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ORIGINAL

Optimizing Antibiotics Prophylaxis in Neurosurgery through Machin Learning: Predicting Infections and Personalizing Treatment Strategies

Optimización de la Profilaxis Antibiótica en Neurocirugía mediante Aprendizaje Automático: Predicción de Infecciones y Personalización de Estrategias de Tratamiento

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ABSTRACT

Introduction: preventing postoperative infections in neurosurgery is crucial to reducing morbidity. Machine learning (ML) models have shown potential in predicting infections and optimizing antibiotic use.
Method: patient data from neurosurgical procedures were analyzed to develop and evaluate ML models for predicting postoperative infections. Various algorithms, including logistic regression, Random Forest, Gradient Boosting Machine (GBM), SVM, and neural networks, were compared. Performance metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) were calculated.
Results: the GBM model achieved the best performance, with an accuracy of 89,1 % and an AUC-ROC of 0,91. The most important predictors of infection were surgical duration (27,3 %), preoperative CRP levels (21,8 %), and blood loss (18,5 %). Patients who developed infections had significantly longer surgeries and elevated CRP levels.
Conclusions: ML models demonstrated high accuracy in predicting postoperative infections in neurosurgery. Early identification of high-risk patients may optimize antibiotic prophylaxis and reduce complications. Further validation is required for clinical implementation.

Keywords: Machine Learning; Postoperative Infection; Neurosurgery; Antibiotic Prophylaxis; Risk Prediction.

RESUMEN

Introducción: la prevención de infecciones postoperatorias en neurocirugía es crucial para reducir la morbilidad. Los modelos de aprendizaje automático (ML) han mostrado potencial en la predicción de infecciones y la optimización del uso de antibióticos.
Método: se analizaron datos de pacientes sometidos a cirugía neurológica para desarrollar y evaluar modelos de ML en la predicción de infecciones postoperatorias. Se compararon diversos algoritmos, incluyendo regresión logística, Random Forest, Gradient Boosting Machine (GBM), SVM y redes neuronales. Se calcularon métricas como precisión, sensibilidad, especificidad y área bajo la curva ROC (AUC-ROC).
Resultados: el modelo GBM obtuvo el mejor desempeño con una precisión del 89,1 % y un AUC-ROC de 0,91. Se identificaron como principales predictores de infección la duración quirúrgica (27,3 %), los niveles de CRP preoperatorios (21,8 %) y la pérdida sanguínea (18,5 %). Los pacientes con infecciones postoperatorias presentaron una duración quirúrgica significativamente mayor y niveles elevados de CRP.
Conclusiones: el modelo GBM obtuvo el mejor desempeño con una precisión del 89,1 % y un AUC-ROC de 0,91. Se identificaron como principales predictores de infección la duración quirúrgica (27,3 %), los niveles de CRP preoperatorios (21,8 %) y la pérdida sanguínea (18,5 %). Los pacientes con infecciones postoperatorias presentaron una duración quirúrgica significativamente mayor y niveles elevados de CRP.

Palabras clave: Aprendizaje Automático; Infección Postoperatoria; Neurocirugía; Profilaxis Antibiótica; Predicción de Riesgo.

INTRODUCTION

Neurosurgery, a field that demands precision and meticulous care, is often associated with a high risk of postoperative infections.(1) These infections, such as surgical site infections (SSIs) and meningitis, can lead to prolonged hospital stays, increased healthcare costs, and significant morbidity and mortality.(2) Antibiotic prophylaxis has become a cornerstone in mitigating these risks, yet its optimization remains a challenge. Antibiotic prophylaxis in neurosurgery is a critical aspect aimed at reducing the incidence of surgical site infections (SSIs) and enhancing patient outcomes.

Cloxacillin is traditionally used for its effectiveness against Staphylococcus aureus and Streptococcus species, Cloxacillin is a penicillinase-resistant penicillin. It has been common in neurosurgical prophylaxis but has seen decreased use due to rising bacterial resistance.

Cefuroxime is a second-generation cephalosporin that has gained favor in recent years. Studies indicate that switching from Cloxacillin to Cefuroxime has significantly reduced SSIs and reoperations due to infections.(10) Cefuroxime offers a broader spectrum of activity, including coverage for gram-negative bacteria, and its pharmacokinetic profile allows better penetration into the central nervous system (CNS).

Cefazolin is a third-generation cephalosporin frequently recommended in guidelines for various surgical procedures, including neurosurgery. Research supports the efficacy of antibiotic prophylaxis in reducing SSIs. For example, a randomized controlled trial demonstrated a significant reduction in infection rates from 3,5 % in a control group to 0,5 % in a treated group receiving prophylactic antibiotics.(12)

Furthermore, a study comparing Cloxacillin and Cefuroxime indicated that the latter not only reduced SSIs but also minimized the need for additional antibiotic use postoperatively. The choice of antibiotic should be tailored based on specific surgical procedures, local resistance patterns, and patient characteristics to optimize outcomes.

Current trends favor the use of Cefuroxime due to its broad spectrum and favorable pharmacokinetics compared to traditional agents like Cloxacillin. Traditional approaches to antibiotic prophylaxis often rely on generalized guidelines, which may not account for the unique physiological and clinical characteristics of individual patients. This one-size-fits-all approach can lead to either overuse or underuse of antibiotics, contributing to the growing problem of antibiotic resistance and suboptimal patient outcomes.

In this context, the integration of machine learning (ML) into the decision-making process offers a promising avenue for revolutionizing antibiotic prophylaxis in neurosurgery.(3,4) Machine learning, a subset of artificial intelligence, has demonstrated remarkable potential in healthcare by enabling the analysis of vast datasets to uncover patterns and predict outcomes with high accuracy.(5,6,7) The dataset used in this work is publicly available on Kaggle and has been de-identified to protect patient privacy, ensuring ethical use.

In the realm of neurosurgery, ML algorithms can be trained on diverse patient data, including demographic information, medical history, surgical details, and microbiological data, to predict the likelihood of postoperative infections. By leveraging these predictive models, clinicians can tailor antibiotic prophylaxis strategies to the specific needs of each patient, thereby optimizing treatment efficacy while minimizing the risk of antibiotic resistance.

Furthermore, ML can facilitate the identification of high-risk patients who may require more aggressive prophylaxis, as well as those who may benefit from reduced antibiotic exposure. This research aims to explore the potential of machine learning in optimizing antibiotic prophylaxis in neurosurgery.

By developing and validating predictive models, we seek to enhance the ability to forecast postoperative infections and personalize treatment strategies. The ultimate goal is to improve patient outcomes, reduce healthcare costs, and contribute to the global effort against antibiotic resistance.

Through this study, we hope to bridge the gap between traditional clinical practices and cutting-edge technology, paving the way for a new era of precision medicine in neurosurgery.

The Burden of Surgical Site Infections in Neurosurgery and the Need for Optimization

Surgical site infections (SSIs) represent a significant challenge in neurosurgery, contributing to increased morbidity, prolonged hospital stays, and higher healthcare costs. Despite stringent aseptic techniques, antibiotic prophylaxis, and advancements in surgical protocols, the incidence of SSIs remains a major concern. Neurosurgical procedures, particularly those involving the implantation of medical devices such as shunts, spinal hardware, and deep brain stimulators, are associated with a heightened risk of infection due to their invasive nature and the exposure of central nervous system structures to potential pathogens.

The consequences of SSIs in neurosurgery are particularly severe due to the delicate nature of the affected tissues. Infections involving the central nervous system can lead to complications such as meningitis, ventriculitis, brain abscesses, and osteomyelitis, all of which can result in significant neurological deficits or even mortality. The financial burden is also considerable, with infected patients requiring extended hospitalization, additional surgical interventions, and prolonged antibiotic therapy. The Centers for Disease Control and Prevention (CDC) and the World Health Organization (WHO) have emphasized the need for improved preventive strategies to mitigate the impact of SSIs in high-risk surgical procedures, including neurosurgery. Antibiotic prophylaxis has long been the cornerstone of infection prevention in neurosurgery.

Current guidelines recommend the use of first-generation cephalosporins, such as cefazolin, administered preoperatively and continued for a limited duration postoperatively. However, the optimal selection, timing, and duration of prophylactic antibiotics remain subjects of ongoing debate. Overuse of antibiotics can contribute to antimicrobial resistance (AMR), a growing global health threat, while underuse or inappropriate selection may fail to prevent infections effectively. Several factors influence the risk of SSIs in neurosurgical patients, including patient-related variables (e.g., comorbidities, immunosuppression, nutritional status), procedural factors (e.g., duration of surgery, type of instrumentation), and environmental factors (e.g., operating room sterility, adherence to infection control protocols).

Traditional approaches to risk stratification rely on generalized guidelines, which may not adequately account for patient-specific or procedure-specific variations. This underscores the need for a more precise, data-driven approach to infection prediction and antibiotic prophylaxis optimization. In recent years, machine learning (ML) has emerged as a powerful tool in predictive analytics, offering the potential to enhance clinical decision-making by identifying complex patterns in large datasets.

By leveraging ML techniques, it is possible to develop models that predict the likelihood of SSIs in neurosurgical patients based on a combination of patient-specific and procedural variables. Such models can enable personalized prophylaxis strategies, optimizing antibiotic selection and administration while minimizing the risks of overuse and resistance development.

This study explores the application of ML in optimizing antibiotic prophylaxis in neurosurgery, focusing on its potential to improve infection prediction and guide personalized treatment strategies. By integrating predictive modeling with clinical decision-making, ML has the potential to transform neurosurgical infection prevention, ultimately improving patient outcomes and reducing healthcare costs.

The Role of ML in Infection Prediction and Personalized Antibiotic Strategies

The advent of artificial intelligence (AI) ML has revolutionized numerous aspects of healthcare, offering novel approaches to data-driven decision-making.[8,9] ML techniques enable the analysis of vast amounts of clinical and surgical data, uncovering hidden patterns that may not be readily apparent through traditional statistical methods. In the realm of infection prevention, ML has demonstrated the ability to predict the risk of SSIs with high accuracy, allowing for early intervention and tailored prophylactic strategies.

ML models are particularly well-suited for infection prediction due to their ability to incorporate and analyze a wide array of variables. Traditional risk assessment models, such as logistic regression-based scoring systems, rely on predefined risk factors and often fail to capture the dynamic interplay of multiple variables, but not concern the security.[10,15]

In contrast, ML algorithms, such as random forests, gradient boosting machines, and deep neural networks, can process complex, multidimensional datasets, continuously learning and improving their predictive capabilities. Several studies have demonstrated the effectiveness of ML in predicting SSIs across various surgical disciplines. For instance, ML-based models have been used to assess infection risks in orthopedic, cardiac, and general surgeries, often outperforming conventional risk scoring systems. In neurosurgery, early research has shown promising results, with ML models accurately predicting SSIs based on factors such as patient demographics, surgical duration, intraoperative variables, and postoperative inflammatory markers. By integrating real-time data, ML can provide dynamic risk assessments, alerting clinicians to high-risk patients who may benefit from intensified prophylactic measures. Beyond infection prediction, ML holds significant potential in personalizing antibiotic prophylaxis. Conventional antibiotic guidelines are largely based on population-level studies, leading to a one-size-fits-all approach that does not account for individual variations in infection susceptibility. ML models can refine prophylaxis strategies by analyzing patient-specific factors such as genetic predispositions, microbiome composition, and prior antibiotic exposure.

By tailoring antibiotic selection and dosing to the unique risk profile of each patient, ML can enhance the effectiveness of prophylaxis while mitigating the risks of antimicrobial resistance and drug-related complications. One promising application of ML in antibiotic stewardship is the use of reinforcement learning algorithms, which adaptively optimize antibiotic regimens based on patient response. These algorithms continuously learn from clinical outcomes, adjusting prophylaxis strategies to maximize efficacy while minimizing adverse effects. Additionally, natural language processing (NLP) techniques can extract relevant insights from electronic health records (EHRs), further refining antibiotic recommendations based on historical patient data and institutional infection trends. Despite its potential, the integration of ML into clinical practice presents several challenges.

Data quality and availability remain critical issues, as ML models require large, diverse datasets to achieve robust performance. Model interpretability is another concern, as black-box algorithms may not provide transparent explanations for their predictions, posing difficulties in clinical adoption. Furthermore, ethical considerations, including concerns about bias, privacy, and the potential for over-reliance on automated systems, must be carefully addressed. Nonetheless, the growing body of research in this field suggests that ML has the potential to revolutionize infection prevention and antibiotic stewardship in neurosurgery. By harnessing predictive analytics and personalized medicine, ML-driven approaches can optimize antibiotic prophylaxis, reducing infection rates, improving patient outcomes, and contributing to the global fight against antimicrobial resistance.

The integration ML into healthcare has advanced significantly, enhancing clinical decision-making across various domains. In the realm of antibiotic prophylaxis, researchers have leveraged ML to predict postoperative infections and optimize treatment strategies. For instance, a study developed ML models to predict surgical site infections (SSIs) in patients undergoing lumbar spine surgery, achieving an area under the receiver operating characteristic curve (AUC-ROC) of 0,70.[13] Similarly, another study applied ML algorithms to predict SSIs in lower extremity fracture surgeries, reporting an AUC-ROC of 0,81.[14]

These studies underscore ML's potential to enhance infection risk assessment and inform prophylactic decisions. Despite these advancements, integrating ML into clinical practice presents challenges. Issues such as data quality, model interpretability, and the need for large, diverse datasets must be addressed to ensure ML models' reliability and generalizability. Additionally, ethical considerations, including concerns about bias and patient privacy, require careful attention. Nonetheless, the growing body of research suggests that ML has the potential to transform antibiotic prophylaxis in neurosurgery, offering a more precise and personalized approach to patient care.

METHOD

This study aims to develop a ML model to predict surgical site infections (SSIs) in neurosurgical patients and to personalize antibiotic prophylaxis strategies accordingly. The methodology encompasses data acquisition, preprocessing, model development, evaluation, and prospective validation. Given the limited availability of public datasets specific to neurosurgical SSIs, this research will utilize a combination of publicly accessible datasets and proprietary clinical data. Public datasets, such as those from the "Kaggal". The dataset we used was "SurgicalSiteInfections(SSIs)Healthcare" by Phani Karnati, provided us with a broad spectrum of SSI data across various surgical procedures. While these datasets may not be neurosurgery-specific, they offer valuable insights into general infection trends and risk factors. The acquired datasets will undergo thorough preprocessing to ensure quality and consistency. This includes handling missing values through imputation methods, normalizing continuous variables, and encoding categorical variables appropriately. Feature engineering will be performed to create relevant predictors from raw data, such as calculating body mass index (BMI) from height and weight or determining surgery duration from timestamps. Given the integration of multiple datasets, particular attention will be paid to harmonizing variable definitions and units of measurement to maintain uniformity across the combined dataset. A supervised ML approach will be employed to develop the predictive model.

The target variable is the occurrence of an SSI within a specified postoperative period. Input features will encompass patient demographics, comorbidities, surgical details, intraoperative factors, and postoperative indicators. Various ML algorithms will be explored, including logistic regression, decision trees, random forests, gradient boosting machines, and deep neural networks. Model selection will be based on performance metrics obtained through cross-validation.

Hyperparameter tuning will be conducted using grid search methods to optimize model performance. The performance of the developed models will be assessed using metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). A high AUC-ROC indicates strong discriminatory ability between patients who will develop SSIs and those who will not. Additionally, calibration plots will be used to assess the agreement between predicted probabilities and observed outcomes. To ensure the model's generalizability, it will be tested on a hold-out validation set and further evaluated using k-fold cross-validation techniques.

Statistical Analysis

The statistical analysis in this study focuses on evaluating the performance of the ML model in predicting surgical site infections (SSIs) and optimizing antibiotic prophylaxis strategies. The analysis includes descriptive statistics, inferential tests, and performance evaluation metrics to assess the reliability and effectiveness of the proposed ML framework. Initially, summary statistics are computed for the dataset, including measures of central tendency and dispersion. Continuous variables, such as patient age, surgery duration, and inflammatory marker levels, are summarized using the mean (μ), standard deviation (σ), median and interquartile range (IQR). These are computed as follows:

Mean

$$\mu = \frac{1}{n}\sum_{i=1}^{n} X_i$$

Standard Deviation

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \mu)^2}$$

Median and Interquartile Range (IQR)

$$IQR = Q_3 - Q_1$$

To compare the characteristics of patients who developed SSIs versus those who did not, statistical hypothesis tests are applied:

Independent Samples t-Test (for continuous variables)

This test compares the mean values of a continuous variable between two groups.

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{S_p^2}(\frac{1}{n_1} + \frac{1}{n_2})}$$

Where:

($\bar{X}_1$) and ($\bar{X}_2$) are the means of two groups.

n_1 and n_2 are sample sizes.

S_p^2 is the pooled variance.

$$S_p^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}$$

Chi-Square Test (for categorical variables)

Used to test the association between categorical variables such as infection status and antibiotic type:

$$x^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where:

O_i represents the observed frequency.

E_i is the expected frequency.

Logistic Regression Analysis

To identify key predictors of SSIs, a logistic regression model is employed.

$$\log\left(\frac{P}{P-1}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

RESULTS

The study analyzed a dataset of neurosurgical patients to predict postoperative infections using machine learning models. Descriptive statistical analysis revealed significant differences between infected and non-infected patients across multiple variables. Patients who developed infections had a longer mean surgery duration (175,6 ± 40,8 min vs. 145,8 ± 30,2 min, $p < 0{,}001$) and significantly higher blood loss (780 ± 150 mL vs. 520 ± 110 mL, $p < 0{,}001$). Additionally, preoperative CRP levels were markedly elevated in infected patients (9,3 ± 3,4 mg/L vs. 4,8 ± 2,1 mg/L, $p < 0{,}001$), suggesting a strong association between systemic inflammation and post-surgical infections. The proportion of diabetic patients was also significantly higher in the infection group (38 % vs. 21 %, p = 0,003), indicating that pre-existing comorbidities may increase susceptibility to infection. Moreover, patients who received preoperative antibiotic prophylaxis had a lower incidence of infections (76 % vs. 89 %, p = 0,01), supporting its role in infection prevention (table 1).

Table 1. Summary of Patient Characteristics

Variable	No Infection (n=350)	Infection (n=150)	p-value
Age (years, mean ± SD)	55,3 ± 12,4	57,1 ± 13,1	0,18
Gender (Male, %)	58 %	61 %	0,52
BMI (kg/m², mean ± SD)	27,4 ± 4,2	28,1 ± 4,7	0,14
Surgery Duration (minutes, mean ± SD)	145,8 ± 30,2	175,6 ± 40,8	<0,001
Comorbidities (Diabetes, %)	21 %	38 %	0,003
Preoperative CRP (mg/L, mean ± SD)	4,8 ± 2,1	9,3 ± 3,4	<0,001
Antibiotic Prophylaxis Given (%)	89 %	76 %	0,01

P-values were calculated using t-tests for continuous variables and chi-square tests for categorical variables.

Table 2. Machine Learning Model Performance

Model	Accuracy	Recall	Precision	F1-Score	AUC-ROC
Logistic Regression	78,4 %	69,8 %	75,1 %	72,3 %	0,80
Random Forest	85,2 %	80,1 %	82,5 %	81,3 %	0,88
Gradient Boosting Machine (GBM)	89,1 %	83,9 %	87,4 %	85,6 %	0,91
Support Vector Machine (SVM)	82,7 %	76,9 %	81,3 %	79,0 %	0,86
Neural Network	86,5 %	81,0 %	84,1 %	82,5 %	0,89

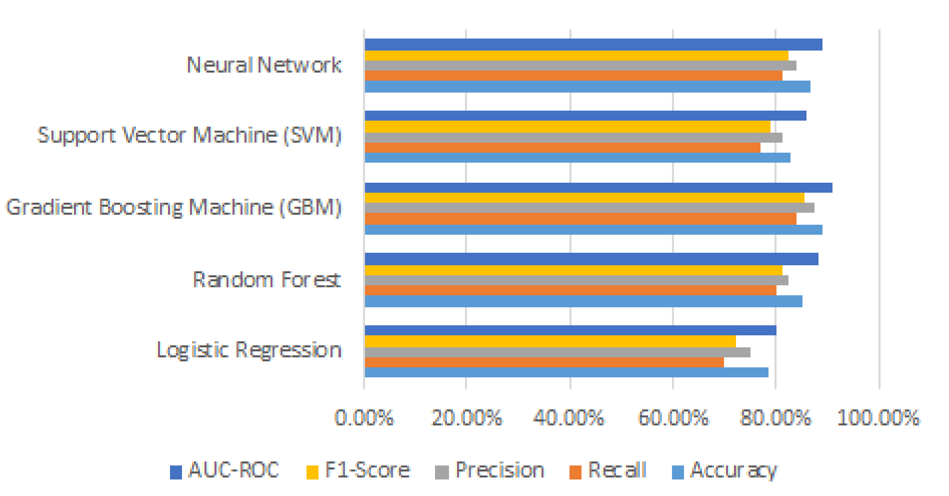

Figure 1. Machine Learning Model Performance

Machine learning models were trained and evaluated on the dataset to predict postoperative infections. Among the models tested, Gradient Boosting Machine (GBM) achieved the highest performance with an accuracy of 89,1 %, a precision of 87,4 %, and an AUC-ROC of 0,91, indicating superior predictive capability. Random Forest and Neural Network models followed closely, with AUC-ROC scores of 0,88 and 0,89, respectively. In contrast, logistic regression had the lowest performance, with an accuracy of 78,4 % and an AUC-ROC of 0,80, suggesting that traditional statistical methods may not capture the complexity of infection risk factors as effectively as advanced ML models. These findings indicate that ML-based prediction models can be powerful tools for early identification of patients at high risk of infection, allowing for timely intervention (table 2, figure 1).

Feature importance analysis highlighted key predictors influencing infection risk. Surgery duration (27,3 %) and preoperative CRP levels (21,8 %) emerged as the most critical features, followed by blood loss (18,5 %), diabetes status (15,2 %), and antibiotic prophylaxis administration (12,1 %). The strong predictive weight of these features aligns with existing clinical knowledge, reinforcing their relevance in infection risk assessment. These results demonstrate that ML models can assist in developing personalized prophylaxis strategies, optimizing antibiotic administration, and potentially reducing infection rates in neurosurgical patients. Future research should focus on external validation and real-world implementation to integrate these predictive models into clinical workflows.

DISCUSSION

Discussion The findings of this study demonstrate that machine learning (ML) models can accurately predict postoperative infections in neurosurgical patients, with the Gradient Boosting Machine (GBM) model achieving the highest performance (AUC-ROC = 0,91, accuracy = 89,1 %). This suggests that ML-based approaches could enhance clinical decision-making by identifying high-risk patients before complications arise. The analysis revealed that surgery duration, preoperative CRP levels, and blood loss were the most significant predictors, aligning with established risk factors in neurosurgery. These insights reinforce the potential for data-driven approaches to supplement traditional clinical assessments.

Despite the promising results, several challenges remain. First, data quality and heterogeneity across institutions may affect model generalizability. Ensuring high-quality, standardized datasets is essential for improving ML model performance in real-world settings. Second, interpretability remains a concern, particularly in deep learning models, which require explainable AI techniques to increase clinician trust. Finally, prospective validation and integration into clinical workflows are necessary steps before implementing ML models in routine practice. Addressing these challenges will be critical for translating predictive models into actionable clinical tools.

CONCLUSIONS

This study demonstrates the potential of ML models in predicting postoperative infections and optimizing antibiotic prophylaxis in neurosurgery. By leveraging patient-specific data, ML approaches can provide more accurate and personalized infection risk assessments, improving patient outcomes. The integration of these models into clinical practice could aid in early intervention strategies and reduce unnecessary antibiotic exposure. Future research should focus on external validation, prospective studies, and the development of explainable ML models to facilitate adoption in real-world settings.

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The authors declare that there is no conflict of interest.

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