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Business Decision making through Big Data Analytics using Machine Learning Technique

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Abstract: In the era of digital transformation, businesses are increasingly leveraging big data analytics and machine learning techniques to enhance decision-making processes. This paper explores the integration of these technologies, highlighting their significant impact on strategic and operational decisions. Big data analytics provides a foundation for understanding complex datasets, while machine learning techniques enable predictive modeling, pattern recognition, and automated decision-making. These tools collectively improve accuracy, efficiency, and agility in business operations. The key benefits include enhanced customer insights, optimized supply chain management, improved risk management, and innovative product development. Despite challenges such as data quality, technical expertise, and privacy concerns, the strategic application of big data analytics and machine learning offers substantial opportunities for businesses to gain a competitive edge. This paper underscores the transformative potential of these technologies in driving informed, data-driven decisions and fostering a culture of continuous innovation and adaptability in the business landscape.

Keywords: *Big Data Analytics, Machine Learning, Decision-Making, Predictive Modelling, Data-Driven Strategies, Operational Efficiency, Strategic Decision-Making*

1. Introduction

Machine learning and big data analytics provide the groundwork for comprehending the methods and resources used by businesses for making decisions. The goal of big data analytics is to find useful trends, patterns, and correlations in massively complex data sets. With this method, companies may learn important things and base their judgements on evidence-based data. Machine learning, on the other hand, is an AI subfield that allows computers to learn and become better at things on their own without human intervention. In this part, we will delve into the spectrum of machine learning and big data analytics, covering the many sectors and applications that are using these technologies to propel commercial success. Big data analytics and machine learning are powerful tools that organisations can use to make strategic choices. It's important for businesses to grasp what these terms mean and how they may be used so they can make informed decisions that affect their operations and bottom line. Big data analytics and machine learning together could change the game for how companies function and make choices. Organisations may learn more about customer habits, market tendencies, and the dynamics of competition by using massive amounts of data and sophisticated algorithms. Consequently, this paves the way for improved forecasting, risk management, and consumer service. Additionally, these methods may be used to automate mundane jobs, which means that people can be used for more creative and strategic work. In conclusion, companies in a wide range of sectors stand to gain a great deal of value and an edge in the marketplace by combining big data analytics with machine learning. "Big data analytics" means analysing huge and complicated data sets to find trends, patterns, and insights that businesses may use to make better choices. Statistical and mathematical methods are used to examine data from numerous sources, such as internet interactions, client transactions, and social media. Machine learning, in contrast, is a branch of AI that allows computers to automatically improve their performance over time by learning from data rather than being expressly programmed to do so. Businesses looking to optimise their operations and strategies may benefit from the vast array of applications within this sector, which includes predictive modelling, recommendation systems, and anomaly detection, among many others. Data created by many different industries, including media and entertainment, banking, and healthcare, is growing at an exponential pace and might reach 175 petabytes by 2025. We talk about "Big Data" when we have large, complicated databases that are organised, unstructured, or partially structured. There are a lot of data kinds in it, and it might have missing or unknown values. It's also quite large. The volume and complexity of big data make it unsuitable for conventional database management techniques and storage on a single computer. Data size is only one factor in deciding whether it is big data or not. In this era of rapidly developing digital technologies, the business-driven strategy has revolutionised the way businesses carry out their day-to-day operations. The enormous amount of data is easily accessible since the kind

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of storage has expanded in parallel with data collection. The quantity of data is always growing as more and more sources contribute to it. Specific procedures are required to save this data for examination and, eventually, to ascertain its value. Organisations should strive to maximise the value they get from their huge data warehouse. Companies and their associated parties also possess the resources that allow them to store and classify data in different ways. Almost all users nowadays have access to their own personal gadget, such a smartphone or laptop. Many of these gadgets store vast quantities of data that might be useful to businesses. Following that, the third "Big data" refers to data that varies in amount, variety, and velocity; with the technologies available today, it becomes difficult to maintain and manage. Data that is considered huge may comprise a wide variety of formats, such as video, audio, clickstream, emotion, location-based information, and information about user sessions on websites.[1]Thus, several big data analytics methods are required, with consideration given to aspects like data size, variety, and change frequency, as well as storage and processing processes. Furthermore, such enormous databases need painstaking research to glean valuable insights. Companies are looking for a solution and some standards for managing big data as the need for exploiting it to take advantage of opportunities continues to rise [4]. What ways are there for using big data analytics into decision-making? Our study paper aims to address that exact question. Central to the research goals of designing and testing the framework is the incorporation of big data methodologies and technologies into the decision-making process.[15] By embracing the framework, decision-makers may improve the decision-making process by setting the bar higher.in The framework incorporates the distinguishing elements of big data analytics, such as its life cycle, the necessary architecture and infrastructure, and the tools for mapping the multiple decision-making processes.[6]

Big Data is useful for dealing with data sets that are growing at an exponential rate, making them difficult to handle with conventional database management systems [14]. However, there is no longer enough time for commonly used software tools and storage methods to store and manage the data process due to the enormous dimensions of big data.[5]Big data is characterized by its three primary properties: volume, velocity, and diversity. Data in terms of volume may be thought of as static, whereas data in terms of velocity can be thought of as dynamic, changing at a specific pace or depending on its creation method over time. The last category is variation, which is a distinct format for data [6]. When large data sets can be analyzed using sophisticated analytics methods, Big Data analytics is used. The year 19 Business alternatives may be bolstered, shown, and supported by analytics obtained in bigger data sets. The more data there is, the more obstacles there are to handling it.If competent analytics can't help improve decision-making, reduce risk, and unearth hidden insights in data, then the data's useful information will stay concealed indefinitely. It is not always necessary to automate the judgments; instead, data-based analysis employing big data methods and technologies should be used to cross-check them. In terms of the value of the retrieved information, this will assist the folks comprehend better. On the other hand, there has been a lot of study on the subjects of management decision-making processes, and they are quite essential. There are four steps to making a decision: thinking, planning, considering alternatives, and finally acting. Several paths lead to the big data analysis pipeline, each with its own set of challenges and decision points.[16]Determining what data to obtain, how to depict it after extraction and cleanup, and how to incorporate it with other sources may all contribute to this kind of decision-making. In order for big data analysis to provide real value, it is necessary to properly prepare for all of these challenges and choices. Because they are always eager to act on well-informed decisions whenever the chance presents itself, decision-makers should be adept at spotting and maximizing big data's potential to enhance the traditional decision-making process [2]. In order to provide decision-makers with valuable insights, research should be able to explain how methodologies and tools might be merged with big data to enhance decision-making [9].

To thrive in today's complex business contexts, companies must be nimble enough to foresee potential challenges and adjust accordingly [1]. Businesses began incorporating more data sources into their decision-making processes as a result of the growing complexity of the problem. Finding trustworthy open/public data sources, maintaining them, and integrating them with internal data presents a variety of challenges for enterprises. If companies can streamline their decision-making processes and conquer these big data challenges, they will gain a competitive advantage. Volume, velocity, diversity, authenticity, and value are the five defining qualities of big data, which is still a controversial concept [2]. In order to make informed decisions, business leaders need access to pertinent data. In order to make informed decisions, business leaders need access to pertinent data. "Big Data Analytics" refers to the practice of applying analytics to massive datasets [3]. Statistics, data mining, machine learning, SNA, signal processing, pattern recognition, optimization, visualization, and a host of other techniques and approaches are all at your disposal for optimizing and making the most of BDA [4]. Boosted openness, improved strategic decision-making, and streamlined operations. Two of the most commonly recognized big data opportunities, according to a BDA-based framework for strategic decision-making, are improved customer service and the creation of new, superior goods and services [5, 6]. Due to problems with people, culture, and processes, less than 20% of businesses have implemented BDA into their supply chains [8, 9]. As a result, top-level executives play a pivotal role in realizing the benefits of BDA, which include cost savings, increased agility, and better service levels [7]. Critical factors are those that influence analytics deliverables and decisions. A number of aspects influence it, including the information quality, organizational capability, technical capacity, analytical competency, talent or human potential, and the efficacy of its execution [10]. Research on the consequences of BDA adoption has, to be honest, received less attention from academics. In order to aid in successful decision-making, this research seeks to provide a conceptual model of evaluating BDA implementation and to identify and assess the aspects and qualities that influence BDA implementation. In light of the evident need for smart business models that can spot data-action possibilities throughout the decision-making process and transform data into knowledge and an advantage over competitors, management researchers have put forward data-driven approaches. Supporting references [11, 12]. As an actual ideology, data-driven decision-making (DDDM) prioritizes evidence over gut feelings and experience when making strategic decisions. It stresses the need of data management in all decision-making and encourages top-down efforts to foster an innovative culture. As a result, there has to be a system in place to ensure that various kinds of businesses are using data analysis approaches to their full potential.

2. Data Analytics

Analyzing raw data to refurbish information for knowledge acquisition is the goal of data analytics, a scientific and statistical instrument. When faced with real-world problems, data analytics and data work together to develop complicated conclusions based on multiple viewpoints. In order to address empirical approaches in real-world decision-making, analytics is tasked with collecting, storing, processing, and analyzing data. Analytics may be generically categorized into four types: descriptive, inferential, predictive, and prescriptive [1]. Analyzing large amounts of data in real-time, with varying data structures, is known as Big Data Analytics, and it is an extension of data analytics. Due to the exponential growth of data, big data serves as a frontier for innovation, competitiveness, productivity, and business forecasting [2]. Making important decisions is made easier with the use of analytics on such massive data sets, which uncover previously unseen patterns, correlations, market trends, customer needs, and future suggestions [3]. Using Big Data Analytics, a wide range of businesses are able to better manage, analyze, and evaluate their data in order to spot untapped possibilities. Big Data Analytics has several uses, including improving operations, cutting costs, making better decisions, improving service systems, and developing better products. In order to represent Big Data, sophisticated storage structures are used. Such enormous Big Data Structures are beyond the capabilities of conventional database management systems. Managing massive amounts of data calls for a fresh strategy. Therefore, as a data analytics pre-processing stage, an expert system is included to analyze Big Data.

3. Role of Machine Learning In Big Data Analytics

Data scientists use Machine Learning, a technological technique, to build logic out of data by turning data into knowledge. The area of Machine Learning has produced several effective algorithms for the purpose of learning patterns, gaining insights, and making predictions based on past occurrences. In today's world, there is a dearth of information despite the abundance of data. Both organized and unstructured data types are used to describe this mountain of information. Data that is organized in tables is called structured data, while data that is in an irregular form, such pictures, papers, audio, video, etc., is called unstructured data. Automated machines construct models to handle massive volumes of unstructured data with little to no human involvement. By enhancing prediction for data-driven choices, Machine Learning offers effective analytical methods for collecting information. Strong emails, spam filters, easy text, voice recognition, online search engines, game creation, and self-driving automobiles are all made possible by its prominent position in computer science. By studying the properties of distributed parallel data, a model may be fine-tuned to address a wide range of issues throughout the learning process. The data that is supplied into the system determines how learning models are formed. It is crucial to execute calculations in a distributed parallel environment utilizing Machine Learning methods due to the complexity and massiveness of the data. The ever-increasing volume of data has prompted the development of more sophisticated Machine Learning algorithms. Because of the inherent complexity of modern business processes, multi-core processors are essential, since single-core systems are ill-equipped to deal with the enormous data structures encountered. Hadoop, a Big Data distributed file system, can hold enormous amounts of data, grow at an exponential rate, and continue to function normally in the event of a storage infrastructure failure. Using low-cost computers that distribute calculations amongst themselves, analytics clusters and multi-core processors are constructed. Combining big data with machine learning allows departments to process more complicated data.

It is important to think outside the box when using data that comes from various sources. Analytics often make use of pre-existing data. It is possible to gauge a company's success using these analytics. Forecasting is spawned from this assessment. A number of factors contribute to the evolution of forecasting, including technological progress, the proactive nature of organizations, and the capacity for intelligent thought and sound judgments. To get a deeper comprehension of the current data and to aid in predicting, predictive analytics is the way to go. In order to proactively engage in the difficulties surrounding future capitalization and to get insights from predictive solutions for developmental activities, decision makers are actively seeking these things out. Helping professionals in the field see the connections between organized and unstructured data, it draws pertinent conclusions. Since big data analytics (BDA) often deals with raw data that is neither labelled nor categorized, DL's capacity to analyze and learn from massive volumes of unstructured data makes it a valuable tool. This survey article delves into a thorough examination of cutting-edge DL methods used in BDA. This review primarily aims to describe the fundamental approaches employed in BDA and to demonstrate the importance of DL and its taxonomy. Additionally, it delves into the DL approaches used in huge IoT data applications, illuminating their intricacies and obstacles along the way. In recent years, DL and BDA have both grown into thriving scientific and technological research communities. Deep learning (DL) is a machine learning approach that uses supervised and unsupervised learning methods to automatically learn deep architectures with several layers of representation and to uncover hidden representations in deep structures. Applications in crucial domains like as computer vision, audio and voice processing, and natural language processing have achieved extraordinary success with it [3]. Also, IT companies are very interested in DL research initiatives, and they gather and analyze huge volumes of digital data daily.

Due to DL's ability to handle large volumes of both labelled and unlabeled data, it is essential for the resolution of many BDA issues. These include, but are not limited to, the following: scalability of algorithms, high dimensionality, and format variations in raw data, unsupervised and un-categorized data, limited supervised or labelled data, noisy and poor-quality data, handling online fast-flowing data streams, and so on. Another reason DL architectures are great for integrating heterogeneous data is that they can model complicated behaviors' in multimodal datasets and learn data variation factors by giving abstract representations of them [4,5]. Deep learning is very useful for a wide variety of tasks, including classification, prediction, clustering, regression, association rule mining, and more, and it has found a particularly attractive and widespread use in the data produced by IoT devices. The Internet of Things (IoT) and deep learning (DL) were two of the most talked-about tech developments of 2017 [6].

This study provides a comprehensive review of DL approaches that considers the vast array of real-world issues and activities. We do this by offering a taxonomy of DL approaches used in BDA, which we divide into three main categories: hybrid learning, generative learning, and discriminative learning. The way different DL approaches learn and apply to real-world issues determines which category they fall into. In particular, this study reviews the literature on BDA with DL, finds applicable approaches, and gives researchers and practitioners advice. In addition, we include a thorough literature evaluation on each DL approach that is suitable for data types used in IoT applications, and we explain the benefits of using DL techniques in massive IoT data. The report also examines the current benchmarked datasets and delves into the DL benchmarked frameworks used in BDA. Furthermore, it evaluates the suitable applications of each DL approach as well as their strengths and limitations. Analyzing various DL algorithms within the framework of big data and large IoT data analytics is the primary contribution of this study. We show that the most popular DL methods are useful for data-intensive applications by analyzing large datasets.

4. Related Works

The significance of combining data collecting and management with creative interpretation of information is indeed emphasized by research [14]. Marketing management research [15] lays out the steps involved in making decisions, and Data Driven Decision Making may provide a framework for using big data analysis along the process.

The content of a management decision is significantly affected by the evaluation and selection of the final choice according to the correct methods, as stated by E. S. Balashova et al. [15]. It is possible to identify the economic, organizational, legal, technical, and social aspects that separate management choices from judgments made by people on a daily basis.

Micro and macro environments are both considered part of the company's external environment. More specifically, it is the focus of studies conducted by marketers. There are factors in the microenvironment that the firm may control, and which have an effect on the organization's behavior and the success of its objectives [16, 17].

Forces in a corporation's macro-environment may have a significant effect on the company as a whole, yet no one company can change this. So long as the organization is flexible enough to adapt to new circumstances and has good enough knowledge of the macro environment to predict when things will change, everything will be OK [18].

In their broader analysis of decision-making performance, Visinescu et al. [19] considered decision effectiveness and efficiency, which include accuracy and resource utilization, as well as other metrics. Improving upon the idea of Visinesce et al. [19], Shamim et al. [20] provide an explanation of decision-making performance within the framework of big data-driven decision-making, focusing on effectiveness and efficiency.

As a comprehensive approach to processing and analyzing big data for value generation, BDA is defined by Wamba et al. [21]. Currently, it is considered a crucial part of making things more effective and efficient, which has both strategic and operational ramifications.

Akhtar et al. [22] looked at the positive correlation between teams that are knowledgeable about big data, activities that are driven by big data, and company performance. Large data-savvy teams' talents and plans were also emphasized. The authors stress the need of diverse skill sets and knowledge bases in big data teams since it is very unlikely that a single expert would be aware of it.

Through the mediating effect of dynamic capabilities, Mikalef et al. [23] found that BDA capabilities—including physical, intangible, and human skills—had a positive association with innovation. Additionally, they note that the correlation between BDA skills and creativity is moderated by contextual variables including volatility, diversity, and aggression. A competitive performance boost is the result of a company culture that values evidence-based decision-making [24] and uses resources in a synergistic fashion.

2.1 Data Processing, Data Analytics, and "Big Data"

Data science is an essential framework for analysing and making sense of data releases. To incorporate data science, the closest notion today is specific extraction utilising data processing. There are a plethora of field techniques and data processing algorithms. In this paper, we propose that a minimal and concise set of fundamental principles may include all of this data.in [13]. All sectors of company operations make use of these approaches. Services like customized marketing and advertising are part of comprehensive business software. Using data science, businesses may examine consumer actions to manage impairment and raise expectations. The financial sector makes use of data science for a variety of purposes, including the calculation of trade and credit ratings, the investigation of fraud, and the management of personnel. Also used in marketing and supply chain management by retail firms. In an effort to transform into data processing organizations, some companies have cut ties with data science.in [13] Nevertheless, data science encompasses more than just data handling and algorithm processing. Successful data researchers should be able to examine business problems from an information perspective. Data analysis thinking follows a basic framework. Many parts of "traditional" education are included into data science. One should be familiar with the fundamentals of causal analysis. Data science depends on the great majority of conventionally studied topics in mathematics.in [13]. Additionally, there are some areas that need knowledge about a certain program me as well as insight, innovation, sensibility, and specifics. Data scientists have a framework for dealing with problems related to data extraction thanks to the principles and guidelines provided by data science.in [13]

5. Methodology

Big data analytics has become a crucial trend for many organizations due to the massive amounts of data being gathered daily. They may analyze and make judgments based on their huge volumes of data, which may include crucial information that may be used to address various issues. To make good judgments, decision-makers need access to relevant information. These days, it seems like every piece of data has an online connection. In order to extract useful information from large datasets that are subject to frequent updates, big data analysis is used. This effort's final objective is to integrate big data analytics with decision-making. The proposed work created a framework called Data Analytics and Business Decision Making (DA-BDM) is a framework that was used across the many stages of decision-making as shown in Fig 1.

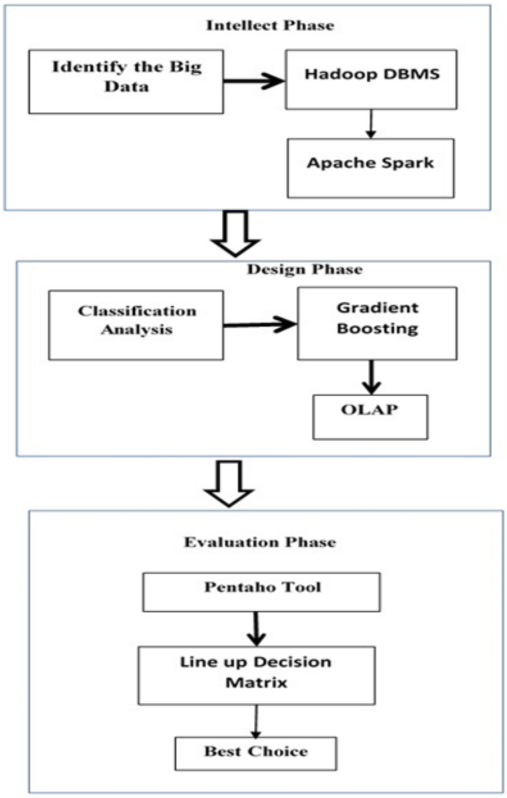

Fig. 1 Block Diagram of Proposed Framework

The decision-making process begins with the intellect phase, when information about potential obstacles and possibilities is received from many sources, both internal and external. The collected data may subsequently be archived. Analyzing the stored data makes advantage of in-memory caching and optimized query execution to conduct fast searches against data of any size, in contrast to the prior system's rather poor performance while processing large-scale data.

The second part of the framework is the design phase, where data mining and machine learning are used to improve accuracy. The proposed framework uses classification analysis to retrieve important and relevant information about the data and meta data, which is divided into different classes. It also uses machine learning to effectively mine the data for useful information, which helps overcome regression problems and the complexity of big data analysis. Business insight software can process mining data, enabling analysts to get data insight via the provision of reliable, collaborative access to several multidimensional representations of information in a timely manner.

The next phase is evaluate is to assess the effects of the suggested solution, which includes data mining, reporting, information dashboards, data integration, and ETL capabilities to overcome the issues of memory scalability. This means that in order to boost the company's results, the recommended framework lays out the optimal course of action.

6. Conclusion

Utilizing machine learning methods to analyses huge data has become crucial for making educated decisions in today's commercial world. By combining these cutting-edge technologies, companies may gain a competitive advantage and stimulate innovation by deriving useful insights from massive volumes of data. With the help of machine learning and big data analytics, corporate decision-making has a bright future. Analytical capacities will be further enhanced by developments in quantum computing, artificial intelligence, and the Internet of Things (IoT). Better models, real-time analytics, and the ability to combine data from many sources will be possible as a result of ongoing progress in these areas. Companies need to embrace a data-driven decision-making culture to be flexible and responsive. In today's data-driven world, organizations may seize new opportunities, fuel development, and ensure long-term success by embracing sophisticated analytics and machine learning.

References

[1] Hu, H., Wen, Y., Chua, T., & Li, X. (2014). Toward scalable systems for big data analytics: A technology tutorial. IEEE Access, 2, 652-687. https://doi.org/10.1109/ACCESS.2014.2332453

[2] Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. Computers and Operations Research, 98, 254-264. https://doi.org/10.1016/j.cor.2017.07.004

[3] Barbosa, M. W., Vicente, A. D. L. C., Ladeira, M. B., & Oliveira, M. P. V. D. (2018a). Managing supply chain resources with big data analytics: A systematic review. International Journal of Logistics Research and Applications, 21(3), 177-200. https://doi.org/10.1080/13675567.2017.1356331

[4] Chen, C. P., & Zhang, C.-Y. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on big data. Information Sciences, 275, 314-347. https://doi.org/10.1016/j.ins.2014.01.015

[5] Cao, G., & Duan, Y. (2017). How do top- and bottom-performing companies differ in using business analytics? Journal of Enterprise Information Management, 30(6), 874-892. https://doi.org/10.1108/JEIM-04-2016-0080

[6] Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. Computers and Operations Research, 98, 254-264. https://doi.org/10.1016/j.cor.2017.07.004

[7] Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. Journal of Business Research, 70, 263-286. https://doi.org/10.1016/j.jbusres.2016.08.001

[8] Verma, S., & Bhattacharyya, S. S. (2017). Perceived strategic value-based adoption of Big Data Analytics in emerging economy. Journal of Enterprise Information Management, 30(3), 354-382. https://doi.org/10.1108/JEIM-10-2015-0099

[9] Adrian, C., Abdullah, R., Atan, R., & Jusoh, Y. Y. (2017). Factors influencing the implementation success of Big Data Analytics: A systematic literature review. In 2017 International Conference on Research and Innovation in Information Systems (ICRIIS) (pp. 1-6). IEEE. https://doi.org/10.1109/ICRIIS.2017.8002453

[10] Hagerty, J. (2014). Become a data-driven company in five steps. Retrieved from https://www.ibmbigdatahub.com/blog/become-data-driven-company-five-steps

[11] Simone, C., Barile, S., & Calabrese, M. (2018). Managing territory and its complexity: A decision-making model based on the viable system approach (VsA). Land Use Policy, 72, 493-502. https://doi.org/10.1016/j.landusepol.2018.01.002

[12] Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in numbers: How does data-driven decision making affect firm performance? Available at SSRN: https://doi.org/10.2139/ssrn.1819486

[13] Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. Big Data, 1(1), 51-59. https://doi.org/10.1089/big.2013.1508

[14] Xu, Z., Frankwick, G. L., & Ramirez, E. (2016).

Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. Journal of Business Research, 69(5), 1562-1566. https://doi.org/10.1016/j.jbusres.2015.10.017

[15] Balashova, E. S., & Gromova, E. A. (2017). Espacios, 38(53).

[16] Mogilko, D., Iliashenko, V., Chantsev, V., & Schmit, V. (2019). In IBIMA 2019: Education Excellence and Innovation Management through Vision 2020 (p. 8603).

[17] Gutman, S., & Rytova, E. (2019). In ACM International Conference Proceeding Series.

[18] Fedorova, G. V., & Shishkanova, G. A. (2018). Journal of Economy and Entrepreneurship, 8(97).

[19] Visinescu, L. L., Jones, M. C., & Sidorova, A. (2017). Improving decision quality: The role of business intelligence. Journal of Computer Information Systems, 57(1), 58-66. https://doi.org/10.1080/08874417.2016.1181496

[20] Shamim, S., Zeng, J., Choksy, U. S., & Shariq, S. M. (2019). Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level. International Business Review, 101604. https://doi.org/10.1016/j.ibusrev.2019.101604

[21] Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356-365. https://doi.org/10.1016/j.jbusres.2016.08.009

[22] Akhtar, P., Frynas, G., & Mellahi, K. (2019). Big data-savvy teams' skills, big data-driven actions, and business performance. British Journal of Management, 30, 252-271. https://doi.org/10.1111/1467-8551.12333

[23] Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and the moderating effect of the environment. British Journal of Management, 30(2), 272-298. https://doi.org/10.1111/1467-8551.12343

[24] Gonnade, P., & Ridhorkarb, S. (2024). Empirical analysis of decision recommendation models for various processes from a pragmatic perspective. *Multidisciplinary Reviews*, *7*(8), 2024159. https://doi.org/10.31893/multirev.2024159