https://doi.org/10.48047/AFJBS.6.Si4.2024.5048-5059

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

Designing a Decision Support System Framework Leveraging Big Data Analytics for Business Organization

Rajni, Dr. S. P. Singh

Research Scholar,Dept of Computer Science and Engineering,
NIMS Institute of Engineering and Technology (NIET),
NIMS University, Rajasthan, Jaipur (Raj.)-303121, INDIA
Email: jhajhariarajni18@gmail.com

Professor,Dept of Computer Science and Engineering,
NIMS Institute of Engineering and Technology (NIET)
NIMS University, Rajasthan, Jaipur (Raj.), 30312,INDIA
Email: *sp.singh@nimsuniversity.org*

Volume 6, Issue Si4, Aug 2024

Received: 15 June 2024

Accepted: 25 July 2024

Published: 15 Aug 2024

doi: 10.48047/AFJBS.6.Si4.2024.5048-5059

Abstract: Decision Support System (DSS) is a computer-based information system designed to aid organizations in their decision-making processes. It helps managers and decision-makers make more informed and successful choices by providing relevant information, models, and analytical tools. In this synopsis, we propose the development of a Big Data Analytics framework to enhance the efficiency of a DSS within a cloud environment. This paper presents a comprehensive framework for a Business Decision Support System (BDSS) leveraging Big Data Analytics to enhance decision-making processes within enterprises. The proposed system integrates large-scale data collection, advanced data processing, and real-time analytics to provide actionable insights for strategic business decisions. By employing cutting-edge techniques in machine learning, data mining, and predictive analytics, the framework addresses the challenges of data variety, volume, and velocity, offering robust support for complex decision-making scenarios. The BDSS framework is designed to be adaptable across various industries, providing a scalable solution that optimizes business performance, enhances competitive advantage, and supports proactive decision-making. Case studies demonstrate the system's effectiveness in improving operational efficiency, customer satisfaction, and overall business outcomes.

Keywords: Decision Support System, Business Analytics, Big Data Analytics, Big Data.

I. INTRODUCTION

In today's data-driven world, organizations face increasingly complex challenges in making timely and informed decisions. The vast amount of data generated across various sources, combined with the need for real-time insights, has necessitated the evolution of traditional Decision Support Systems (DSS) into more sophisticated, data-centric solutions. Big Data Analytics offers a powerful approach to harnessing this data, enabling organizations to derive actionable insights and improve decision-making processes. This paper introduces a framework for an advanced DSS that leverages Big Data Analytics within a cloud environment. By integrating scalable data processing, machine learning algorithms, and real-time analytics, the proposed framework aims to enhance the efficiency, accuracy, and effectiveness of decision-making across various industries [4-6]. The cloud-based architecture ensures flexibility, scalability, and accessibility, making it an ideal solution for organizations seeking to optimize their decision-making capabilities in a rapidly changing business landscape.

Big Data Analytics (BDA) involves the examination and interpretation of vast and complex data sets to uncover patterns, trends, and insights that can inform business decision-making. It encompasses the processing and analysis of large volumes of data from diverse sources and formats using advanced analytical methods and technologies, including machine learning, data mining, predictive modeling, and artificial intelligence [1-4]. BDA has become a critical tool for businesses aiming to stay competitive in today's data-driven economy. By leveraging data-driven insights, companies can make informed decisions, gaining a deeper understanding of their customers, markets, and operations (Figure 1).

Figure 1: Characteristics of Big Data

The primary objective of Big Data Analytics (BDA) is to empower organizations to make informed, data-driven decisions that can significantly enhance business operations, elevate customer experiences, reduce operational costs, and ultimately boost revenue [2]. By leveraging the vast amounts of data available, BDA enables businesses to extract actionable insights that drive strategic decision-making and optimize various aspects of their operations. BDA's versatility allows it to be applied across a wide range of industries, including healthcare, finance, retail, manufacturing, and beyond. For instance, in healthcare, BDA can improve patient outcomes by enabling personalized treatment plans and optimizing resource allocation. In the finance sector, it plays a crucial role in fraud detection, risk management, and algorithmic trading. Retail businesses use BDA for customer segmentation, personalized marketing, and inventory management, while manufacturing industries benefit from its application in supply chain optimization and predictive maintenance [9]. By harnessing the power of BDA, organizations can gain a competitive edge in their respective markets. It enables them to operate more efficiently, cut costs, and increase profitability by making precise, data-backed decisions. Furthermore, BDA enhances customer experiences by allowing businesses to tailor their products and services to meet individual needs and preferences, thereby fostering customer loyalty and driving revenue growth. Ultimately, BDA serves as a vital tool for organizations aiming to thrive in a rapidly evolving, data-centric world.

A. *Cloud computing environment*

A cloud computing environment is a flexible and scalable computing model that provides on-demand access to a shared pool of computing resources, such as servers, storage, databases, and applications, via the internet. This model enables users to access and utilize these resources from anywhere in the world, using any internet-enabled device, without needing to manage or maintain the underlying infrastructure. This convenience allows organizations to focus on their core activities while leveraging powerful computing capabilities. Cloud computing services are typically provided by Cloud Service Providers (CSPs), which operate vast data centers equipped with extensive computing power that is shared among numerous customers. These CSPs offer various deployment models to suit different organizational needs, including public cloud, private cloud, hybrid cloud, and multi-cloud environments.

In a *public cloud* environment, the CSP makes computing resources available to multiple customers over the internet. Although the underlying infrastructure is shared, advanced virtualization and security technologies ensure that each user's data and applications remain isolated and secure. This model is cost-effective and highly scalable, making it ideal for businesses with varying workloads and budget constraints. A *private cloud* environment, on the other hand, is dedicated exclusively to a single organization. The resources are not shared with other users, providing greater control, security, and customization. Private clouds can be hosted on-premises within the organization's own data center or off-premises by a third-party provider. This model is particularly beneficial for organizations with stringent security, compliance, or performance requirements. A *hybrid cloud* environment combines elements of both public and private clouds, allowing businesses to distribute their data and applications between the two based on specific criteria such as security, performance, and cost-effectiveness. This approach provides the flexibility to optimize resource usage and balance the advantages of both public and private cloud environments. Lastly, a *multi-cloud* strategy involves using services from multiple cloud providers, allowing organizations to avoid vendor lock-in and leverage the unique strengths of each provider (Figure 2)

Figure 2: Big Data Analytics process

B. *Decision Support System (DSS)*

A Decision Support System (DSS) is a computer-based information system designed to aid organizations in their decision-making processes by providing managers and other decision-makers with the necessary information, models, and analytical tools to make well-informed and effective choices [8]. A typical DSS is composed of three key components: the user interface, the database, and the decision model [9]. The user interface serves as the platform through which users interact with the system, offering a straightforward and intuitive means of accessing and utilizing the system's features. The database contains the relevant data and information needed for decision-making, which can be sourced from both internal and external channels. This data serves as the foundation for the system's analysis. The decision model leverages the analytical tools and data stored in the database to generate insights, forecasts, and recommendations that support the decision-making process [10-11]. Together, these components enable organizations to navigate complex decision scenarios, improving outcomes through data-driven insights and strategic analysis. There are different types of DSS, including:

C. *Integration of technologies*

Scalability: BDA produces vast quantities of data that must be processed, stored, and evaluated. The infrastructure required to manage the amount, diversity, and velocity of data created by BDA is provided by cloud computing. [12] Organizations may increase or decrease their computing capacity as required by using cloud services without having to pay for the construction and upkeep of their own data centres.

Agility: Using the cloud gives businesses the ability to swiftly deploy and set up computer resources, which is crucial for BDA and DSS. [13] Organizations may quickly adapt to changing business demands and benefit from cutting-edge technology by employing cloud-based services.

Collaboration: The ability to access and share data and insights produced by BDA and DSS by various users is made possible by cloud computing. This is especially crucial in distributed work settings when teams are dispersed throughout the globe.

Cost Savings: Cloud computing provides cost savings by reducing the need for organisations to invest in expensive hardware and software. With BDA and DSS, cloud computing enables organisations to pay for the resources they use rather than investing in costly infrastructure.

Security: In order to shield user data and applications from online dangers and breaches, cloud computing provides cutting-edge security methods and compliance certifications. Businesses may gain from improved security and compliance capabilities by combining BDA and DSS with cloud computing.

Better decision-making: By combining BDA, cloud computing, and DSS, decision-makers are given access to timely and relevant information, insights, and suggestions[14, [15]. Decision-makers may improve company results by using the data and analytical tools offered by BDA and DSS. This allows them to make more educated choices. [16] Decision-makers may access data and apps from anywhere in the cloud-based environment, which helps them make choices quickly.

organizations may significantly benefit from the combination of BDA, cloud computing, and DSS in terms of scalability, agility, collaboration, cost savings, security, and enhanced decision-making. [17] Organizations may gain a competitive edge by using these complementary technologies to make data-driven choices and increase their overall efficiency and effectiveness.

II. LITERATURE REVIEW

As a research topic, both Decision Support Systems (DSS) and Big Data encompass a broad spectrum of studies, each exploring different dimensions of their interplay in decision-making processes. Some research has focused on the overarching role Big Data can play in enhancing the decision support process, examining how vast datasets can be leveraged to improve decision accuracy, timeliness, and relevance. Other studies delve into more specific aspects, such as developing models, algorithms, and methodologies that utilize Big Data analytics to support and automate decision-making. For instance, the research by [18] offers a theoretical exploration of the organizational and technical elements involved in decision-making, specifically examining how Big Data interacts with business intelligence systems. This study highlights the complex, interrelated relationships between Big Data and business intelligence, demonstrating how these interactions can influence and enhance the decision-making process within organizations. Such research underscores the multifaceted nature of DSS and Big Data, revealing the depth and breadth of investigation required to fully understand and harness their potential in various decision-making contexts.

Table 1: Review of Literature

Aspect	Description
Benefits of Cloud-Based BDA for DSS [17]	Singh et al. (2019) found that cloud-based BDA platforms help organizations reduce costs, increase flexibility, and improve decision-making quality. The study also emphasized the importance of data security and privacy when adopting cloud-hosted BDA platforms.

Machine Learning in Cloud-Based BDA for DSS [18]	Khan et al. (2020) explored the use of machine learning algorithms within cloud-based BDA for corporate DSS. They found that machine learning can help organizations derive insights from large datasets, leading to better decisions. The study also highlighted the importance of data pre-processing and quality in decision-making processes involving machine learning.
Challenges in BDA and Cloud Integration for DSS [19]	Ahmed et al. (2019) identified challenges in managing and analyzing large datasets within cloud-based BDA for DSS. Key issues include data governance, integration, and quality.
Need for Specialized Skills [20]	Zheng et al. (2020) highlighted the need for specialized skills and knowledge in managing and analyzing big data within cloud environments. They stressed the importance of investing in training and development to equip personnel with the necessary expertise.
Competitive Advantage Through Cloud-Based BDA [21]	Dixit et al. (2021) concluded that using cloud-based BDA platforms can give businesses a competitive advantage by delivering faster, more accurate, and relevant insights. The study also emphasized the importance of data governance, privacy, and security in cloud-based BDA.
Use of Machine Learning in BDA for DSS [25]	Niu et al. (2021) investigated the application of machine learning algorithms in cloud-based BDA for DSS. They found that machine learning can help organizations identify patterns and trends in their data, improving decision-making. The study also stressed the need for high-quality data pre-processing.
Cloud Computing as a Platform for BDA [28]	Fazal et al. (2022) examined cloud computing as a scalable and flexible platform for managing and analyzing big data in the context of DSS. They highlighted the importance of data governance and management in this environment.
Complexity of Managing Large Datasets [27]	Jadhav et al. (2021) discussed the complexity of managing and analyzing large datasets within cloud-based BDA for DSS, focusing on issues related to data governance, integration, and quality.
Training and Development Needs [24]	P. K. Kurotschka (2021) noted that organizations must invest in training and development to acquire the necessary skills and knowledge for managing big data in cloud environments.
Machine Learning for Data-Driven Decisions [26]	Hussain et al. (2022) highlighted the role of machine learning algorithms in cloud-based BDA for DSS, enabling organizations to identify patterns and trends for better decision-making. They emphasized the importance of data pre-processing and quality in these processes.
Data Visualization Techniques [22]	Aggarwal et al. (2022) explored the use of data visualization techniques in BDA for DSS, finding that these techniques help organizations quickly understand their data and extract actionable insights.
Training and Skill Development [23]	Mukherjee et al. (2022) emphasized the need for businesses to invest in training and development to build the necessary skills for managing and analyzing big data within cloud environments.

III. RESEARCH METHODOLOGY

The research methodology for this study involved a comprehensive literature review to identify key elements and trends in Decision Support Systems (DSS) and Big Data analytics. This was followed by the development of a conceptual framework that integrates Big Data analytics into DSS, aimed at enhancing decision-making processes [29-32]. The proposed framework was then critically analyzed and will be evaluated through a case study approach, focusing on its practical application and impact on data quality and decision outcomes within an organizational setting. This mixed-method approach ensures both theoretical depth and practical relevance.

a. Statement of the Research Problem

The evolution of machine learning beyond traditional statistical methods has ushered in a new era in data science. However, to fully harness the potential of these advancements, it is essential to develop a novel framework for data processing and modeling that significantly enhances accuracy. Existing frameworks may fall short in addressing the complexity and scale of modern datasets, particularly in the context of decision support systems. Therefore, our research aims to create a robust and efficient framework that integrates advanced machine learning techniques with big data analytics to achieve superior accuracy and reliability in decision-making processes.

b. Research Approach

Our research approach focuses on identifying and addressing anomalies within datasets, which is crucial for improving the accuracy and reliability of predictive models. The process begins with data pre-processing, where essential techniques such as feature extraction and localization are employed to prepare the data for analysis. These steps ensure that the data is clean, relevant, and ready for further processing. The proposed framework will then be evaluated using pre-labeled test data to assess its effectiveness. The research methodology will be implemented through a series of carefully designed steps, each contributing to the overall goal of developing a more accurate and efficient decision support system.

c. Literature Survey

The literature survey phase involves a thorough review of existing research papers and studies related to big data analytics, machine learning, and decision support systems. This review will help us understand the problem's background, explore existing solutions and techniques, and identify the current performance limitations of these methods. By examining various studies, we aim to build a strong foundation for our research and ensure that our proposed framework addresses the gaps and challenges identified in the literature.

d. Sampling Design and Data Set(s) Selection

For this research, we will utilize standard benchmarking datasets relevant to decision support systems, such as sales, production, or service data from well-known organizations. The selection of these datasets is critical, as they provide a basis for testing and validating the proposed framework. Additionally, we will employ a data collection strategy that includes both primary and secondary methods. The pre-processing phase will involve innovative data augmentation techniques aimed at improving performance. By storing the data on the cloud, we will enhance efficiency and reduce the need for extensive local storage, making the process more scalable and accessible.

e. Big Data Analytics

To conduct big data analytics, we will use tools such as IBM Cognos, HADOOP, or WEKA for exploratory data analysis and predictive analytics. These tools will help us gain insights into the data and refine our models for better forecasting and decision-making. During the predictive analytics training process, we will fine-tune specific parameters and potentially develop custom neural network or deep learning models from scratch. Our objective is to create a robust data augmentation method that optimizes performance and efficiency. The final outcome of our research will be a generalized framework that integrates various processes into a cohesive pipeline, applicable to decision support systems leveraging big data analytics in a cloud computing environment. This framework aims to enhance decision-making accuracy and efficiency across a wide range of applications.

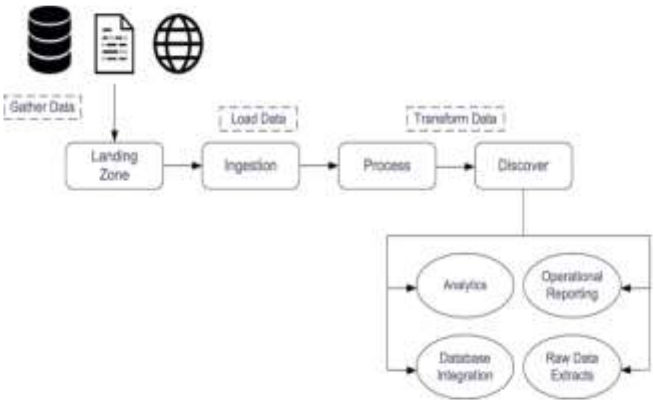

Figure 3: The process of Big Data Analytics (BDA)

The process of Big Data Analytics (BDA) generally follows a structured workflow that includes several critical steps (Figure 4):

1. ***Data Acquisition:*** This initial step involves collecting and gathering relevant data from a variety of sources, such as social media platforms, customer feedback systems, sales transactions, sensors, and other enterprise systems. The data can be in different formats, including structured, semi-structured, or unstructured, and may consist of text, images, audio, and video. The goal of data acquisition is to compile a comprehensive dataset that reflects the diverse aspects of the business or domain being analyzed.
2. ***Data Preprocessing:*** Once the data is collected, it must undergo preprocessing to ensure it is clean, accurate, and ready for analysis. This step involves several sub-processes:

   - *Data Cleaning:* Identifying and addressing issues such as missing or inconsistent data, and removing any duplicates that could distort analysis.
   - *Data Transformation:* Converting data into a standard format that can be easily analyzed. This may involve normalization, scaling, or encoding categorical variables.
   - *Data Integration:* Combining data from multiple sources to create a unified dataset. This may also involve resolving conflicts in data formats and structures.
   - *Feature Extraction:* Selecting and transforming relevant features that are most useful for analysis. This step is crucial for reducing dimensionality and improving the performance of analytical models.

3. ***Data Storage:*** The processed data is then stored in a suitable environment that supports efficient access and analysis. Depending on the volume, velocity, and variety of the data, this could be a traditional data warehouse, a Hadoop cluster, or cloud-based storage. The choice of storage solution depends on the specific needs of the organization, including

the scale of data, the speed of access required, and the complexity of the analytics to be performed.

4. ***Data Analysis:*** In this phase, various analytical techniques are applied to the data to uncover patterns, relationships, and insights. BDA employs a combination of:

    - *Descriptive Analytics:* Summarizes historical data to understand what has happened over a given period.
    - *Diagnostic Analytics:* Explores data to determine why something happened, often using statistical techniques and data mining.
    - *Predictive Analytics:* Uses statistical models and machine learning algorithms to forecast future outcomes based on historical data.
    - *Prescriptive Analytics:* Recommends actions that should be taken to achieve desired outcomes, often by simulating various scenarios and evaluating the potential impact of different decisions.

5. ***Data Visualization and Reporting:*** The final step involves presenting the results of the analysis in a way that is meaningful and understandable to stakeholders. This is typically done using data visualization tools that create charts, graphs, and dashboards. Effective data visualization helps to communicate complex insights clearly, enabling decision-makers to quickly grasp key findings and make informed decisions.

IV. PROPOSED FRAMEWORK

The proposed framework addresses the challenges of analyzing very large datasets, which can lead to misleading findings and negatively impact decision-making. While decision-makers often rely on intuition and experience to filter out irrelevant data, this approach is ineffective on a larger scale. The framework integrates key components data preparation, data analytics, decision-making, and an insights repository to ensure the quality and relevance of analyzed data within a decision support system. By transitioning raw data into meaningful information, the framework facilitates continuous improvement through insights from past decisions. Technologically, it requires seamless integration between the decision support system, data stream mining, traditional data warehousing, and the insights repository.

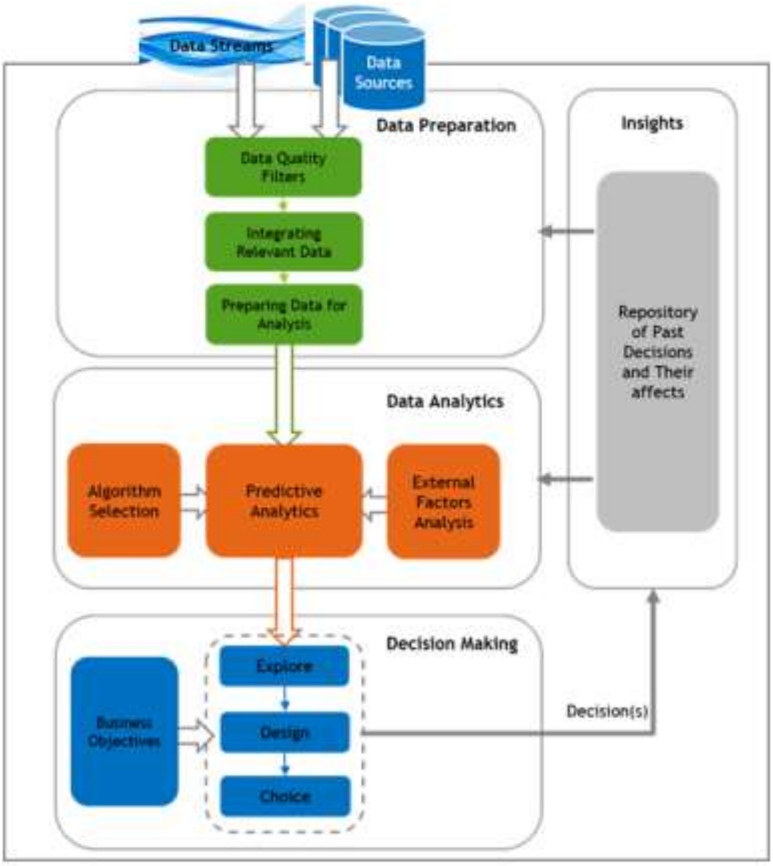

Figure 5: Framework for Effective Big data Analytics for Decision Support Systems

1) Data Preparation Component

The data preparation component gathers input from traditional sources like databases and transactional systems, as well as dynamic sources such as social media or mobile data streams. To integrate these diverse data streams, the decision support system needs interfaces with these systems, either directly within the organization or through web services for external sources. The first step in this component involves data quality filtering, where data is evaluated based on criteria such as metadata, relevance, accuracy, completeness, and timeliness to ensure high-quality input for analysis. This step is critical, especially when dealing with Big Data, which may not have been originally intended for analysis and can otherwise lead to irrelevant or incorrect insights. Next, relevant data is integrated, ensuring that any additional data sources that could enhance analysis are included. The final step is preparing the data for analysis by performing necessary transformations or cleansing. The main advantage of this component is that it ensures the data's quality and relevance while also combining relevant datasets to provide context to initial findings.

2) Data Analytics Component

The data analytics component takes the filtered and prepared data and applies a predictive analytic approach. Selecting the appropriate algorithm for analysis is crucial and depends on factors specific to the problem domain. This component needs a library of algorithms categorized by business domain and relevant external factors to ensure the best match for the problem at hand. Once the appropriate algorithm is chosen, the predictive analytics model generates potential outcomes, which are presented to the decision-maker as recommendations and visualizations. The model requires ongoing monitoring to ensure predictive accuracy within acceptable limits and should be continually improved by comparing its results with traditional models. For this, the decision support system needs a predictive monitoring subsystem.

3) Decision Making Component

The decision-making component processes the set of recommendations and visualizations produced by the data analytics component. In the exploration phase, decision-makers interact with the system to review outcomes and recommendations. Moving into the design phase, they select the most relevant elements to develop alternatives, ultimately choosing the best decision that aligns with business objectives and is supported by robust data and recommendations. This component requires an interactive dashboard subsystem that allows decision-makers to filter and organize alternatives effectively.

4) Insights Component

The insights component ensures that decisions and their outcomes are stored in a repository for future reference, feeding back into subsequent cycles of data preparation, analytics, and decision-making. The decision support system must be linked to a knowledge base repository capable of sorting, filtering, and organizing insights for later use. This connection should be automated to improve decision-making over time, with alerts for inefficiencies identified based on past decisions or recommendations. The key benefit of this component is its role in refining quality factors as needs evolve, while also enabling data analytics to learn from the success rates of past predictions to enhance future analyses.

V. CONCLUSION

This paper analyzed related works in the fields of Decision Support Systems (DSS) and Big Data to identify key elements crucial for enhanced decision-making. It provided an in-depth examination of data-driven DSSs and Big Data analytics, emphasizing their significance in this research. To optimize the use of Big Data analytics within DSSs, a framework was proposed to guide decision-makers in effectively implementing and utilizing DSSs that align with relevant Big Data sources. The paper also highlighted best practices and emerging trends in Big Data analytics as they relate to DSSs, serving as key examples for this study. Future research will involve evaluating the proposed framework within an organization through a case study approach, focusing on the quality aspects of data analysis and their impact on Big Data analytics. Additionally, future work will explore practical applications of

REFERENCES

[1] K. Vassakis, E. Petrakis, and I. Kopanakis, ‘Big data analytics: applications, prospects and challenges’, *Mobile big data: A roadmap from models to technologies*, pp. 3–20, 2018.

[2] P. Akhtar, J. G. Frynas, K. Mellahi, and S. Ullah, ‘Big data-savvy teams’ skills, big data-driven actions and business performance’, *British Journal of Management*, vol. 30, no. 2, pp. 252–271, 2019.

[3] M. Seyedan and F. Mafakheri, ‘Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities’, *Journal of Big Data*, vol. 7, no. 1, pp. 1–22, 2020.

[4] B. B. P. Rao, P. Saluia, N. Sharma, A. Mittal, and S. V. Sharma, ‘Cloud computing for Internet of Things & sensing based applications’, in *2012 Sixth International Conference on Sensing Technology (ICST)*, 2012, pp. 374–380.

[5] A. E. Youssef, 'Exploring cloud computing services and applications', *Journal of Emerging Trends in Computing and Information Sciences*, vol. 3, no. 6, pp. 838–847, 2012.

[6] K. Ren, C. Wang, and Q. Wang, 'Security challenges for the public cloud', IEEE Internet computing, vol. 16, no. 1, pp. 69–73, 2012.

[7] T. Dillon, C. Wu, and E. Chang, 'Cloud computing: issues and challenges', in *2010 24th IEEE international conference on advanced information networking and applications*, 2010, pp. 27–33.

[8] G. DeSanctis and B. Gallupe, 'Group decision support systems: a new frontier', *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, vol. 16, no. 2, pp. 3–10, 1984.

[9] J. K. Levy, 'Multiple criteria decision making and decision support systems for flood risk management', *Stochastic Environmental Research and Risk Assessment*, vol. 19, pp. 438–447, 2005.

[10] A. Intezari and S. Gressel, 'Information and reformation in KM systems: big data and strategic decision-making', *Journal of Knowledge Management*, 2017.

[11] O. Lavastre, A. Gunasekaran, and A. Spalanzani, 'Supply chain risk management in French companies', *Decision Support Systems*, vol. 52, no. 4, pp. 828–838, 2012.

[12] V. Grover, R. H. L. Chiang, T.-P. Liang, and D. Zhang, 'Creating strategic business value from big data analytics: A research framework', *Journal of management information systems*, vol. 35, no. 2, pp. 388–423, 2018.

[13] M. H. ur Rehman, I. Yaqoob, K. Salah, M. Imran, P. P. Jayaraman, and C. Perera, 'The role of big data analytics in industrial Internet of Things', *Future Generation Computer Systems*, vol. 99, pp. 247–259, 2019.

[14] M. K. Saggi and S. Jain, 'A survey towards an integration of big data analytics to big insights for value-creation', *Information Processing & Management*, vol. 54, no. 5, pp. 758–790, 2018.

[15] A. Popovič, R. Hackney, R. Tassabehji, and M. Castelli, 'The impact of big data analytics on firms' high value business performance', *Information Systems Frontiers*, vol. 20, pp. 209–222, 2018.

[16] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, 'Intelligent manufacturing in the context of industry 4.0: a review', *Engineering*, vol. 3, no. 5, pp. 616–630, 2017.

[17] S. Ren, Y. Zhang, Y. Liu, T. Sakao, D. Huisingh, and C. M. Almeida, 'A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions', *Journal of cleaner production*, vol. 210, pp. 1343–1365, 2019.

[18] A. Mohamed, M. K. Najafabadi, Y. B. Wah, E. A. K. Zaman, and R. Maskat, 'The state of the art and taxonomy of big data analytics: view from new big data framework', *Artificial Intelligence Review*, vol. 53, pp. 989–1037, 2020.

[19] K. Abbas, M. Afaq, T. Ahmed Khan, and W.-C. Song, 'A blockchain and machine learning-based drug supply chain management and recommendation system for smart pharmaceutical industry', *Electronics*, vol. 9, no. 5, p. 852, 2020.

[20] T. Zheng, M. Ardolino, A. Bacchetti, M. Perona, and M. Zanardini, 'The impacts of Industry 4.0: a descriptive survey in the Italian manufacturing sector', *Journal of Manufacturing Technology Management*, vol. 31, no. 5, pp. 1085–1115, 2020.

[21] A. Dixit, D. P. Sharma, S. K. Sharma, and M. Dhaka, 'A brief review of Data Analytics approach for Small and Medium Scale Enterprises over Clouds', in *2021 International Conference on Computational Performance Evaluation (ComPE)*, 2021, pp. 878–885.

[22] D. Berdik, S. Otoum, N. Schmidt, D. Porter, and Y. Jararweh, 'A survey on blockchain for information systems management and security', *Information Processing & Management*, vol. 58, no. 1, p. 102397, 2021.

[23] S. Maheshwari, P. Gautam, and C. K. Jaggi, 'Role of Big Data Analytics in supply chain management: current trends and future perspectives', *International Journal of Production Research*, vol. 59, no. 6, pp. 1875–1900, 2021.

[24] P. K. Kurotschka *et al.*, 'General practitioners' experiences during the first phase of the COVID-19 pandemic in Italy: a critical incident technique study', *Frontiers in Public Health*, vol. 9, p. 623904, 2021.

[25] Y. Niu, L. Ying, J. Yang, M. Bao, and C. B. Sivaparthipan, 'Organizational business intelligence and decision making using big data analytics', *Information Processing & Management*, vol. 58, no. 6, p. 102725, 2021.

[26] S. Hussain *et al.*, 'Aspect2Labels: A novelistic decision support system for higher educational institutions by using multi-layer topic modelling approach', *Expert Systems with Applications*, vol. 209, p. 118119, 2022.

[27] V. V. Jadhav and R. Mahadeokar, 'The fourth industrial revolution (I4. 0) in India: challenges & opportunities', *Management*, vol. 6, pp. 105–109, 2019.

[28] R. Fazal, M. A. Shah, H. A. Khattak, H. T. Rauf, and F. Al-Turjman, 'Achieving data privacy for decision support systems in times of massive data sharing', *Cluster Computing*, vol. 25, no. 5, pp. 3037–3049, 2022.

[29] Laudon, K. and Laudon, J. (2006) Management Information Systems: Managing the Digital Firm, 9th Edition, Upper Saddle River New Jersey, Pearson – Prentice Hall.

[30] Power, D. J. (2004). Specifying an Expanded Framework for Classifying and Describing Decision Support Systems. The Communications of the Association for Information Systems, 13(1), 52.

[31] Sagiroglu, S., & Sinanc, D. (2013). Big data: A review. In Collaboration Technologies and Systems (CTS), 2013 International Conference on (pp. 42-47). IEEE.

[32] Tsai, C. W., Lai, C. F., Chao, H. C., & Vasilakos, A. V. (2015). Big data analytics: a survey. Journal of Big data, 2(1), 1-32.