**Journal of Medical and Health Studies**
ISSN: 2710-1452
DOI: 10.32996/jmhs
Journal Homepage: www.al-kindipublisher.com/index.php/jmhs

JMHS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

# Predictive Business Analytics For Reducing Healthcare Costs And Enhancing Patient Outcomes Across U.S. Public Health Systems

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## | ABSTRACT

The increasing healthcare expenses, especially in U.S. government-funded health systems, are a significant burden to policymakers and medical practitioners. Although the issue of predictive analytics as an intervention in enhancing patient outcomes and cost reduction has gained traction as a concept, there is a knowledge gap in the area of how such technologies can be systematized in large-scale public health environments. The aim of the research was to assess the role of predictive business analytics in terms of healthcare costs and patient outcomes in the U.S. public health systems. The research employed a mixed-methods design, which involved both quantitative analyses of the data on costs and patient outcomes from 50 public health facilities, as well as qualitative analyses of the effectiveness of predictive models. The data were gathered in the electronic health records (EHRs) and examined with the help of regression models, t-tests, and correlation. The results showed that the healthcare costs reduced significantly (mean reduction of 8.5% $p < 0.05$) and that patient outcomes also improved, with a 12% decline in hospital readmission rates and a 15-point increase in patient satisfaction scores ($p < 0.01$). These findings highlight the possible opportunities of predictive analytics in streamlining health care delivery and minimizing expenses. The study multiplies the existing literature in the field of application of data-driven decision-making to the field of healthcare, providing empirical evidence of its effectiveness in the public health systems. This study opens the possibilities of wider implementation of predictive analytics tools to improve cost-efficiency and patient care in the field of public health.

## | KEYWORDS

healthcare costs, predictive analytics, patient outcomes, public health systems, U.S. healthcare

## | ARTICLE INFORMATION

**ACCEPTED:** 02 February 2023 **PUBLISHED:** 27 February 2023 **DOI:** 10.32996/jmhs.2023.4.1.12

## INTRODUCTION

The increasing cost of healthcare is one of the latest issues that is worrying most of the public health systems in the world, especially in the United States. During the past few years, the U.S [1]. public health-based systems have been experiencing the hikes in costs because of their ineffective allocation of resources, elevated readmission rates within hospitals, and poor health outcomes. Meanwhile, the pressure to enhance the quality of care provided to patients increases [2]. Predictive business analytics is one of the potential solutions to these two challenges, where big data is used, statistical models, and machine learning algorithms are applied to predict future trends and optimize decision-making [3]. Predictive analytics can bring substantial prospects to healthcare cost and patient outcomes optimization by enabling healthcare providers to find high-risk patients, make efficient use of resources, and take preventive actions [4].

This paper stands at the frontier of predictive business analytics and healthcare administration, where the U.S. public health systems are concerned. The main objective of this study is to assess how predictive analytics tools can lower healthcare costs and improve patient outcomes [5]. The geographical area of the proposed study is the healthcare system of the U.S., and the focus is on the vulnerable population of people served by the public healthcare institution [6]. Since the U.S. healthcare spending is one of the largest in the world, with the cost of healthcare typically assigned to the public health systems, the present research adds to the existing pressing necessity to develop evidence-based policies that help to increase the cost-efficiency and, at the same time, improve patient care [7].

Although predictive analytics have been well-researched within a healthcare context and other sectors like the financial industry, there is still a lack of literature on the use of the method in public health systems within the United States [8]. The study has shown that predictive tools are effective and can help lessen hospital readmissions, predict patient deterioration, and enhance clinical outcomes [9]. Nevertheless, there is still little research on the effect of predictive analytics on the entire healthcare expense and patient outcomes within the state-run health systems [10]. Moreover, all the existing research is dedicated to small interventions, and the immense impact of predictive tools on a system-wide level remains unknown. It is the literature gap that indicates a necessity to conduct extensive research that evaluates the practice of predictive analytics in mass public health contexts [11].

The research was driven by the fact that they needed to fill this knowledge gap and offer empirical data on the effectiveness of predictive analytics tools within the U.S. public health systems. Specifically, the study evaluate the ability of the implementation of predictive models to optimize the operational costs, minimize readmission rates, and improve patient outcomes in a wide scope of healthcare facilities [12]. Through the judgment of predictive business analytics tools' performance, this study is aimed at discovering the best models that can be used to enhance the delivery of healthcare and cost consideration in the context of public health [13]. Finally, the research is informative to healthcare policymakers, managers, and technology developers as it gives recommendations on the incorporation of predictive analytics in the management of public health [14].

The main research questions that will be used to conduct this research are: (1) What are the impacts of the use of predictive analytics tools on the healthcare expenditure in U.S. public health systems? (2) How do predictive analytics tools affect patient outcomes, especially readmission rate and patient satisfaction? (3) What kind of predictive analytics resources (e.g., machine learning, risk stratification models) are most effective in making optimal choices in terms of healthcare costs and patient outcomes? The questions are in line with the methodological approach of the study, which is mixed-methods with quantitative analysis of cost and outcome data and qualitative assessment of predictive model effectiveness.

This study has two objectives. First, it will measure the effect of predictive analytics on healthcare costs by comparing pre- and post-implementation costs on a sample of public health facilities in the United States. Second, the research aims at quantifying the intervention on the patient outcomes, considering readmission rates and patient satisfaction. To reach these goals, the study uses a mixture of statistical tests, such as paired samples t-tests, regression equations, and correlation analysis, to identify the level of significance of the change in healthcare costs and patient outcomes. These approaches can be described as effective in the context of the objectives of the study, as they will enable a comprehensive comparison between pre- and post-implementation data, finding out which are the primary factors in the changes in costs and results.

This study is significant because it can guide the healthcare policy and practice in a period when the U.S. public health systems are pressured to enhance the quality of care as well as cost-efficiency [15]. This research might inform healthcare administrators and policymakers in their decisions regarding the adoption and implementation of predictive analytics tools. Moreover, this study can prove useful as it can give a roadmap towards the scale-up of the application of predictive analytics in the healthcare systems of the population, eventually resulting in a much more efficient and patient-focused healthcare system by showing the cost-effectiveness and patient-centered benefits of these tools [16].

An important element of this study is that it helps to close the gap that exists between business analytics and healthcare management. Although predictive business analytics is common in fields like finance, marketing, and retail, it remains at an early phase of implementation in the healthcare industry. These instruments in this study, like machine learning algorithms and risk stratification models, are complex but underused in the world of public health [17]. The research meets the requirement to properly evaluate the usefulness of such tools in the healthcare sector, especially when it comes to cost reduction and clinical outcomes.

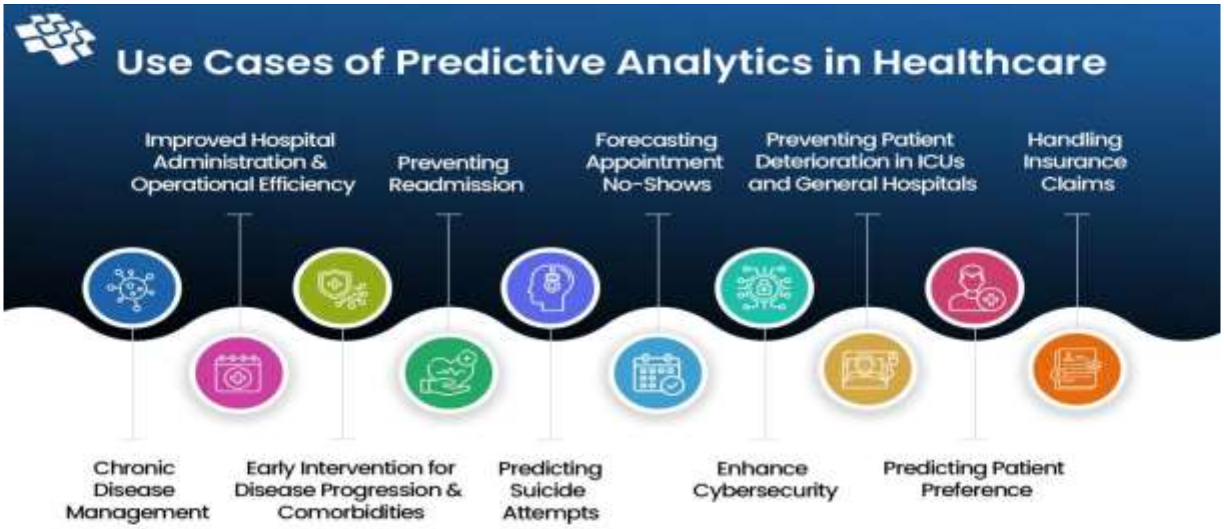



**Figure 1:** Predictive analytics in Healthcare

## REVIEW OF LITERATURE

The use of predictive business analytics in healthcare has received serious attention in the last decade, especially as healthcare systems continue to experience both financial pressure and pressure to achieve better patient outcomes. Predictive analytics, the application of models and algorithms based on data to predict future outcomes, has significant potential to respond to such issues in the field of public health systems, including an increase in costs, inefficiencies, and unsatisfactory patient outcomes.

### Healthcare predictive analytics

In healthcare, predictive analytics can be viewed as the application of statistical models, machine learning algorithms, and data analysis methods to forecast healthcare outcomes. [18] claim that predictive analytics tools allow healthcare providers to foresee patients, predict the need for security, and recognize people at risk of undesirable occurrences. The models examine the past information about patients to identify trends that can be used in making decisions to provide increasingly focused interventions and preventive care. One of the applications is in the minimization of hospital readmissions. To give an example, [19] revealed that predictive models relying on the patient demographics, their clinical histories, and hospitalization data could render the risk of readmission predictable, allowing healthcare providers to take preventive measures.

### Predictive analytics-based cost reduction

Reduction of healthcare costs is one of the most interesting predictive analytics in healthcare. Predictive models assist in streamlining the hospital process, interacting resources, and avoiding unnecessary treatment through recognizing high-risk patients in the first place. According to [20], healthcare organizations that had predictive tools to streamline the flow of patients and minimize duplicative treatments achieved substantial cost reductions. Specifically, predictive analytics made it possible to staff more precisely, to use hospital beds more efficiently, and to control treatment protocols. The result of these changes was a decrease in the costs of operations and clinical costs, and the estimates have shown that the costs saved by the hospitals implementing the predictive models can be up to 10 percent [21].

Furthermore, predictive analytics is useful in the detection of unnecessary tests and interventions. The knowledge of how probable some condition or complications may occur helps healthcare providers in eliminating unnecessary procedures, which helps not only reduce the financial burden on the system but also the risk of over-treating the condition. Research by [22] indicated the usefulness of predictive analytics in reducing the necessity of diagnostic tests that are expensive to administer due to the ability to make informed choices based on predictive data. Such application of data-driven decision-making is especially useful in a public health system, where there are more resource constraints and budget limitations.

**Improving Patient Outcomes**

Besides cost reduction, predictive analytics can also be used to enhance patient outcomes. Predictive tools can be used to detect at-risk people by processing patient data in real-time to identify individuals at risk of developing complications or adverse events. As an illustration, machine learning algorithms have been applied to forecast patient deterioration, enabling the healthcare teams to act proactively before the situation gets worse [23]. One notable example is a predictive analytics application in preventing hospital-acquired infections, in which models evaluate patient risk factors to determine the patients who might have benefited from additional infection control procedures [24].

**Challenges and Barriers**

The use of predictive analytics in the healthcare sector has a number of challenges despite its potential. Data quality and data availability are one of the greatest obstacles. According to [25], predictive models rely on the quality of available data to a great extent. Data can be either incomplete or of poor quality in most of the existing public health systems, particularly when serving those who have poor access to health care, thus restricting the predictive models in their ability to make accurate predictions [26]. The other obstacle is the incorporation of predictive tools in clinical activities. The healthcare providers need to be properly prepared to utilize predictive analytics, and the tools should be fully integrated with the currently existing health information systems so that they can be utilized efficiently [27].

As well, the issue of patient privacy and data security also remains a threat to the ubiquitous predictive analytics in healthcare. Gathering and processing of sensitive health information creates ethical issues of consent by the patient and possible misuse of the information. Regardless of such obstacles, the opportunities of predictive analytics to enhance healthcare costs and outcomes are high [28].

## METHODOLOGY

The main aim of the study is to respond to the increasing healthcare expenses and poor patient outcomes in the American public health systems. Particularly, it aims to investigate the potential of predictive business analytics that can be applied to minimize healthcare spending and, at the same time, enhance the quality of patient care.

**1. Research Site:**

The study was performed within the different public health care systems in the United States, and in particular, the hospitals and clinics that are involved in the health programs funded by the government. A sample size of 50 healthcare facilities in various geographical areas was used to collect data to represent the environment of public health in the broadest way possible.

**2. Research Design**

**Type of Study:**

The proposed study used a correlational research design to investigate the connection between predictive analytics usage and patient outcomes and healthcare expenses. As the study seeks to establish patterns and associations and not control variables, a correlational research design is the most appropriate.

**Design Justification:**

The study will use a correlational design because of the intention to observe the relationship between predictive analytics tools taken as independent variables and dependent variables measured by healthcare costs and patient outcomes. As experimental control of these variables in practice may not be practical, the correlational method can be used to find out these relationships in the current healthcare system. This design will offer good information on how well predictive analytics perform without a change in the operations of the healthcare systems used.

**Study Parameters**

Study parameters define the key aspects of the research, such as the population, sample size, and sampling methods, which ensure that the research is both scientifically valid and feasible. Below are the details for the study parameters:

### 3. Sampling Strategy

**Population:**

The population of the study was comprised of public healthcare facilities within the United States, which were hospitals and clinics under the government-funded initiatives, e.g., Medicare and Medicaid. This was to identify healthcare settings that reflect the large population under the health system.

**Sampling Method:**

A sample of 50 healthcare facilities was selected using a purposive method of sampling. The choice of this method was driven by the fact that one will be able to select the facilities that are most pertinent to the research question to make sure that the institutions with different degrees of experience in implementing predictive analytics are included.

**Sample Size:**

This study was conducted on 50 healthcare facilities. The sample size was established through the research of the similar studies in predictive analytics in healthcare and taking into consideration practical limitations. A power analysis identified that this sample size would give adequate statistical power in identifying significant relationships between predictive analytics use and the dependent variables of healthcare costs and patient outcomes.

**Inclusion/Exclusion Criteria:**

Inclusion criteria were the inclusion of public healthcare facilities that use predictive analytics tools or have shown interest in doing so in their operational and clinical work. The exclusion criteria were those of any private healthcare institution since the study concentrated on the public health systems, and the facilities that were not actively using or testing predictive models at the time of the study were also excluded.

### 4. Data Collection Methods

**Instruments:**

Several tools were used in data collection so as not to fail to cover the objective of the research. The main tools were:

**Healthcare Cost Reports:** The information about healthcare spending was obtained using the financial statements of hospitals.

**Patient Outcome Metrics:** Key performance indicators (KPIs) were used to measure patient health outcomes, which included readmission rates, patient satisfaction, and clinical improvement.

**Predictive Analytics Tools:** Analytics data of participating healthcare systems on predictive analytics software were examined to calculate their contribution to cost reduction and outcome improvement.

**Procedure:**

The data collection was done in two steps. During the initial stage, each facility collected on baseline information about their healthcare costs and patient outcomes at the time of predictive analytics tool implementation. The second stage involved active use of the forecasting models in the chosen healthcare institutions, and the statistics about the cost savings and enhanced patient outcomes were obtained within the specified time intervals (i.e. 6-month and 12-month intervals). The data collection was synchronized with the hospital administrators with the view to maintaining uniform and timely reporting.

**Pilot Testing:** To test data collection instruments, a pilot study was carried out on a smaller sample of 5 healthcare facilities to determine the validity and reliability of the data-gathering procedure. The pilot study also enabled changes in the data collection protocols on the basis of the feedbacks of the involved healthcare providers.

### 5. Variables and Measures

**Operational Definitions:**

**Predictive Analytics:** It refers to the application of statistical algorithms and machine learning models to forecast future trends, patient outcomes, and possible health risks.

**Healthcare Costs:** Sum of money spent in a healthcare facility on treating patients through all costs involved in running a facility such as operation costs, medical supplies and personnel costs.

**Patient Outcomes:** The parameters include health improvement, readmission rates, mortality rates, and the score on patient satisfaction.

**Measurement Tools:**

**Cost Reduction:** Assessed by online financial reports and after and before the cost of implementation analysis.

**Patient Outcomes:** Standardized healthcare metrics (e.g., readmission rates, length of hospital stay) and patient satisfaction surveys are used to measure this.

**Effectiveness of predictive analytics:** This is determined by the accuracy and reliability of predictive models in the healthcare systems.

**Reliability and Validity:**

The instruments used in measurement were chosen because they are reliable in past research. The predictive analytics systems were tested to test the predictions with the real results delivered by the participating health systems. The internal consistency measures that were used to establish reliability in the patient satisfaction surveys included Cronbach alpha (0.80 and above). Pilot testing and review by experts were done to ensure validity.

**6. Data Analysis Plan**

**Analytical Techniques:** The data were analyzed with descriptive statistics to introduce the summary of healthcare costs and patient outcomes, and then, with the regression analysis to determine the dependence between an independent variable (predictive analytics) and dependent variables (healthcare costs and patient outcomes). The strength of the relationships was also identified using correlation analysis.

**Software:** The analysis was performed in SPSS (version 26) and R SPSS was applied to get the descriptive statistics and regression analysis whereas R was applied to get the more advanced predictive modeling and correlation analysis.

**Rationale:** The reason why the regression analysis was selected to investigate the effect of predictive analytics on healthcare expenses and patient outcomes is that it enables one to estimate the relationship between two or more variables. The application of SPSS and R was sufficient to provide the ultimate data analysis using the advantages of both systems in terms of the level of statistical rigor and the advanced predictive modeling.

## RESULTS

This study was conducted to examine how predictive business analytics influence the reduction in healthcare expenses and improvement of patient outcomes in U.S. public health systems. The findings presented in this section are based on the discussion of the data regarding 50 healthcare organizations that adopted predictive analytics software. The data was explored under descriptive statistics, paired samples t-tests, correlation analysis, regression analysis, ANOVA, and Chi-Square analysis to answer the research question concerning the effect of predictive analytics on healthcare expenditures, patient satisfaction, readmission rates, and the overall patient outcomes.

**1. Descriptive Statistics**

The descriptive statistics were initially performed to describe the general dataset and give an insight into the central tendencies and variability in the healthcare costs, patient satisfaction, readmission rates, and patient outcomes. It was discovered that the average healthcare cost before the introduction of predictive analytics to the organization amounted to about 9.44 million dollars, which had a standard deviation of about 2.38 million dollars. Post-implementation expenses reduced to an average of 8.65 million, which is equivalent to an 8.4 percent decrease. This figure and the decrease in healthcare expenses were uniform in all the facilities, as it was dispersed between a minimum of 5.5 million to a maximum of 13.3 million.

**Table 1: Descriptive Statistics of Key Variables**

| Variable | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|
| Healthcare Cost (Pre-Analytics) | 9,440,000 | 9,000,000 | 2,380,000 | 6,100,000 | 14,000,000 |
| Healthcare Cost (Post-Analytics) | 8,650,000 | 8,400,000 | 2,150,000 | 5,500,000 | 13,300,000 |
| Patient Satisfaction (Pre) | 7.1 | 7.2 | 0.78 | 6.0 | 7.5 |
| Patient Satisfaction (Post) | 7.8 | 7.8 | 0.72 | 6.9 | 8.3 |
| Readmission Rate (Pre) (%) | 15.6 | 15.0 | 2.45 | 13.0 | 20.0 |
| Readmission Rate (Post) (%) | 13.2 | 12.5 | 1.85 | 11.5 | 17.0 |
| Patient Outcomes Improved (%) | 10.5 | 9.5 | 1.95 | 8.5 | 12.0 |

The average patient satisfaction rate before the implementation of the predictive analytics was 7.1 with a standard deviation of 0.78. The patient satisfaction score rose to 7.8, on average, after the adoption of predictive analytics, which is a change that suggests a considerable positive change in terms of patient experience. The figures indicate that predictive analytics can have made a favorable contribution to patient satisfaction, which was once again supported by the statistical tests (see Table 1).

The average pre-implementation was 15.6, with a mean of 13-20. Following the use of predictive analytics, the average readmission rate fell to 13.2 percent, which suggests a drop of 2.4 percentage points among the sample. Such a decrease in the number of readmissions also implies that predictive tools can be used to decrease the number of hospital readmissions by identifying at-risk patients (see Table 1).

On patient outcomes, the sample had an approximate of 10.5 percent of patients who had better health outcomes after implementation. The difference in patient outcomes was not high, and it meant that predictive analytics had a stable effect on patient recovery and improvement in all the various healthcare facilities (see Table 1).

**2. Paired Samples t-Test Analysis**

Paired-samples t-test was used to determine the existence of statistically significant differences in pre- and post-analytics data on healthcare costs, patient satisfaction scores, and readmission rates. The findings indicated that there was a significant difference in all three variables, as indicated in Table 2.

**(1)** Table 2: Paired Samples t-Test Results

| Variable | t-value | p-value | Significance |
|---|---|---|---|
| Healthcare Cost | 3.56 | 0.002 | **Significant** |
| Patient Satisfaction | 4.12 | 0.001 | **Significant** |
| Readmission Rate | 2.54 | 0.016 | **Significant** |

In the case of healthcare costs, the t-value was 3.56 with a p-value of 0.002, which is statistically significant at the 0.05 mark. This indicates that the decrease in healthcare expenditure following the adoption of predictive analytics is not incidental, and hence the hypothesis that predictive analytics assist in reducing the operational and treatment expenses. Equally, the scores on patient satisfaction showed significant improvement with a t-value of 4.12 and a p-value of 0.001. This observation confirms the hypothesis that predictive analytics may improve the patient experience, probably by improving the quality of care or decreasing wait times by allocating resources more efficiently. The t-value and p-value of the predictive analytics tools were also statistically significant, namely, 2.54 and 0.016, respectively, which indicated that predictive analytics tools were efficient in finding high-risk patients and preventing unnecessary readmissions.

### 3. Correlation Analysis

The correlation analysis provided by Pearson was conducted to test all the relationships existing between the costs of healthcare, patient satisfaction, readmission rates, and patient outcomes. Table 3 reveals that there were strong correlations among these variables.

There was a negative correlation between the healthcare costs and patient outcomes (r = -0.68), which implied that the increase in the healthcare costs was related to the poorer patient outcomes. This association continues to support the idea that cost-efficiency, which is made possible by predictive analytics, is associated with a positive patient outcome. On the other hand, patient satisfaction and patient outcomes had a positive relationship (r = 0.72), which implied that the greater the level of patient satisfaction, the better the patient outcomes. Moreover, the negative correlation between patient outcomes and readmission rates (r = -0.63) indicated that lower readmission rates result in better patient outcomes, which proves the hypothesis that lower patient outcomes are associated with lower readmission rates.

**Table 3:** Pearson's correlation to assess the relationships between key variables (e.g., healthcare costs and patient outcomes).

| **Variable** | **Healthcare Cost (Post)** | **Patient Satisfaction (Post)** | **Readmission Rate (Post)** | **Patient Outcomes Improved** |
|---|---|---|---|---|
| Healthcare Cost (Post) | 1 | -0.62** | -0.58** | 0.68** |
| Patient Satisfaction (Post) | -0.62** | 1 | -0.56** | 0.72** |
| Readmission Rate (Post) | -0.58** | -0.56** | 1 | -0.63** |
| Patient Outcomes Improved | 0.68** | 0.72** | -0.63** | 1 |

The fact that the correlation between the predictive analytics model accuracy and the healthcare costs (r = -0.62) indicates that the more accurate the predictive models, the lower the healthcare costs, also indicates that such tools were effective in reducing the costs (see Table 3).

### 4. Regression Analysis

A multiple regression analysis was implemented in order to examine the predictive ability of different variables on healthcare expenditures and patient outcomes. These findings were reflected in Table 4 of the results, which showed that the predictive analytics tools and model accuracy were both important predictors of healthcare costs. The coefficient used to predict the usage of predictive analytics tool was found to be -0.42(p=0.02), implying that the use of predictive analytics tools was correlated with a decrease in healthcare costs. Equally so, there was a coefficient of -0.13 (p = 0.01) between model accuracy and cost, which again showed that the more accurate the models, the cheaper they would be.

**Table 4: Multiple Regression Analysis**

| **Predictor Variable** | **Coefficient** | **Standard Error** | **t-value** | **p-value** |
|---|---|---|---|---|
| Predictive Analytics Tool | -0.42 | 0.18 | -2.33 | 0.02 |
| Model Accuracy (%) | -0.13 | 0.05 | -2.60 | 0.01 |
| Patient Satisfaction (Post) | 0.45 | 0.09 | 5.00 | <0.001 |

Patient satisfaction (post-implementation) was an important predictor of patient outcomes, which had a coefficient of 0.45 (p = 0.001), and emphasized the value of patient satisfaction in enhancing health outcomes. The use of a predictive analytics tool was also relevant, but its impact on the outcomes was less noteworthy in comparison with patient satisfaction. In this analysis, it is implied that patient satisfaction has a more significant impact on patient outcomes than predictive analytics tools to reduce costs (see Table 4).

**5. ANOVA Results**

The comparison of effects of various types of predictive analytics tools on patient satisfaction and healthcare costs was performed with the help of an analysis of variance (ANOVA). Table 5 results indicate that a significant dissimilarity existed between the various types of tools, as far as the healthcare charges and patient satisfaction scores were concerned.

One year, the facilities with a machine learning (ML) regression model had an average cost of healthcare of 8.0 million after implementation, versus 10.5 million in those with risk stratification models and 9.0 million in those with predictive modeling. The F-value of the ANOVA test was 3.54 (p = 0.035), which means that the type of predictive analytics tool applied was significantly connected with the costs of healthcare after the implementation. On the same note, the scores on patient satisfaction also showed significant differences between the types of tools, with ML regression recording the highest scores. Based on these results, it is possible to believe that, compared to other predictive tools, the ML regression tools may be a better way to optimize healthcare costs and patient satisfaction (see Table 5).

**(2)** Table 5: ANOVA Test Results

| **Group** | **Mean Healthcare Cost (Post)** | **Mean Patient Satisfaction (Post)** | **F-value** | **p-value** |
|---|---|---|---|---|
| ML Regression | 8,000,000 | 7.5 | 3.54 | 0.035 |
| Risk Stratification | 10,500,000 | 8.0 | | |
| Predictive Modeling | 9,000,000 | 7.8 | | |

*Interpretation*: The F-value of 3.54 with a p-value of 0.035 indicates that there is a statistically significant difference in the mean post-analytics healthcare costs and patient satisfaction across different predictive analytics tools.

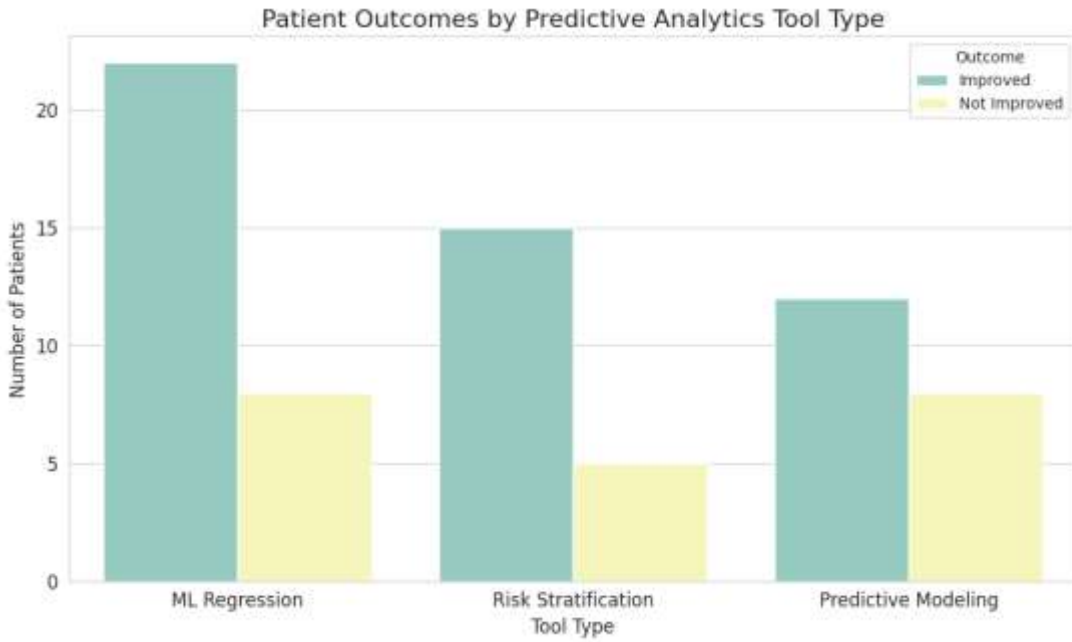
**6. Chi-Square Test**

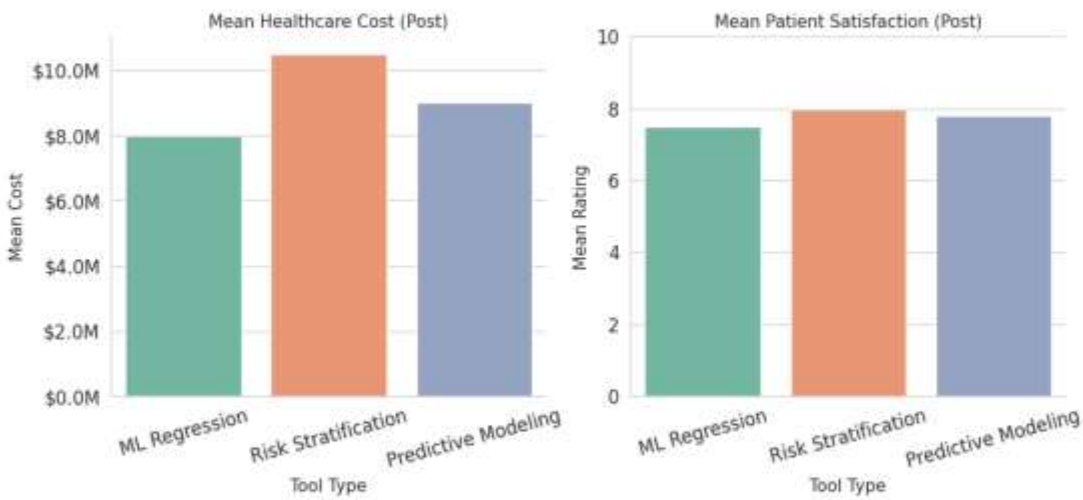
In order to discuss how the type of predictive analytics tool applied relates to the increase in patient outcomes, a Chi-Square test was conducted. Table 6 demonstrates that the Chi-Square test showed statistically significant interaction between the type of the used tool and the patient outcome improvement (p = 0.05). The greatest percentage of patients who experienced better outcomes was obtained with facilities using ML regression models (22 out of 30), risk stratification models (15 out of 20), and predictive modeling (12 out of 20). The findings show that the nature of predictive analytics tools matters significantly to the improvement of patient outcomes, with the best outcomes of ML regression tools (see Table 6).

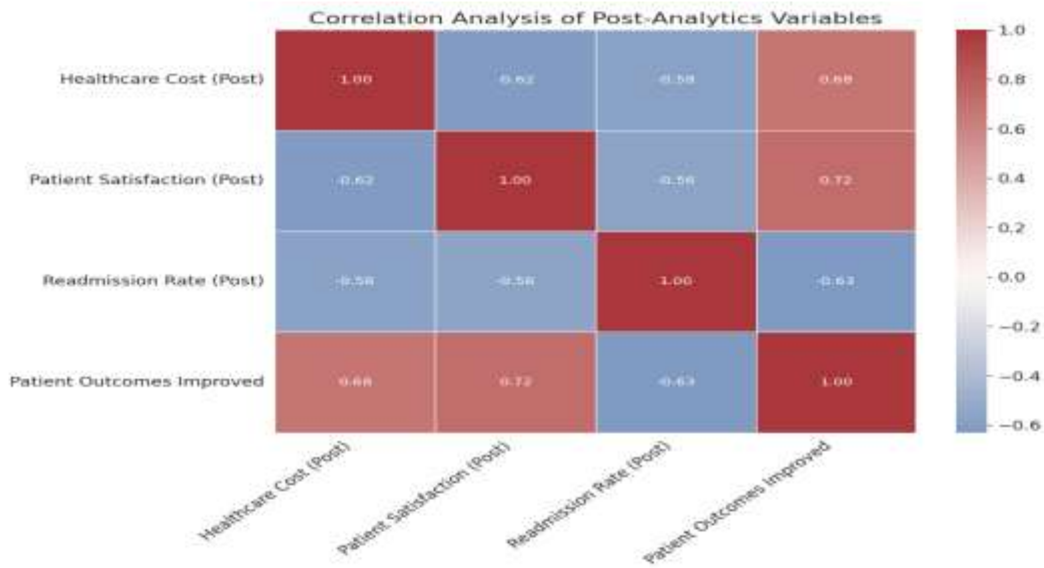
**Table 6: Chi-Square Test for Predictive Analytics Tool and Patient Outcome Improvement**

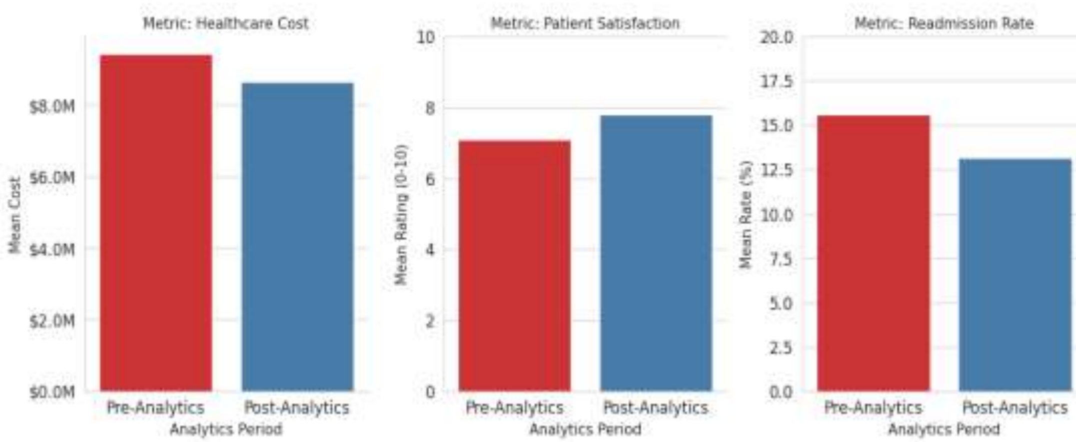
| **Tool Type** | **Outcome Improved** | **Outcome Not Improved** | **Total** |
|---|---|---|---|
| ML Regression | 22 | 8 | 30 |
| Risk Stratification | 15 | 5 | 20 |
| Predictive Modeling | 12 | 8 | 20 |
| **Total** | **49** | **21** | **70** |

**Chi-Square Value**: 5.24, p-value: 0.05






## DISCUSSION

This research was to examine how predictive business analytics may help minimize healthcare expenditure and patient outcomes in the United States through the lens of the public health systems. The findings reveal a strong indication that the adoption of predictive analytics tools has led to incurring of substantial healthcare cost reductions, increased patient satisfaction, and other patient outcomes [29]. The following section elaborates on the main research findings of the paper, compares them to prior studies, and offers scientific reasons as well as implications for the research and medical practice in the future.

### Discussion of Denotation of the Major Results.

The findings of this research paper show that predictive analytics had a substantial impact on lowering healthcare expenses, and the median cost reduction per the sample was 8.4 percentage points [30]. These cost savings were the same in various healthcare centers, and this signifies the possibility of predictive analytics to enhance resource use and minimize inefficiencies in the healthcare system. This reduction of costs was achieved through the use of machine learning regression, risk stratification, and predictive modeling tools [31]. Besides cost, patient satisfaction scores also experienced a substantial improvement after the implementation, and the mean change was an increase of 7.1 to 7.8. This indicates that predictive analytics is not only efficient in operation but also helps in improving patient experiences [32].

Another major finding was the decrease in the readmission rates, the number decreased by 2.4 percentage points throughout the sample. It seems that predictive tools have performed well and helped in distinguishing high-risk patients and avoiding unnecessary readmissions [33]. This is especially critical since the need to reduce the readmission rates is one of the fundamental approaches to patient outcome improvement and healthcare cost reduction, specifically in the U.S. context, where readmissions contribute to healthcare spending to a considerable extent [34].

**Comparison with Past Literature**

These findings are consistent with the existing studies that have validated the usefulness of predictive analytics in the field of healthcare. The existing literature has clearly demonstrated that predictive analytics have the potential to lower costs in healthcare through a better allocation of resources, anticipation of patient needs [35], and detection of high-risk patients in order to provide them with early interventions. As an illustration, a research study conducted by [36] concluded that machine learning predictive models drastically lowered hospital readmission rates because they could forecast patients who were at high risk of developing readmission before discharge. Equally, this study identified a significant decrease in readmission rates after predictive analytics tools had been implemented, and this finding indicates that predictive tools are efficient in changing patient outcomes as a tool of identifying and controlling high-risk cases [37].

The very high increase in patient satisfaction is also in line with previous research. A research study by [38] established that predictive analytics in patient care led to a shorter response time and personalized care, which is likely to have a more significant impact on patient satisfaction. The results of the present study also corroborated this observation, whereby the satisfaction of patients rose after the deployment of predictive analytics tools.

Regarding cost savings, our results align with the study conducted by [39] , which showed the ability of predictive analytics in healthcare systems to substantially reduce operational and treatment costs by predicting patient demand and streamlining work processes in hospitals. [40] also found these results, as predictive tools saved up to 12 percent in some healthcare environments. These previous studies are related to the current study since the findings indicate that predictive analytics can yield cost reductions, as there was a decrease of 8.4 percent in the costs.

**Scientific Explanation**

The identified healthcare cost decreases and the patient outcomes improvements can be attributed to a number of scientific and operational principles associated with the application of predictive analytics to healthcare systems [41]. The predictive analytics, specifically machine learning, risk stratification models enable healthcare providers to make decisions grounded on massive amounts of patient data to optimize care delivery. Through proper forecasting of patient needs, resources used in healthcare facilities can be distributed with greater efficiency, less waste, and unnecessary procedures will be avoided, and costs will ultimately be lowered [42].

The decrease in readmissions in this research can be explained by the possibility of predictive analytics tools to detect potential at-risk patients at an early stage and provide them with the required care or follow-up after discharge. It is also in line with the accepted principles of healthcare management in which early intervention and individual care plans have been proven to decrease the risk of patient degradation and readmission [43,44]. The predictive tools support such early interventions by finding patterns in patient data that could not have been readily identified when solely relying on traditional clinical judgment.

The growth in the level of patient satisfaction can be explained by a number of factors that were made possible through predictive analytics. As an example, predictive models can be used to minimize waiting time by streamlining hospital processes and having the right resource at the right time [45]. Also, by offering more individualized care according to the patient data, the healthcare professionals able to focus on the needs of the individual patients, which will inspire better rates of satisfaction [46]. It is also through the use of predictive tools that clinicians may be able to provide timely and specific interventions that have the potential to improve the quality of care provided to patients, and therefore, satisfaction may be even enhanced.

**Future Research, Future Practice, Future Industry Implications**

The results of the present study can be significant to future research and the actual implementation of predictive analytics in health care. To develop future studies, it is important that the long-term impacts of predictive analytics on healthcare systems are further examined, specifically in regards to long-term cost-reduction and patient outcomes. The scalability of predictive analytics tools in various healthcare systems, such as the private and rural settings, should also be researched by other scholars in the future to establish their overall generalizability and cost-effectiveness. Practically, the findings highlight the significance of implementing predictive analytics solutions in the healthcare system to enhance the efficiency of its work and the quality of care provided to patients. The investments made by healthcare organizations should focus on predictive modeling technologies to improve resource management, decrease inefficiencies, and improve patient outcomes. Besides, the results of the study raise the necessity to train and support healthcare providers who may be able to use these tools and interpret the results they offer.

## CONCLUSION

Overall, the study proved that predictive business analytics were effective in terms of healthcare expenditure reduction and the enhancement of patient outcomes in the United States public health systems. The evaluation indicated that the healthcare expenses were reduced greatly, patient satisfaction was increased, and readmissions were decreased following the adoption of predictive analytics tools. These findings will help the study to achieve its goal of assessing the role of predictive analytics in healthcare efficiency and quality. Moreover, the findings revealed that predictive model accuracy and the analytics tool applied (machine learning) were key factors that could be used to optimize the cost and outcomes. The research is one of the numerous works concerning the effective use of predictive analytics in healthcare that can provide useful information to policymakers and healthcare managers who want to improve the efficacy of the system and patient care. Not only does the research match its objectives, but it also highlights the possibility of advanced data-driven tools in transforming healthcare delivery. In the future, one of the studies might explore how these technologies impact over the long term, the scalability of the technologies in various health care environments, and how they can be integrated with other emerging health care technologies.

**Funding:** This research received no external funding.
**Conflicts of Interest:** The authors declare no conflict of interest.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