Leveraging Business Intelligence and Operations Research for Enhanced Decision-Making in Healthcare

Mahmoud M. Ismail[*1], Heba R. Abdelhady [2]

[1,2] Faculty of computers and Informatics, Zagazig University, Zagazig, 44519, Egypt
Emails: mmsabe@zu.edu.eg; HRAbdelhady@fci.zu.edu.eg
*Correspondence: mmsabe@zu.edu.eg

Abstract

This paper explores the potential of leveraging business intelligence (BI) and operations research (OR) techniques to enhance decision-making in healthcare organizations. We propose a novel BI framework that includes three main components: data collection and management, data analysis and reporting, and decision-making support. Our framework leverages existing BI tools and techniques, such as data mining and visualization, to provide healthcare organizations with a comprehensive and integrated view of their operations. The framework also integrates clinical data with financial and operational data to provide a more holistic view of the organization. Healthcare organizations face numerous challenges, including rising costs, changing regulations, and the need to improve patient outcomes. By leveraging the proposed framework, healthcare organizations can make data-driven decisions that optimize resource allocation, streamline processes, and improve patient care. The paper provides use cases of how BI and OR have been successfully applied in healthcare organizations and discusses the potential for future research and applications in this field. Ultimately, our framework highlights the importance of using data-driven approaches to improve decision-making in healthcare organizations and suggests that the integration of BI and OR techniques has significant potential to achieve this goal.

Keywords: Operation Research; Business Intelligence; Decision-Making; Healthcare system

1. Introduction

Business Intelligence (BI) is a set of tools, technologies, and processes that enable healthcare organizations to collect, integrate, and analyze data from multiple sources to generate insights and support decision-making. BI applications in healthcare involve a combination of data warehousing, data mining, statistical analysis, and visualization techniques to provide decision-makers with a comprehensive and integrated view of their operations. By leveraging BI, healthcare organizations can identify trends and patterns in clinical, financial, and operational data, gain insights into patient outcomes, optimize resource allocation, and improve operational efficiency. The adoption of BI in healthcare is likely to increase as healthcare organizations continue to focus on improving patient outcomes, reducing costs, and enhancing the overall quality of care.

Operations Research (OR) is a discipline that employs mathematical modeling and analytical techniques to solve complex problems and support decision-making. In healthcare OR can be used in conjunction with BI to provide decision-makers with insights that go beyond descriptive analysis, enabling them to make data-driven decisions that are optimized for a range of criteria. The coupling of OR with BI in healthcare can help healthcare organizations to optimize resource allocation, streamline processes, and improve patient outcomes. The use of OR models can provide healthcare organizations with a deeper understanding of their operations and enable them to test different scenarios to determine the best course of action. Ultimately, the coupling of OR with BI can help healthcare organizations to make more informed and data-driven decisions that improve patient care and organizational efficiency.

DOI: https://doi.org/10.54216/AJBOR.030104
Received: March 04, 2021 Accepted: July 15, 2021

The application of BI in healthcare decision-making faces several challenges. One of the major challenges is the complexity and heterogeneity of healthcare data, which is often scattered across various systems and formats. This makes it difficult to integrate and analyze the data effectively. Additionally, there are concerns about data privacy and security, as healthcare data is sensitive and subject to strict regulatory requirements. This, in turn, poses many research questions that shape the motivation of our research.

1) How can a new BI framework be designed and implemented in healthcare organizations to improve decision-making?
2) How can existing BI tools and techniques be leveraged to provide a comprehensive and integrated view of healthcare operations?
3) How can clinical, financial, and operational data be integrated to provide a more holistic view of healthcare organizations?
4) How effective is the current study in improving decision-making and optimizing resource allocation in healthcare organizations?
5) What are the implications of our study for future research and practice in the field of healthcare BI?

This study seeks to answer these research questions through the presentation of case studies and analysis of the proposed BI framework.

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that uses algorithms and statistical models to analyze data, identify patterns, and generate insights that can support decision-making. In healthcare, ML can be used to enhance both BI and OR by enabling more sophisticated analysis of clinical, financial, and operational data. ML algorithms can be used to generate more accurate predictions of patient outcomes, optimize resource allocation, and identify patterns that are not easily detectable using traditional analysis methods. By combining ML with BI and OR, healthcare organizations can generate more precise and actionable insights, enabling them to make more informed and data-driven decisions. The use of ML in decision-making in healthcare has the potential to revolutionize the way healthcare organizations operate, improve patient outcomes, and enhance the overall quality of care.

To this end, the main contribution of the paper is the development of a new BI framework that incorporates ML algorithms to enhance decision-making in healthcare organizations. Our framework includes three main components: data collection and management, data analysis and reporting, and decision-making support. ML algorithms are used to analyze clinical, financial, and operational data to identify patterns, trends, and insights that can inform decision-making. We evaluate our framework on real use cases to know how the framework has been successfully implemented in healthcare organizations to improve resource allocation, patient outcomes, and operational efficiency. As a whole, the incorporation of ML algorithms in the proposed BI framework provides a powerful tool for healthcare decision-makers to make more informed and data-driven decisions.

The remaining parts of this study are planned as follows. First, the literature is reviewed in Section 2. The methodology of our research is explained in section 3. The results are presented in section 4. Then, we discuss the experimental findings and observations in section 5. The conclusions are derived in section 6.

2. Literature Review:

In this section, an extensive analysis of the literature concerning the utilization of BI and OR techniques in healthcare settings is presented. The discussion covers a range of techniques including data mining, predictive analytics, simulation modeling, and optimization. A critical evaluation of the advantages and limitations of these techniques in making informed decisions within the healthcare field is provided. In [5], the authors proposed a framework for developing a domain-specific BI maturity model, which consisted of six stages, including defining the scope and objectives of the model, identifying the relevant stakeholders and their needs, selecting appropriate BI maturity models, adapting and customizing the model, validating and refining the model, and using the model for BI maturity assessment and improvement. They applied the framework to the healthcare domain, demonstrating how it can be used to develop a BI maturity model that is tailored to the specific needs and characteristics of this industry. In [6], the authors investigated the relationship between BI maturity and hospital agility, which refers to a hospital's

DOI: https://doi.org/10.54216/AJBOR.030104
Received: March 04, 2021 Accepted: July 15, 2021

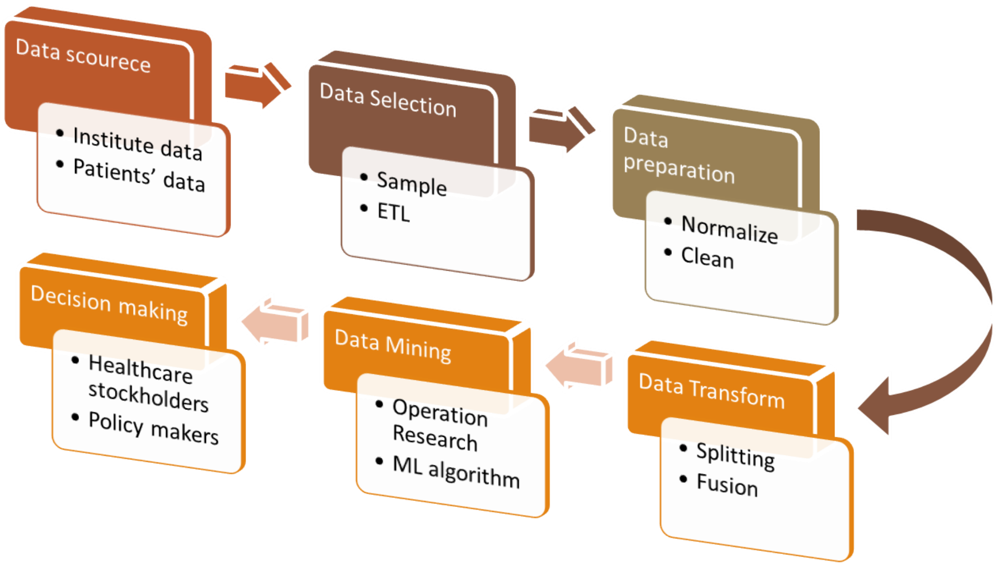

Figure 1:Illustration of the proposed BI framework for improved decision-making in healthcare industry.

ability to respond to changes in its environment. They conducted a survey of 68 hospitals in Taiwan and used a structural equation modeling (SEM) approach to analyze the data. Their findings suggest that BI maturity was positively associated with hospital agility and that this relationship is mediated by the hospital's ability to learn and adapt. In [7], the authors explored the factors that influence a company's BI capability, specifically the role of top management support, user participation, and analytical decision-making orientation. They surveyed 240 companies and highlighted the importance of a company's organizational culture in fostering BI capability and suggested that companies with a more analytical and data-driven culture are more likely to have higher BI capability. In [8], the authors applied the concept of BI success to the context of healthcare information systems based on a case study of a Danish hospital's implementation of a BI system and used a combination of interviews and surveys to evaluate the success of the implementation. They reported six dimensions of BI success: system quality, information quality, use, user satisfaction, individual impact, and organizational impact. Their findings suggested that the implementation was successful in terms of system quality and information quality, but that there was room for improvement in terms of use and user satisfaction. In [9] the authors presented a literature review of OR applications in the field of radiotherapy, with a focus on resource planning and use. They identified and analyzed 51 relevant studies, which use a variety of OR techniques, including mathematical modeling, optimization, and simulation. They provided a summary of the different OR applications, including treatment planning, scheduling, staffing, inventory management, and capacity planning, which highlighted the benefits of using OR in radiotherapy, such as improved patient outcomes, increased efficiency, and cost savings. In [10], the authors presented a comprehensive review of the literature on big data analytics in healthcare, which analyzed 93 relevant studies, covering a range of topics related to big data analytics, including data sources, data processing techniques, predictive modeling, and decision support systems. They reported several key themes in the literature, including the importance of data quality, the need for collaboration and integration across different healthcare stakeholders, and the potential benefits of big data analytics, such as improved clinical decision-making, patient outcomes, and healthcare system performance. In [11], the paper presented a systematic literature review of data mining and predictive analytics applications for the delivery of healthcare services. They analyzed 56 relevant studies, which cover a range of topics related to data mining and predictive analytics, including prediction of healthcare outcomes, patient segmentation, and disease diagnosis. They identified several key themes in the literature, including the importance of data quality and feature selection, the need for interpretability and explainability of predictive models, and the potential benefits of data mining and predictive analytics, such as improved patient outcomes, reduced costs, and increased efficiency. In [12], the authors presented a case study of the development of a roadmap towards precision medicine within the ISMETT hospital, using a maturity model for business intelligence in healthcare. They described the design and implementation of the maturity model, which is based on a set of criteria related to data management, analytics capabilities, and organizational culture. They then applied the model to evaluate the current state of business

DOI: https://doi.org/10.54216/AJBOR.030104
Received: March 04, 2021 Accepted: July 15, 2021

intelligence maturity within the hospital, and to identify areas for improvement. In [13], the authors discussed the use of BI for decision-making in economics, with a focus on overviewing the main concepts and technologies related to BI, including data warehousing, data mining, and dashboards. They also discussed some of the challenges associated with implementing BI in the financial industry, such as data quality, security, and privacy concerns. They presented several case studies to illustrate the application of BI in different areas, including risk management, portfolio optimization, and economic forecasting. In [14], the authors focused on the adoption and usage of enterprise resource planning (ERP) systems by small and medium-sized enterprises (SMEs) during times of crisis, and how this can contribute to BI. They described a study that was conducted in Greece during the financial crisis, which examined the factors that influence SMEs' decisions to adopt and use ERP systems. They found that perceived usefulness and perceived ease of use were the main factors that influenced SMEs' intentions to adopt ERP systems, while compatibility, relative advantage, and complexity were also important factors. In [15], the authors provided a comprehensive review of the emergence of big data research in operations management, information systems, and healthcare. They highlighted the importance of big data in addressing complex business problems and identifying new opportunities for innovation. They discussed the contributions of past research in these domains and outline a future research roadmap for leveraging big data.

3. Methodology:

Businesses that employ BI and OR have the better information management and hence make wiser choices. Understanding how a company's most important structures, personnel, and resources interact is key to business intelligence. Executives in the healthcare business use this information to make more informed decisions, while users in the health industry rely on immediate data to improve information management, foster greater communication and understanding, and lessen the likelihood of adverse events. If done properly, BI and OR systems could have a major effect. Inaccuracies in expenditure or value estimations between units can be avoided, and the board of directors can conduct a real-world effect analysis, with the use of a unified information source. Companies must gather case studies from both effective and unsuccessful initiatives and share this material with seasoned physicians so as to keep their team up-to-date on the current advancements in healthcare. According to the current literature, the recommended framework for the components that affect BI development and adoption is shown in Figure 1. Workers in the health industry who make use of a BI system will assess the system's structure. To learn how the proposed variables affect the growth and adoption of BI in public hospitals, a quantitative survey will be carried out. The primary goals of this system are the standardisation and harmonisation of planning and reporting processes, and the provision of relevant information and knowledge to public hospital employees in Greece in order to better inform their decision-making. The primary goal of this research is to determine what needs to be changed in the current BI system in order to raise the user's approval of it.

Data selection: In order to properly choose data, it is crucial to have a thorough understanding of the existing data, their linkages, and the features of each area. Meaning, context, provenance, application, and storage specifications for data can all be found in a data lexicon. The names, ages, identification numbers, material, and structure of the information provided by patients that can be utilised in our BI framework are all documented in the data dictionary. With this information, the analysis can utilise data from several sources and evaluate their connections with reduced processing expenses and increased efficiency. Data selection involves including some or all of a database's information in an analysis, with the choice depending on the nature of the issue at hand. To prevent overwhelming the process and achieving a certain level of detail in the examination at appropriate periods, it is best to avoid integrating all records.

Data Prepare: It's possible that some of the data in the various archives is skewed or inaccurate. Without proper data cleansing and treatment, the data mining stage will provide meaningless rules, lowering the quality of the analysis. Inadequate data, such as lost values for attributes, incoherent information, and conflicts between the data are just some of the issues observed in the data sources investigated in this study [4]. Filters, which may be applied both supervised and unsupervisedly, allow for the preparation of data. Depending on the nature of the data required for analysis, one may choose to clean either the characteristic or the instance. Preparing data ahead of time allows for a more manageable data set to be produced, which speeds up the procedure for analysing it, particularly in the mining tool phase.

DOI: https://doi.org/10.54216/AJBOR.030104
Received: March 04, 2021 Accepted: July 15, 2021

Data transformation: this refers to a set of operations that involve converting raw data into a more useful format that can be analyzed and used to inform the later data mining methods. They typically involve several steps, including data integration, data aggregation, and data normalization. Data integration involves combining data from different sources into a single, unified dataset. Data aggregation involves summarizing the data to provide a more concise representation of the data, such as calculating averages or totals. Finally, data normalization involves standardizing the data to ensure that it is consistent and comparable across different variables and datasets. By transforming raw data into a more useful format, data transformation operations enable healthcare providers and policymakers to analyze data more effectively and make more informed decisions that improve patient outcomes, optimize resource allocation, and reduce costs.

Data mining: OR methods can be used as data miners in our framework for healthcare data analysis to help identify patterns and relationships in the data. OR methods are mathematical and statistical techniques used to optimize complex systems and processes, and they can be used to identify patterns and relationships in healthcare data that may not be immediately apparent. In particular, Cluster analysis is used to identify groups of similar observations in the data. In other words, we use cluster analysis to identify groups of patients with similar clinical profiles, risk factors, or outcomes. This information can be used to tailor interventions and treatments to specific patient groups and improve patient outcomes.

A prediction ML model is an important form of data mining in our BI framework for healthcare data analysis as it can help healthcare providers and policymakers make data-driven decisions. To do so, we build a simple but effective method for analyzing historical healthcare data on patient outcomes, utilization, and costs, a prediction model can identify trends and patterns that can be used to forecast future outcomes and inform decision-making. The computation of our deep networks can be summarized as follows:

$$f(x) = b + w_1 \cdot x_1 + w_2 \cdot x_2 + \cdots + w_n \cdot x_n \quad (1)$$

$$f(x) = ReLU(b + W^{\top}X) \; where \; W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} and X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad (2)$$

With x and w denote the historical inputs and weights respectively. The Mean Absolute Error (MAE) is used to estimate the loss of deep network in our framework, and is computed as follows:

$$\text{MAE} = \frac{1}{N}\sum_{L=1}^{N} |(Y_{actual}^{L} - \text{Y}_{\text{predict}}^{L})| \quad (3)$$

4. Results

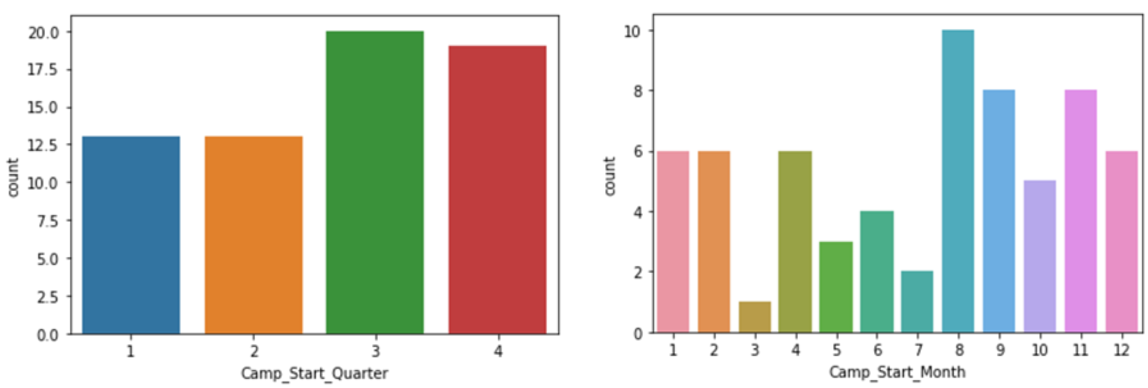

Figure 2.Illustration of the exploratory analysis of the count of health camps on quarterly basis (left) and monthly basis (right).

DOI: https://doi.org/10.54216/AJBOR.030104
Received: March 04, 2021 Accepted: July 15, 2021

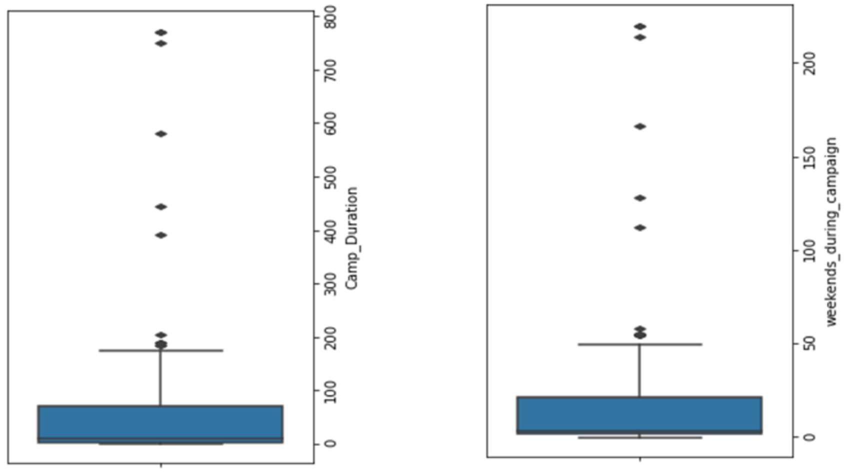

Figure 3. Box blots for the distribution of MedCamp data along camp duration (left) and weekends (right)

The healthcare industry has always been one of the first to adopt new technologies, and as a result, it has reaped many of the benefits of doing so. BI is now widely used in the healthcare industry, and its effects can be seen in many areas, which includes the creation of novel therapies, the management of patient data, health awareness

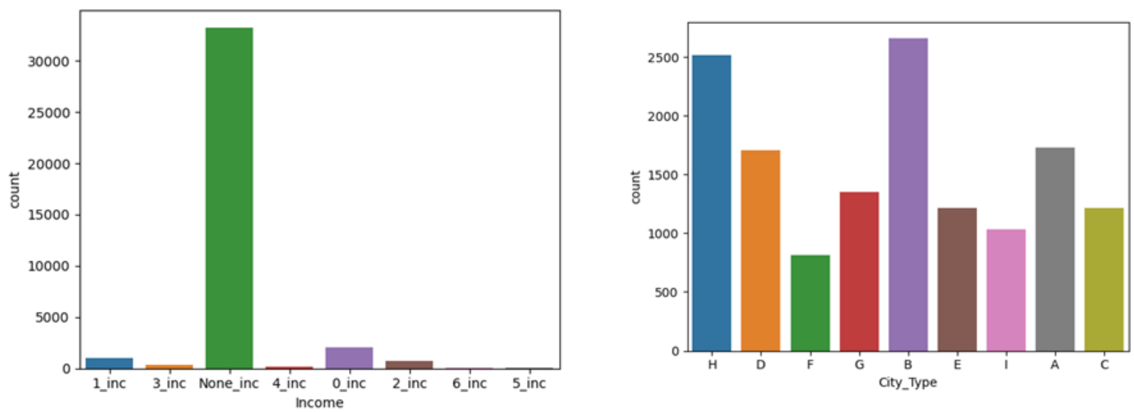

Figure 4. Visualization of frequer ... *d city type (right).*

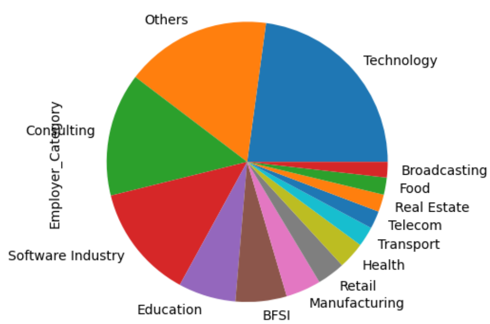

Figure 5. The distribution of patients according to their employment type.

campaigns and records, and the management of chronic diseases. In numerous cities where work life balance is poor, MedCamp hosts health fairs. Workers are contacted and encouraged to sign up for these health fairs. Attendees of a MedCamp can get free health screenings or visit informational booths to learn more about important issues (depending on the camp's style). Over the course of 65 similar events held by MedCamp over the past four years, the organisation has noticed a significant decline in test takers from the initial "Registration" numbers. Over the past four years, they h ave collected and saved information on over 110,000. This data is used as a case study for

DOI: https://doi.org/10.54216/AJBOR.030104
Received: March 04, 2021 Accepted: July 15, 2021

evaluating the proposed framework for BI. The number of supplies you need to transport to and from these camps is a significant expense. Costs can be inflated needlessly if more stock is kept on hand than is necessary. However, people have a negative impression of these medical checkups if you don't have enough of the necessary supplies on hand. In Figure 2, we are analyzing data on the frequency of health camps thru creating a frequency plot that shows the number of health camps held per month or quarter in the past year. Furthermore, Figure 3 shows a box plot for the distribution of health camps over a year can be useful in our study as it provides a visual representation of the distribution of health camps and allows for the identification of outliers and trends. For patient information, our BI framework visualizes the distribution of patients in Figure 4. The distribution of patients is summarized according to the type of employment, as shown In Figure 5.

Further, the descriptive statistics are calculated for patients' profile information, as shown in Table 1. This includes measures such as mean, median, mode, variance, and standard deviation to summarize the data and gain insights into its distribution and variability in our BI framework.

Table 1. Descriptive statistics of the patients' portfolio information.

	Patient_ID	*Online_Follower*	*LinkedIn_Shared*	*Twitter_Shared*	*Facebook_Shared*
count	37633	37633	37633	37633	37633
mean	507148.4	0.022533	0.027077	0.021603	0.023543
std	12411.75	0.148412	0.162311	0.145387	0.151623
min	485678	0	0	0	0
25%	496393	0	0	0	0
50%	507104	0	0	0	0
75%	517882	0	0	0	0
max	528657	1	1	1	1

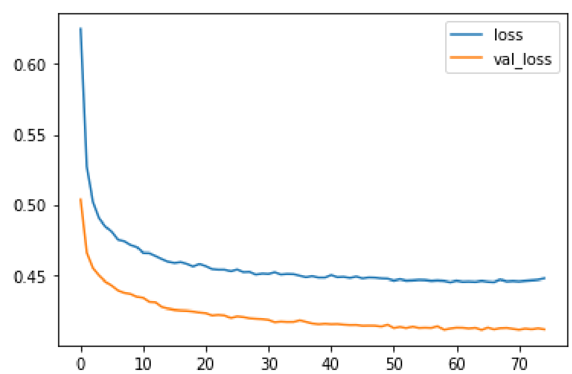

Figure 6. Visualization of learning curves for our framework.

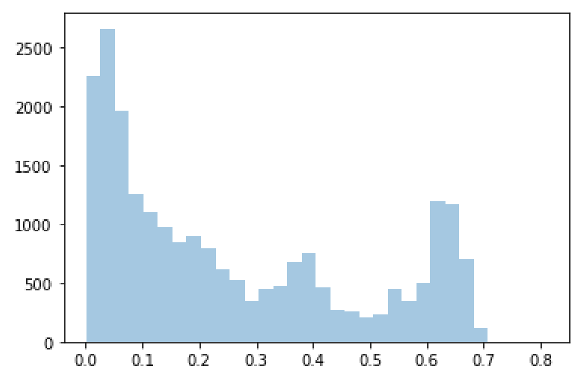

Figure 7. Visualization of KDE for predictions of our model.

In Figure 6, Loss curves are presented as a type of visualization that can be used to analyze the predictive performance of ML models, including the one used in our proposed framework for enhanced decision-making in healthcare. As shown, the loss curve is plotted as a function of the number of iterations or epochs of the training process. The model shows stable learning performance and rapid convergence after 50 epochs. KDE (Kernel Density Estimation) plot is used as a useful tool for visualizing the distribution of model predictions of our ML model, as displayed in Figure 7. From the shape and spread of the KDE plot, we may find certain patterns, which can provide great guidance for decision-makers in terms of targeted interventions or treatment plans.

DOI: https://doi.org/10.54216/AJBOR.030104
Received: March 04, 2021 Accepted: July 15, 2021

5. Discussion:

This study introduces an intelligent BI framework that is applied to real use case of healthcare data to drive valuable insights that can be used to improve and inform policy decisions in healthcare industries. In the early stage of our framework, we gather all relevant healthcare data for your project. This may include data on patient demographics, medical history, diagnoses, treatments, outcomes, and more. With the availability of public data, we replaced this data with a ready to use case study from Kaggle (see previous section). Then, our framework proposes to clean and preprocess the data by removing any duplicates, missing values, or outliers, and transforming the data into a format that is suitable for analysis. After that, we use various data visualization techniques, such as histograms, scatter plots, and box plots, to explore the data and identify any patterns or trends. From these visualizations, we obtain more information about the income of patients, their types of employment, and the type of their cities. Next, we provide descriptive statistics about the data to help decision makers gain insights into the data distribution and variability. Finally, we provide an impressive prediction of the upcoming healthcare values using ML to provide the decision makers with future outlook.

The findings demonstrate that pour framework can help identify patient populations with poor health outcomes, such as high readmission rates or increased risk of complications. This information can be used to improve care delivery and reduce costs by targeting interventions to these populations. In addition, our framework can help healthcare organizations optimize resource allocation by identifying areas where resources are being underutilized or overutilized. For example, by analyzing data on the utilization of operating rooms, healthcare providers can identify times when operating rooms are not being fully utilized and schedule additional surgeries to reduce wait times and improve efficiency. We also can facilitate identifying populations at risk for specific diseases, allowing healthcare providers to focus on preventive measures such as early detection and screening. By identifying populations at high risk for certain diseases, healthcare providers can implement targeted interventions that can prevent or delay the onset of disease.

6. Conclusion

The paper presents a new Business Intelligence (BI) framework that incorporates OR and ML algorithms to enhance decision-making in healthcare organizations. The framework provides decision-makers with a comprehensive and integrated view of their clinical, financial, and operational data, enabling them to make more informed and data-driven decisions. The use of ML algorithms in the framework provides healthcare organizations with a powerful tool for analyzing and interpreting complex data, identifying patterns, trends, and insights that can inform decision-making. The paper provides examples of how the framework has been successfully implemented in healthcare organizations to improve resource allocation, patient outcomes, and operational efficiency.

References

[1]. Ratia, Milla, Jussi Myllärniemi, and Nina Helander. "The new era of business intelligence: Big Data potential in the private health care value creation." *Meditari Accountancy Research* (2018).
[2]. Liang, Ting-Peng, and Yu-Hsi Liu. "Research landscape of business intelligence and big data analytics: A bibliometrics study." *Expert Systems with Applications* 111 (2018): 2-10.
[3]. Ivan, Mihaela, and Manole Velicanu. "Healthcare industry improvement with business intelligence." *Informatica Economica* 19, no. 2 (2015): 81.
[4]. George, Joseph, V. Kumar, and S. Kumar. "Data warehouse design considerations for a healthcare business intelligence system." In *World congress on engineering*. 2015.
[5]. Brooks, Patti, Omar El-Gayar, and Surendra Sarnikar. "A framework for developing a domain specific business intelligence maturity model: Application to healthcare." *International Journal of Information Management* 35, no. 3 (2015): 337-345.
[6]. Shen, Cheng-Che, Ray-E. Chang, Ching Jou Hsu, and I-Chiu Chang. "How business intelligence maturity enabling hospital agility." *Telematics and Informatics* 34, no. 1 (2017): 450-456.

DOI: https://doi.org/10.54216/AJBOR.030104
Received: March 04, 2021 Accepted: July 15, 2021

[7]. Kulkarni, Uday, Jose A. Robles-Flores, and Aleš Popovič. "Business intelligence capability: The effect of top management and the mediating roles of user participation and analytical decision making orientation." *Journal of the Association for Information Systems* 18, no. 7 (2017): 1.

[8]. Gaardboe, Rikke, Tom Nyvang, and Niels Sandalgaard. "Business intelligence success applied to healthcare information systems." *Procedia computer science* 121 (2017): 483-490.

[9]. Vieira, Bruno, Erwin W. Hans, Corine van Vliet-Vroegindeweij, Jeroen Van De Kamer, and Wim Van Harten. "Operations research for resource planning and-use in radiotherapy: a literature review." *BMC medical informatics and decision making* 16 (2016): 1-11.

[10]. Galetsi, Panagiota, and Korina Katsaliaki. "A review of the literature on big data analytics in healthcare." *Journal of the Operational Research Society* 71, no. 10 (2020): 1511-1529.

[11]. Malik, M. M., S. Abdallah, and M. Ala'raj. "Data mining and predictive analytics applications for the delivery of healthcare services: a systematic literature review." *Annals of Operations Research* 270 (2018): 287-312.

[12]. Gastaldi, Luca, Astrid Pietrosi, Sina Lessanibahri, Marco Paparella, Antonio Scaccianoce, Giuseppe Provenzale, Mariano Corso, and Bruno Gridelli. "Measuring the maturity of business intelligence in healthcare: Supporting the development of a roadmap toward precision medicine within ISMETT hospital." *Technological Forecasting and Social Change* 128 (2018): 84-103.

[13]. Dumitru-Alexandru, Bodislav. "Business Intelligence for decision making in economics." *Artificial Intelligence in Financial Markets: Cutting Edge Applications for Risk Management, Portfolio Optimization and Economics* (2016): 125-158.

[14]. Antoniadis, I., T. Tsiakiris, and S. Tsopogloy. "Business Intelligence during times of crisis: Adoption and usage of ERP systems by SMEs." *Procedia-Social and Behavioral Sciences* 175 (2015): 299-307.

[15]. Guha, Samayita, and Subodha Kumar. "Emergence of big data research in operations management, information systems, and healthcare: Past contributions and future roadmap." *Production and Operations Management* 27, no. 9 (2018): 1724-1735.

[16]. Dedić, Nedim, and Clare Stanier. "Towards differentiating business intelligence, big data, data analytics and knowledge discovery." In *Innovations in Enterprise Information Systems Management and Engineering: 5th International Conference, ERP Future 2016-Research, Hagenberg, Austria, November 14, 2016, Revised Papers 5*, pp. 114-122. Springer International Publishing, 2017.

[17]. Trieu, Van-Hau. "Getting value from Business Intelligence systems: A review and research agenda." *Decision Support Systems* 93 (2017): 111-124.

[18]. Ain, NoorUl, Giovanni Vaia, William H. DeLone, and Mehwish Waheed. "Two decades of research on business intelligence system adoption, utilization and success–A systematic literature review." *Decision Support Systems* 125 (2019): 113113.

[19]. Sousa, Maria José, António Miguel Pesqueira, Carlos Lemos, Miguel Sousa, and Álvaro Rocha. "Decision-making based on big data analytics for people management in healthcare organizations." *Journal of medical systems* 43 (2019): 1-10.

[20]. Sangari, Mohamad Sadegh, and Jafar Razmi. "Business intelligence competence, agile capabilities, and agile performance in supply chain: An empirical study." *The International Journal of Logistics Management* (2015).

[21]. Zheng, Wenzhi, Yen-Chun Jim Wu, and Liangyong Chen. "Business intelligence for patient-centeredness: a systematic review." *Telematics and Informatics* 35, no. 4 (2018): 665-676.

[22]. Fink, Lior, Nir Yogev, and Adir Even. "Business intelligence and organizational learning: An empirical investigation of value creation processes." *Information & Management* 54, no. 1 (2017): 38-56.

[23]. Mardani, Abbas, Robert E. Hooker, Seckin Ozkul, Sun Yifan, Mehrbakhsh Nilashi, Hamed Zamani Sabzi, and Goh Chin Fei. "Application of decision making and fuzzy sets theory to evaluate the healthcare and medical problems: a review of three decades of research with recent developments." *Expert Systems with Applications* 137 (2019): 202-231.

DOI: https://doi.org/10.54216/AJBOR.030104
Received: March 04, 2021 Accepted: July 15, 2021