by most businesses.

Therefore, with this change and beginning domination of social media usage, the need for learning how data and subjects relate to each other suggests there is a necessity for a data processing method which considers emotion, sense, everyday practices, and the nexus between data and data technologies such as Big Data, Internet of Things (IoT), and Artificial Intelligence may certainly be the future of all data transactions [7]. Nowadays, there is a need for future data technologies to consider all these factors and be able to process data at rates far exceeding current speeds and abilities. The business process managers participate in ensuring the flexibility, agility, and efficiency of business processes. Parallel processing is beginning to play an important role in data [8]. Therefore, the benefit of using these technologies lies in capturing the scalar nature of data and focusing on the socio-technical processes behind data applications. It begins with a conceptualization of the Personhood of Data, which highlights exactly how distant the subject is from the data resulting in a conceptual language that then provides a method for analyzing the scalar nature of the data [9]. Neuroscience and psychology research has developed into "brain science" where aspects of neuroscience and psychology have been applied to characteristics of leadership. It is hypothesized that harnessing brain abilities can help create optimal human performance in crisis and stressful situations and has the potential to increase leader efficacy through brain science. Although this technology is in its infancy and needs to be further researched, potential managers need skills such as articulation, trust-building, sense-making, and emotional intelligence. Emotional intelligence is composed of several components: self-awareness, self-regulation, motivation, empathy, and social skills [8].

Data, then, becomes a positivistic resource as the data highlights the humanity of the subject through each bit of data-field representation of humanity through the scientific representation of the subject's world [7]. So, with the use of machine learning technologies, data can be processed and analyzed and used not only to humanize daily data activities, stresses, and emotions and sensemaking but to individualize our humanity in the surveillance of the data with separate and scientific representations of new data structures—the distant relationship of data and the embodied life represented by social media and activities only capable of being analyzed by deep technologies.

The simplest form of analysis is comparing the data with similar data synthesized. In addition, information may acquire quality when using techniques of graphical representation that make these correlations, observation techniques analytical data based on mathematical theories, comparing actual data with the theoretical products of a hypothetical model, or observation techniques automatic based on data. Strategic alignment (SA) has attracted the attention of many engineering managers as the global market and social status are changing amid uncertainty. Companies are continually searching for opportunities to improve and strategically improve certain areas of the company's priorities. By searching for SA, an enterprise may find strategic objectives and align the company's mission and vision with the SA to achieve a degree of compatibility.

Stress and smart decision-making and the impact of machine learning

When adverse events occur, strong emotions elicited by neuroactivity facilitate behavioral and cognitive shifts to stabilize the brain's activity and ability to make accurate and quick decisions that can affect the life and death of self or others [10]. This struggle to achieve physiopsychological stability is inherent in brain science studies and essential to smart decision-making studies. However, prolonged exposure to such negative stimuli can affect the brain's ability to make smart decisions and smart decision-making can become maladaptive or disruptive [10]. In the conative and affective and cognitive awareness, results have shown that among six possible paths, all paths are feasible while under stress except the conative, therefore, for consumers, patients, or management's decision-making skills, this effect can follow the hierarchy of cognitive effect following a theoretical perspective that conative, cognitive, and affective has the smallest share [11]. This maladaptation may denote a pivotal point when the body's physiological stress, captained by the stress hormone cortisol, which can trigger neuroactivity and "automaticity" led by the higher-than-normal cortisol levels, affects the brain's ability to make smart decisions and as a defense mechanism, the person's ability to protect themselves [10]. Overwhelming and unpleasant feelings can follow this lack of smart decision-making abilities. Altered memory, altered decision-making, and maladaptive neurocognitive behavior can certainly also be affected by mental state, mental disease, long-standing stressful situations, and other negative stressor situations [10,11].

Shim's study [11] contributed two things: from a theoretical viewpoint, the study provided a truly estimable viewpoint of the heterogeneity of an individual's decision-making process, and this could help marketers gain insight into profiling for purchases that could change the current sales market. Another factor that must be considered is the seriousness of decision-making by certain professionals. For example, a firefighter or paramedic may have to make a split-second decision. Stress could then impact their decision negatively and within a life-threatening scenario. A physician, nurse, pharmacist, policeman, etc. all have jobs that could be highly impacted by a stress-induced decision-making scenario. Stress is also key in decision-making for other highly volatile situations as well because hundreds of decisions are made, some of this within an instant, daily—up to and over 35,000 decisions by any one person within a day. Stress has been defined by the Mental Health Association as "the feeling of being overwhelmed or being unable to cope with mental or emotional pressure" [12]. Research has shown an association between research and disease as well as increased brain activity. It should also be noted that medical professionals have been studied under stress in the past and it was shown that these individuals demonstrated altered judgment, second-guessing decision-making, and taking unhealthy risks. Therefore, it is evident that making decisions under stress can lead to a host of other negative problems if the decisions are made under increased stress or high cortisol levels [12,13].

When confusion exists, circumstances become stressed, and people must make split-second decisions, the cortisol peak can be reached quickly as the body overproduces cortisol to escape the threat to safety. When the cortisol levels have peaked, individuals tend to make mistakes and have flawed decision-making [13]. However, early stress reduction has not received as much attention as the stress response. Using an acute neuroendocrine stressor such as physical exercise, researchers have examined how wide the gap is in the study of using such a positive stressor such as physical activity to promote alertness that decreases the negativity surrounding the increased cortisol response. The stress response in the brain has been widely studied because most decisions have been made under stress, or cause stress themselves, or because the relative consequences of the decision itself, induce stress. Thus, sensitivity and reinforcement feedback play a crucial role in this situation by increasing the positivity of making decisions to the point where the individuals begin to feel fewer negative effects and more positive effects. Decision alternatives can then become more appealing and attractive. This can be measured in individuals by using the Naive Bayesian machine learning technique [13].

Smart decision-making

Decision-making is a central component of management and leadership. A central component of any job is project management where decision-making is the key element. An effective crisis leader or decision-maker can frame problems, foresee solutions, grasp the outcomes of a decision before making it, and ultimately become a smart decision-maker. The highest, most concentrated, and deliberate decisions are made at a higher conceptual level by effective leaders. 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 [14].

The use of AI in smart cities 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 [15]. 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. 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 [15].

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. 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 [16,17].

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 [17]. 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 [18].

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 [19]. 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 [20]. 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 [20]. 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.

Decision making processes can be improved if interacting with the dynamic environment through reinforcement learning (a machine learning method), e.g., Q-learning. Brain science and machine learning work together well. Machine learning leverages current brain research to inform its work. Also, people use machine learning tools to learn more about the workings of the brain. Artificial neural network (ANN) is a machine learning method. Inspired by the mechanism of decision making in human brain, computational models can be developed, for example, brain-inspired decision-making spiking neural network which facilitates decision-making.

Big data and decision support systems

Industry 4.0 is providing increased insight into decision-making for enterprises. This increased importance and focus on decision-making have led to a focus on DSS. Industry 4.0 is awakening a digital transformation where the focus is on advanced analytics and visualization. Exploiting DSSs with a data-driven strategy can have an incredible impact on enterprise strategy. New, unlocked potential and untapped financial rewards are simply waiting around the corner as the world turns to a new form of decision-making and uses technology as the basis for the DSS, which can predict outcomes, increase profits, and more. Visualizations, such as dashboards, enable a higher level of visualizing the company production line than ever before possible [18].

Gathering the data and analyzing the data are key tasks of any computerized programming for an enterprise. By using process mining, companies can also avoid uncertainties. Businesses desire systems and programming than are not only comprehensive but cannot only provide overall efficient process management and real-time performance. Collaborative systems must be centralized, not only to improve production planning and improve automation but to autonomously execute schedules and automatically update decision-making processes. This is the benefit of machine learning and big data for businesses in manufacturing, healthcare, financial areas, legal, etc. [18]. With these changes, organizations have been collecting massive amounts of various types of data (e.g., structured, unstructured, semi-structured) over the last few years and trying to replace traditional analysis methods with big data methods as traditional methods simply cannot process that amount of data. Enterprise has other methods of using big data if analyzed and presented correctly; organizations can use big data to structure a highly effective DSS [21]. For some organizations, big data tools have greatly influenced the tool and die business in the decision-making process by improving decisions at every level. With an improved DSS, an organization can depend less on stressed humans and lean further into a computer-inspired decision-making system.

Machine learning—naïve bayes algorithm

The impact of big data and machine learning techniques continues to be used after the pandemic has ended as producers, managers, and other leaders in the industry have realized the benefits of big data, machine learning, and other technologies. One producer of vegetable production in Greece found that during the pandemic they needed to find an alternative to human skills or an added benefit to human decision-making as the economy continues to change and the global economic and healthcare scene is extremely friable.

Currently, technology is cheaper and easier to use than ever before. Because technology has been implemented for the last two years in creative ways, a DSS is easier to implement and for companies to get buy-in from employees. A DSS can offer valuable experience and decision-making skills for employees and managers, reducing precious costly items and offering dynamic proof that enterprise can benefit from machine learning algorithms in many ways [22]. For example, a DSS was implemented in the farming industry and in one study, Dynamic Artificial Neural Networks (DANN) showed improvement in the yield of tomato plants when managers used a DSS [23]. In another study, farmers initiated a DSS—Naïve Bayes Algorithm, to determine water needs during irrigation, and with the use of the DSS, costs decreased, and output increased exponentially. Human decision-makers simply cannot make the computational decisions necessary to fully utilize a DSS. Therefore, instituting a DSS such as Naïve Bayes algorithm is fostering a better global economy using technology [24].

COVID-19 or SARS-CoV-2 in the 21st century

There is a well-documented negative impact of major stress on decision-making. Long-term residual effects of cortisol continue to saturate the brain's neurons with the "fight or flight" response and this tends to lead to a psychological effect evoked and intended to recalibrate and reset the brain to homeostasis after a long-standing negative effect [10]. However, when the stressor continues to go on and on, there could be horrible detrimental negative effects that could potentially do major harm to the living organism. Significant morbidity by cardiovascular disease, stroke, depression, morbid obesity, and post-traumatic stress disorder (PTSD), can be associated with prolonged elevated levels of cortisol. Furthermore, these same comorbidities can be associated with both poor decision-making and with negative COVID-19 outcomes [10]. With the onset of the 2020 SARS-CoV-2 Pandemic or COVID-19 pandemic, emerging networks such as the Internet of Things (IoT), Big Data, AI, and ANNs were being considered for their ability to comprehend complex automated monitoring, identification, and management through a network of smart devices and parallel processing [3]. Companies began to change the way they did business, and with this change, new SA and additive DWs had to be considered as well as new technologies to prevent privacy leaks in work-from-home jobs, and now, with these additional uses of company facilities, it is up to the enterprise to revise current SA documents and review DW processes [4]. Global pandemics cause chaos in nearly every area of business, personal, and academic life. It is necessary to develop a continually revised SA so that healthcare, financial, personal, and other areas will not be affected by the effects of the global pandemic. A SA can mitigate damage and prepare the enterprise for most situations [3,4]. Thus, the global pandemic called for its consequential negative effects on the health of citizens, the economy, and other effects. Accordingly, new SAs were produced for many companies in different areas of the economy. One method to mitigate the highly negative impacts of the current and future pandemics is to develop a DSS and continue to employ data and analysis.

In the legal profession, technical systems are displacing decision-making and rely on predictive coding and lawyers are continually grappling with what it means to be a lawyer in the age of predicting coding and the ethical and professional legal duties of being a legal professional during the 2020 global pandemic [25]. There are other areas of being in what is possibly a highly constructive system during the fluctuating economic and health-related economy. Another most important tool for consideration during the pandemic which considers a great deal of managerial decision-making and a need for a strong DSS to protect the mission of the enterprise is the field of supply chain or manufacturing [26]. During the global pandemic, the supply chain or field of manufacturing will most certainly experience more fluctuation and uncertainty than ever before. During the pandemic, the supply chain must be protected by managers who are knowledgeable and experienced in a straight-bygone period where managers can assess and improve the resilience of their supply chains by making decisions using strategic level decision-making, or DSS [26].

Metadata directly impacts the quality of data. However, no formal representation has been established, but the formal representation of metadata is enhanced by the quality of a DSS. Except for the quality necessary for a DSS, a metadata qualitative DW first defines qualitative metadata and a user metadata information process [27]. Finally, a complete process of metadata management is used to describe the data. The most important information in a metadata DW is contained for the end-user. Metadata is a promising driver for end-user. Metadata is data about data; by capturing all the information necessary to analyze, design, build and interpret the DW contents. The metadata has two categories of data: business data and technical data [27].

Big Data has emerged as a viable and sustainable network that can analyze massive amounts of data from several sources including social media, sensors, attenuators, etc. to derive a sustainable decision by linking devices together and then developing consistent algorithms which can analyze, manipulate, and manage the connected systems so that a huge bulk of data can then be used for smarter decision-making and post-analysis for various reasons [9].

IoT is a set of disparate devices connected via a common network such as Big Data analytics. The efficient use of the IoT in multiple areas has helped improve productivity and reduce errors [9]. Because smart devices are linked to the network, they can make smarter decisions and post-analysis for various purposes; in other words, the network is connected to these devices using Big Data, which improves the limited resources and management of data with those smart devices to improve power efficiency. Due to the inherent nature of Big Data, including the 7 Vs, improvements can be engaged in networking ability and various approaches in place for recovery, constrained energy, and the huge bulk of storage on the cloud. Therefore, data correlation and multiple characteristics of sensory data can be improved with the use of Big Data and deep technologies [28].

Emerging diseases and deep technologies

When using deep technologies, data scientists prefer R Studio or Python languages, however, they are limited in their speed and memory abilities. Scalability is one of the most important considerations when using machine learning models and parallel data summarizations [29]. Thus, a more successful computational data model can be presented using parallel data summarization because the model requires only a small amount of memory (i.e., RAM) and the algorithm works in three phases, producing a broader statistical and machine learning model which can handle datasets much bigger than the main memory. Designed with a vector-vector outer product with a C++ code to escape the bottlenecking that can happen in deep learning, this system is still faster and with a bigger memory than other parallel systems (e.g., Spark, Hive, Cassandra, etc.), which could become important in such cases as epidemiological disease tracing [29].

Big Data plays a variety of important roles which critically support the world's manufacturing, legal, financial, cybersecurity, and medical systems. Through open-source platforms like Hadoop, etc., information is shared among government and non-governmental facilities regarding emerging diseases, predictions made through computational models, and cybersecurity underlaid for those who must shelter in place and work from home [30]. Johns Hopkins University Center for Systems Science and Engineering (JHU CCSE) has had the closest to actual live data as any other model with error rates of 4.71, 8.54, and 6.13%, respectively. Furthermore, these error rates were based on computational model error rates based on actual infection, death, and hospitalization rates based on data mining using Big Data analytics [31].

Conclusion

The strengths of Big Data analytics cannot be understated in this data-driven society where everything written on social media to the demographic makeup 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 DSS based on an applicable DW is a critical need for enterprises. Exploiting DSSs with a data-driven strategy can have an incredible impact on enterprise strategy. With an improved DSS, an organization can depend less on stressed humans. AI such as machine learning and smart decision-making can reinforce decisions made. Big data is also used proliferatively in the interaction of smart decision-making. For some organizations, big data have greatly influenced the tool in the decision-making process by improving decisions at every level. Privacy and cybersecurity for a DSS and a system of brain-inspired decision-making should also be priorities for future research.

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Conflict of Interest

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

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