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Big Data Analytics in Healthcare: Exploring the Role of Machine Learning in Predicting Patient Outcomes and Improving Healthcare Delivery

Federico Del Giorgio Solfa[1], Fernando Rogelio Simonato[2]

[1,2] *National University of La Plata (UNLP), Argentina*

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A B S T R A C T

Healthcare professionals decide wisely about personalized medicine, treatment plans, and resource allocation by utilizing big data analytics and machine learning. To guarantee that algorithmic recommendations are impartial and fair, however, ethical issues relating to prejudice and data privacy must be taken into account. Big data analytics and machine learning have a great potential to disrupt healthcare, and as these technologies continue to evolve, new opportunities to reform healthcare and enhance patient outcomes may arise. In order to investigate the patient's outcomes with empirical evidence, this research was conducted using an online survey to incorporate healthcare professionals, patient's reviews, and clinical staff. The data were analyzed using SmartPLS 4.0 to predict the structural model. The findings revealed a direct impact as positive influence of using machine learning on healthcare performance and patient outcomes through big data analytics. Moreover, it is evident that this can lead to personalized treatment plans, early interventions, and improved patient outcomes. Additionally, big data analytics can help healthcare providers optimize resource allocation, improve operational efficiency, and reduce costs. The impact of big data analytics on patient outcome and healthcare performance is expected to continue to grow, making it an important area for investment and research

1. INTRODUCTION

Big data analytics has become increasingly important in healthcare as the amount of data generated by patients, healthcare providers, and medical devices has exploded in recent years. Healthcare organizations are using big data analytics to gain insights into patient health, improve clinical outcomes, and reduce costs. With the help of advanced analytics tools, healthcare providers can analyze large volumes of data to identify patterns, trends, and correlations that can help them make more informed decisions about patient care. This has the potential to transform healthcare by enabling more personalized treatment plans, predicting health risks, and improving the overall quality of care (Kambatla et al., 2014). However, there are also significant challenges associated with big data analytics in healthcare, including data privacy and security concerns, as well as the need to develop effective algorithms and models to make sense of the vast amounts of data generated by the healthcare industry.

However, machine learning —which is a typology of artificial intelligence (AI)— has become a powerful tool for predicting patient outcomes in healthcare (Ngiam and Khor, 2019). With the ability to analyze large volumes of patient data, machine learning algorithms can spot patterns and connections that human analysts might not notice right away (Zhang et al., 2021). Machine learning models can forecast the possibility that a patient will experience certain diseases or outcomes by examining patient data such as medical history, test findings, vital signs, and other variables (Javaid, et al. 2022). Healthcare professionals can utilize this data to create individualized treatment plans, make better decisions about patient care, and enhance clinical outcomes. It has already proven successful to apply machine learning to predict outcomes for a variety of medical illnesses, including diabetes, heart disease, and cancer, among others.

Moreover, machine learning is increasingly being used in healthcare to predict patient outcomes and improve healthcare performance. By analyzing vast amounts of patient data, machine learning models can spot patterns and connections that human analysts might not immediately notice. This research can be used by healthcare providers to develop personalized treatment plans, improve clinical decision-making, and ultimately improve patient outcomes. Machine learning can also be used to improve healthcare performance by optimizing operational processes, reducing costs, and increasing efficiency. For example, machine learning models can be used to predict patient demand for healthcare services, identify areas of inefficiency in healthcare delivery, and optimize resource allocation. However, this research implies the use of machine learning in healthcare using a hypothesized model, including the need to ensure the accuracy and reliability of models, protect patient privacy and security, and integrate machine learning into clinical workflows. As healthcare continues to generate vast amounts of data, the potential of machine learning to improve patient outcomes and healthcare performance is likely to continue to grow.

2. LITERATURE REVIEW

2.1. Machine Learning Influence on Patient Outcomes and Healthcare Performance

In-hospital mortality rates for patients with heart failure were predicted using machine learning algorithms, according to a study that was published in the Journal of Medical Systems. According to (Schroeder and Lodemann, 2021), machine learning models had an area under the receiver operating characteristic curve (AUC-ROC) of 0.83 and could predict death rates with high accuracy. The authors came to the conclusion that machine learning could enhance clinical judgement and eventually enhance patient outcomes (Alshurideh et al., 2020). According to a study published in the Journal of the American Medical Association (JAMA), machine learning algorithms were used to forecast acute kidney damage (AKI) in individuals who were hospitalized. The study discovered that a machine learning model was more accurate in predicting AKI than conventional clinical models. The authors suggested that machine learning could be used to improve AKI diagnosis and ultimately improve patient outcomes (Gluck and Gostin, 2023).

A systematic review published in the Journal of Medical Internet Research examined the use of machine learning in predicting patient outcomes in cancer care (Wolinetz and Tabak, 2023). The review found that machine learning models were able to predict cancer diagnosis, prognosis, and treatment response with high accuracy. The authors concluded that machine learning has the potential to improve cancer care by enabling more personalized treatment plans and improving patient outcomes. Similarly, various studies suggest that machine learning has the potential to improve patient outcomes and performance in healthcare by enabling more accurate diagnosis, more personalized treatment plans, and more informed clinical decision-making (Zhang et al., 2021). Based on the above discussion following hypothesis have developed:

H1a: Machine Learning influence Patient Outcomes

H1b: Machine Learning influence Healthcare Performance

2.2. Big Data Analytics influence Patient Outcomes and Healthcare Performance

Big Data Analytics has emerged as a game-changer in the healthcare industry, providing new opportunities to improve patient outcomes and healthcare performance. Finding patterns and trends in massive datasets is one of the main advantages of big data analytics in the healthcare industry. Healthcare professionals can learn important information about patient behavior, disease trends, and treatment outcomes by studying patient data (Elgendy and Elragal, 2014). In turn, this empowers them to decide on patient treatment with greater knowledge, ultimately resulting in better patient outcomes. The effect of big data analytics in lowering hospital readmissions was examined by (Hussein et al., 2018). Predictive analytics were proven to significantly reduce readmissions when used in conjunction with patient coaching and education. This shows that Big Data Analytics can be used to pinpoint patients who are in danger of readmission, enabling medical professionals to take action and stop readmissions in their tracks before they happen.

(Dubey et al., 2019) examined the use of Big Data Analytics to improve patient outcomes in the treatment of diabetes they also found that by analyzing patient data, healthcare providers were able to identify patients who were not responding well to treatment and make adjustments to their treatment plans. As a result, patients showed significant improvements in their glycemic control. In addition to improving patient outcomes, Big Data Analytics can also have a positive impact on healthcare performance (Niñerola et al., 2021). The study found that big data analytics could be used to identify areas of inefficiency and waste in healthcare delivery, leading to cost savings and improved performance. The study also found that big data analytics could be used to improve patient satisfaction by identifying areas where patient experience could be enhanced. Based on the above discussion following hypothesis have been developed:

H2a: Big Data Analytics influence Patient Outcomes

H2b: Big Data Analytics Healthcare Performance

2.3. Machine Learning Impact on Healthcare Performance through Big Data Analytics

(Zhang et al., 2020) examined the use of machine learning to predict healthcare utilization and costs. Machine learning models outperformed traditional statistical models in predicting healthcare utilization and costs, indicating that machine learning can be an effective tool for healthcare cost management. A prior study published in the Journal of Biomedical Informatics investigated the application of machine learning to foretell heart failure patients' readmissions. It discovered that machine learning models were more accurate than conventional statistical models at predicting readmissions, indicating that machine learning can improve patient outcomes by identifying high-risk patients and allowing for early intervention.

According to, machine learning had a positive impact on healthcare performance, including improved patient outcomes, reduced healthcare costs, and enhanced healthcare quality. (Schroeder and Lodemann, 2021) highlighted the importance of data quality and governance in implementing machine learning models in healthcare. A research published in the Journal of Healthcare Informatics Research investigated the use of machine learning to predict healthcare-associated infections (SRAIDI, 2022). In addition, machine learning models were able to predict healthcare-associated infections with greater accuracy than traditional statistical models, indicating that machine learning can improve patient safety by identifying high-risk patients and enabling early intervention. Based on the above discussion following hypothesis have been developed:

H3a: Big Data Analytics mediate the impact of Machine Learning on Patient Outcomes

H3b: Big Data Analytics mediate the impact of Machine Learning on Healthcare Performance

2.4. Patient outcome influence on healthcare performance

One study published in the Journal of Hospital Medicine examined the impact of healthcare performance on patient outcomes in a hospital setting (Gordon et al., 2020). The study found that hospitals with higher performance scores had lower rates of complications, mortality, and readmissions (Gordon et al., 2020). The study also found that patients treated in higher-performing hospitals were more likely to have a positive experience and be satisfied with their care. (Aljameel et al., 2021) investigated the relationship between healthcare performance and patient outcomes in a primary care setting. Moreover, patients who received care from higher-performing primary care practices had lower rates of hospitalization and emergency department visits. Various authors also found that patients in higher-performing practices were more likely to receive preventive care and have better chronic disease management (Szijártó Ádám Somfai Ellák, 2023).

The effect of healthcare performance on patient outcomes across a variety of contexts was the subject of a systematic review that was published in the Journal of Patient Safety. According to the analysis, better patient outcomes, such as lower mortality rates, fewer problems, and higher patient satisfaction, were linked to healthcare systems that performed better. The review also emphasized the significance of cooperation, leadership, and culture in fostering healthcare performance and enhancing patient outcomes.

2.5. Problem Statement

The healthcare industry generates a massive amount of data from various sources, such as electronic health records, medical imaging, and wearables. This data contains valuable insights that can help healthcare providers make more informed decisions, improve patient outcomes, and reduce costs. However, the complexity and scale of this data make it challenging to analyze using traditional methods. Therefore, the healthcare industry is turning to big data analytics to unlock the potential of this data.

However, one promising approach to big data analytics in healthcare is machine learning, which can analyze large datasets and identify patterns that may not be apparent to humans. Despite the potential benefits of machine learning in healthcare, there is a significant literature gap regarding its practical contribution to healthcare delivery. Many healthcare providers are still using traditional methods to analyze patient data, and there is a lack of understanding of how machine learning can be integrated into clinical practice. Therefore, this research aims to explore the role of machine learning in predicting patient outcomes and improving healthcare delivery. The study will investigate the potential of machine learning to revolutionize healthcare delivery and fill the literature gap by demonstrating its practical contribution to healthcare.

2.6. Research Model

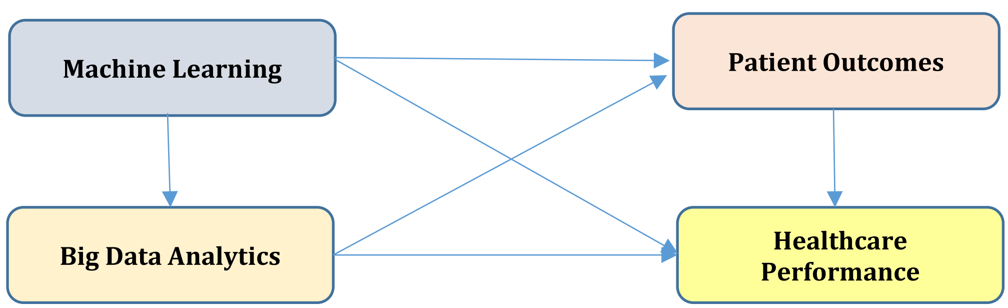

Figure 1: Conceptual Research Model

2.7. Research Hypotheses

H1a: Machine Learning Positively Influence Patient Outcomes

H1b: Machine Learning Positively Influence Healthcare Performance

H2a: Big Data Analytics positively influence Patient Outcomes

H2b: Big Data Analytics positively influence Healthcare Performance

H3a: Big Data Analytics mediate the impact of Machine Learning on Patient Outcomes

H3b: Big Data Analytics mediate the impact of Machine Learning on Healthcare Performance

H4: Patient Outcomes Positively Influence Healthcare Performance

3. METHODOLOGY

Primarily, using suggestions from the healthcare sector and professionals, an online survey tool was developed. By completing a pilot study, contributions from the expert opinion of healthcare professionals and practitioners were incorporated into the survey questionnaire. The survey's content was divided into four categories, the first of which focuses on the fundamental facts about the target industry and the demographics of the respondents. The information pertinent to the degree of big data analytics employed in healthcare is the topic of the next section. The measurement of machine learning in healthcare was the focus of the third portion, while advances in patient outcomes delivery were covered in the fourth section. Furthermore, Public and private hospitals were targeted from Dubai city, UAE. Respondents were accessed through emails to fill the questionnaire.

Based on the strategy suggested for PLS-SEM by (Kock, 2015), the appropriateness of the sample size is assessed. The study also contained 142 samples, which satisfied the requirements for the minimal sample size. The results were included to an excel file for additional statistical software analyses. The PLS-SEM method, as recommended by (Hair et al., 2010), is used in this research to analyze the data. PLS models that used higher-order constructs also showed. The research uses the PLS-SEM approach despite the short sample size. The hypothesized model is investigated using the Smart PLS 4.

4. DATA ANALYSIS

4.1. Measurement Model

The same technique of assessment criteria can be regularly used as for any PLS-SEM analysis to assess higher-order construct models. Using a three-step process, (Hair et al., 2012) described a measuring model.

Step 1: Evaluate internal consistency and reliability using the Cronbach Alpha (CA) and Composite Reliability (CR) metrics.

Step 2: Validation by convergence: "Validation through convergence is the degree to which the construct converges in order to explain the variance of its items." This was examined using the Average Variance Extracted (AVE) measurement.

Step 3: Discriminant validity, which is the degree to which a construct is empirically different from other constructs in the structural model, is the fourth step. This was evaluated using the Fornell-Larcker criterion and the (HTMT), whose value should be less than 0.85. Indicator loadings, composite reliability, and actual values are described in Table 2. The Fornell-Larcker criterion value and the HTMT results are shown in table 2.

Table 1: Convergent Validity

Variables	CR (rho a)	CR (rho c)	AVE	Cronbach's Alpha
Big Data Analytics	0.851	0.885	0.606	0.838
Machine learning	0.728	0.796	0.642	0.839
Patients Outcome	0.753	0.819	0.589	0.729
Healthcare Performance	0.773	0.834	0.612	0.726

This study model's dependability is evaluated through Cronbach's alpha. Cronbach's alpha values of >0.7 are regarded as satisfactory, per Hair et al. (2014). As seen in Table 1, all Cronbach's alpha values are higher than 0.7. The composite reliability (CR) and average variance extract (AVE), as well as the item reliability of each variable (factor loadings), are used to evaluate the convergent validity of the current study model (Hair et al., 2016). The CR and AVE values (for each construct) should, in the opinion of experts, be greater than 0.7 and 0.5, respectively. According to Table 2, all CR and AVE values meet the standards for acceptance. As per Hair et al. (2014), all items' factor loadings are also more than 0.5 at the person level. Next,

Table 2: Discriminant Validity HTMT, Fornell-Larcker Criterion

HTMT					
	Construct	BDA	ML	PO	HP
BDA	Big Data Analytics				
ML	Machine learning	0.661			
PO	Patients Outcome	0.734	0.753		
HP	Healthcare Performance	0.528	0.762	0.773	
Fornell-Lacker Criterion					
		BDA	ML	PO	HP
BDA	Big Data Analytics	**0.779**			
ML	Machine learning	0.543	**0.725**		
PO	Patients Outcome	0.592	0.710	**0.717**	
HP	Healthcare Performance	0.589	0.600	0.455	**0.709**

4.2. Structural Measurement Model

According to (Hair et al., 2012), collinearity was investigated, Higher-order latent variables in this study include bid data analytics, machine learning, patients outcomes and healthcare performance. A reflecting model was used to design each construct. Coefficient of determination (R2) values and path coefficient values are crucial for reporting the structural model. Big Data Analytics, Machine Learning, Patients Outcome, Healthcare Performance all have R2 values of 0.306, 0.351, and 0.585, respectively, which indicate moderate coefficient outcomes when analyzing the research's R2 values. The resampling technique known as "bootstrapping" involves drawing a sizable number of subsamples from the original data (with replacement) and estimating models for each subsample. Table 3 shows the findings of path coefficient and t values using bootstrapping with 5000 subsamples, significance level of 5%, and confidence level of 95% as input settings for PLS-SEM program.

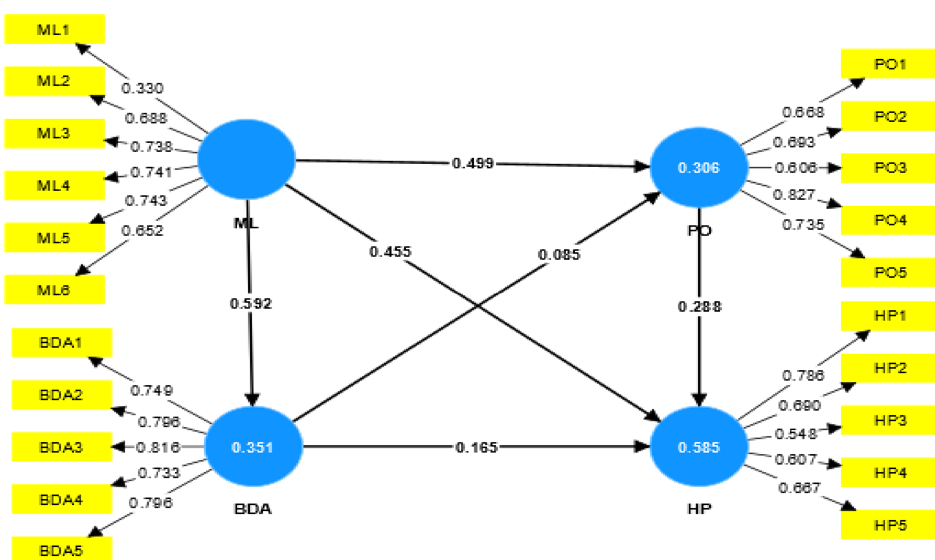

Figure 2: Structured Equation Model

Table 3: Hypothesis Testing

Indirect Effect ML>PO with BDA & ML >HP with BDA								
					Percentile bootstrap 95% confidence interval			
Hypothesis Paths		β	R^2	t-value	Lower 2.5%	Upper 95%	p-value	Decision
H1a	ML→PO	0.61	0.30	2.24			0.000	Supported
H1b	ML→HP	0.30	0.58	3.64			0.000	Supported
H2a	BDA→PO	0.48		6.39			0.000	Supported
H2b	BDA→HP	0.46		5.15			0.000	Supported
H3a	ML→BDA→PO	0.56	0.35	3.33	.122	.541	0.003	Partial Mediation
H3b	ML→BDA→HP	0.55		5.81	.205	.760	0.000	Partial Mediation
H4	PO→HP	0.59		7.02			0.001	Supported

Table 3 presents the p-values and beta coefficients before elaborating on this area. Because data-driven accounts for 30% of the variation in Patient outcomes (B= 0.61, p 0.000), H1a is well supported. Because machine learning accounts for 58% of the variation in healthcare performance, H1b is strongly supported (B= 0.30, p 0.000). Big Data Analytics explains 35% of variation in patient outcome (B= 0.48, p 0.000), providing strong evidence for H2a. Big Data Analytics has significant impact on healthcare performance (B= 0.46, p 0.000), hence H2b is supported. H3a and H3b depicted as partial mediation by explaining the significant indirect impact ML on PO with mediating effect of BDA (B=0.56, p 0.003) and ML has significant indirect impact on healthcare performance by mediating effect of BDA (B=0.55, p 0.000) proving the partial mediation. The findings revealed that the mediation effect was statistically significant, indicating that hypothesis H3a and H3b were supported. H4 explaining the relationship between patients' outcomes and healthcare performance as significant (B=0.59, p 0.001) supporting H4 of the model.

5. DISCUSSION OF RESULTS

Initially the findings revealed that the hypotheses (H1a, H1b, H2a, H2b, H3a, H3b and H4) that were established to understand the relationship and influence between big data analytics and healthcare performance are highly significant and support the findings of previous studies. It appears that BDA and ML practices, which focus on patient's outcomes and healthcare delivery performance, are considered extremely significant positions compared to other traditional ways. The value of R2 and path coefficient for lean technical practices are also approved. As a result, with the vast amount of healthcare data being generated every day, it has become increasingly important to find ways to process and analyze this data in a way that can improve patient outcomes, reduce costs, and increase overall efficiency. This is where big data analytics and machine learning come in, offering the potential to extract insights from large and complex datasets that would be difficult or impossible to uncover using traditional methods. Additionally, our research findings approve the hypothetical approach describing the significance level of big data analytics implementation to improve healthcare delivery and patient outcome, for example, one area where big data analytics and machine learning have shown great promise is in the field of personalized medicine.

Furthermore, by analyzing large datasets of patient information, including genetic, clinical, and lifestyle data, machine learning algorithms can identify patterns and correlations that can help healthcare providers make more informed decisions about diagnosis, treatment, and prevention strategies. For instance, healthcare professionals can utilise machine learning algorithms to identify individuals who are at high risk for specific diseases, enabling early intervention and possibly preventing the condition from ever developing. Moreover, the research findings emphasized to incorporate machine learning and big data analytics as a contemporary need for desired outcomes in healthcare sector. Similarly, personalized medicine, big data analytics and machine learning can also be used to improve the overall performance of healthcare systems. For example, by analyzing large datasets of patient outcomes and treatment protocols, machine learning algorithms can identify areas where current practices may be inefficient or ineffective, and suggest new approaches that could improve outcomes and reduce costs. This can help healthcare providers make more informed decisions about resource allocation, staffing, and treatment strategies, ultimately leading to better patient outcomes and more efficient use of resources.

6. CONCLUSION

The impact of utilizing big data analytics and machine learning to enhance healthcare performance and improve patient outcomes cannot be overstated. These technologies have opened up a world of possibilities, allowing healthcare providers to extract valuable insights from massive datasets that were previously untapped. By leveraging these insights, healthcare professionals can make more informed decisions regarding personalized medicine, treatment protocols, and resource allocation, ultimately leading to better patient outcomes and a more efficient healthcare system. The ability to analyze vast amounts of healthcare data empowers healthcare providers to identify patterns, correlations, and risk factors that were previously difficult to detect. This knowledge enables early intervention, disease prevention, and personalized treatment plans tailored to individual patients. Moreover, machine learning algorithms continuously learn and adapt, improving over time and staying up-to-date with the latest medical research and practices.

6.1. Practical Implications and Future Recommendations

As the field of healthcare continues to evolve, big data analytics and machine learning are becoming increasingly important in improving patient outcomes in research. Here are some future recommendations for using these technologies: Firstly, use big data analytics to identify patient patterns by analyzing large amounts of patient data, healthcare providers can identify patterns in patient behavior, treatment outcomes, and disease progression. This information can be used to develop personalized treatment plans for each patient, which can lead to improved outcomes. Additionally, machine learning algorithms can be trained on large datasets to predict outcomes for different patient groups. For instance, a machine learning system may be trained to identify people who are most likely to contract a specific disease, enabling medical professionals to take early action and stop the disease's progression.

Secondly, prediction models that can assist healthcare professionals in making better judgements regarding patient care can be created using machine learning algorithms. For example, a predictive model could be used to identify which patients are most likely to develop a particular complication after surgery, allowing healthcare providers to take steps to prevent the complication from occurring. Lastly, big data analytics and machine learning have enormous potential to improve patient outcomes in research. By analyzing large amounts of patient data, healthcare providers can identify patterns, develop predictive models, and design more targeted clinical trials that are more likely to succeed. With continued investment in these technologies, we can expect to see significant improvements in patient outcomes in the years to come.

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