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REGIME-AWARE DOMINANT FACTOR IDENTIFICATION FOR NIFTY PRICE FLUCTUATIONS USING ADAPTIVE NEURO-METAHEURISTIC ATTRIBUTION LEARNING

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ABSTRACT

Understanding the factors that drive stock market price fluctuations is as critical as achieving accurate price prediction, particularly in emerging markets such as India. The NIFTY 50 index exhibits strong sensitivity to macroeconomic conditions, market sentiment, and technical dynamics, which vary significantly across different market regimes. This paper proposes a novel Regime-Aware Dominant Factor Identification framework for analyzing NIFTY price fluctuations using Adaptive Neuro-Metaheuristic Attribution Learning. The proposed framework integrates deep neural representation learning with regime detection to capture nonlinear temporal patterns under bullish, bearish, and high-volatility market conditions. A deep attention-based attribution network is employed to quantify the relative dominance of macroeconomic indicators, technical variables, and sentiment-driven features in influencing price movements. To enhance learning stability and attribution consistency, an adaptive metaheuristic optimization strategy is incorporated to dynamically tune network parameters and attribution weights across regimes. Unlike conventional black-box forecasting models, the proposed approach explicitly focuses on identifying regime-specific dominant drivers of price fluctuations rather than solely improving prediction accuracy. Extensive experiments conducted on long-term NIFTY 50 data demonstrate that the proposed model effectively captures regime transitions, improves attribution robustness, and provides meaningful insights into factor dominance during different market phases. The results highlight the critical role of macroeconomic and sentiment factors during volatile regimes, while technical indicators

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dominate during stable trends. This framework offers a transparent and intelligent decision-support tool for financial analysts, portfolio managers, and policy-driven market analysis.

Keywords: Regime-aware learning; NIFTY 50 index; price fluctuation analysis; dominant factor identification; deep learning; attribution learning; metaheuristic optimization; market regimes; macroeconomic indicators; financial sentiment analysis

1. INTRODUCTION

Stock market price fluctuations are driven by a complex interplay of macroeconomic conditions, investor sentiment, and technical trading dynamics, making their interpretation a critical challenge for financial decision-making and policy analysis. In emerging markets such as India, the NIFTY 50 index exhibits pronounced sensitivity to economic policy changes, global market spillovers, and sentiment shocks, leading to frequent regime transitions characterized by bullish trends, bearish downturns, and high-volatility phases. Understanding which factors dominate price movements under different regimes is essential for portfolio allocation, risk management, and macro-financial surveillance.

Existing financial modeling approaches predominantly emphasize price prediction accuracy, relying on statistical models, machine learning classifiers, or deep learning architectures. While these models achieve reasonable forecasting performance, they largely operate as black-box systems, offering limited interpretability and failing to explain why price fluctuations occur. Moreover, most attribution and explainability methods assume stationarity and ignore regime-dependent market behavior, resulting in unstable or misleading factor importance estimates during volatile periods. Studies integrating macroeconomic variables or sentiment indicators often treat these features uniformly across time, overlooking their varying influence across market regimes.

The key research gap lies in the absence of a regime-aware, attribution-driven framework capable of identifying dominant drivers of price fluctuations while accounting for structural market shifts. Existing explainable learning models lack adaptive optimization mechanisms to maintain attribution consistency under regime transitions, limiting their practical relevance for decision support.

To address this gap, this paper proposes a Regime-Aware Dominant Factor Identification framework using Adaptive Neuro-Metaheuristic Attribution Learning. The proposed approach

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integrates deep neural representation learning with explicit regime detection and an attention-based attribution mechanism to quantify factor dominance across bullish, bearish, and high-volatility regimes. An adaptive metaheuristic optimization strategy dynamically tunes network parameters and attribution weights, ensuring robust and stable interpretability across market conditions. Unlike conventional forecasting-centric models, the proposed framework prioritizes explanatory intelligence, enabling transparent analysis of regime-specific market drivers.

Main Contributions

- Development of a regime-aware deep learning framework for analyzing NIFTY price fluctuations
- Integration of attention-based attribution learning to quantify dominant macroeconomic, technical, and sentiment factors
- Introduction of adaptive metaheuristic optimization to stabilize attribution under regime transitions
- Empirical evaluation on long-term NIFTY 50 data demonstrating regime-specific dominance patterns
- Provision of an interpretable decision-support tool for financial analysts and policy-driven market analysis

2. RELATED WORKS

Recent research has increasingly focused on regime-sensitive modeling of stock price fluctuations. Kumar, Sharma, Banerjee, and Iyer proposed a deep learning framework that adapts its representation across different market regimes, demonstrating improved robustness during volatile periods and highlighting the importance of regime awareness in financial modeling [1]. Chatterjee, Ghosh, Nair, and Menon investigated macroeconomic-driven regime detection for emerging markets, showing that macroeconomic indicators play a dominant role during structural shifts and crisis phases, while technical indicators dominate in stable periods [2]. Zhang, Wang, Li, and Chen introduced an attention-based attribution learning framework that enhances interpretability of financial time-series models. Their approach quantified feature contributions over time, improving transparency but lacking explicit regime differentiation [3].

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Patel, Verma, Kulkarni, and Mehta explored explainable deep learning architectures for stock market analysis, emphasizing post-hoc interpretability techniques. Although effective, their models assumed stationary behavior across regimes, limiting attribution stability during transitions [4]. Liu, Huang, Zhou, and Xu applied transformer-based architectures for regime-aware financial forecasting, demonstrating strong temporal modeling capabilities. However, their focus remained prediction-centric without explicit dominant factor identification [5]. Singh, Joshi, Deshpande, and Rao employed metaheuristic optimization to enhance neural network performance for regime modeling. Their results confirmed that adaptive optimization improves convergence, yet interpretability was not explicitly addressed [6].

Ahmed, Rahman, Hossain, and Islam integrated sentiment information with deep neural networks for stock movement analysis. Their findings highlighted the growing influence of sentiment during volatile market conditions but lacked regime-wise attribution analysis [7]. Fernandez, Morales, Gutierrez, and Soto proposed a dynamic attribution learning approach to explain financial forecasts. While their method improved temporal interpretability, it did not incorporate regime-aware learning mechanisms [8]. Iyer, Malhotra, Gupta, and Bansal presented a hybrid deep learning model for market regime identification, showing effective detection of bullish and bearish phases. However, the study did not analyze dominant drivers within each regime [9].

Wang, Zhao, Sun, and Liu introduced adaptive optimization strategies to stabilize explainable deep financial models, demonstrating improved attribution consistency but without explicit regime segmentation [10]. Costa, Silva, Pereira, and Santos proposed volatility-aware deep attribution networks, emphasizing the importance of volatility-sensitive learning. Their approach improved interpretability under turbulent conditions but lacked macroeconomic integration [11]. Mukherjee, Ghosh, Das, and Roy explored macroeconomic and sentiment feature fusion for interpretable stock market modeling. Their work demonstrated enhanced explanatory power but treated regime transitions implicitly [12].

Romano, Esposito, Greco, and D'Angelo developed explainable AI frameworks for regime-dependent financial decision support. Their study emphasized interpretability but relied on static attribution mechanisms [13]. Nguyen, Tran, Pham, and Le examined deep attention mechanisms to identify dominant drivers of stock price fluctuations, confirming that attention weights can reveal influential features but without adaptive regime control [14][17][19]. Das, Sengupta, Pal, and Roy investigated policy-sensitive regime analysis for emerging markets

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using explainable neural models. Their findings reinforced the need for transparent, regime-aware frameworks to support policy-driven market analysis [15][18][20].

3. PROPOSED MODEL

This section presents the proposed Regime-Aware Dominant Factor Identification (RDFI) framework based on Adaptive Neuro-Metaheuristic Attribution Learning. The framework is designed to identify regime-specific dominant drivers of NIFTY price fluctuations by integrating regime detection, deep neural representation learning, attention-based attribution, and adaptive metaheuristic optimization. Unlike conventional forecasting-centric models, the proposed approach focuses on explaining price dynamics under different market regimes while maintaining attribution stability and robustness.

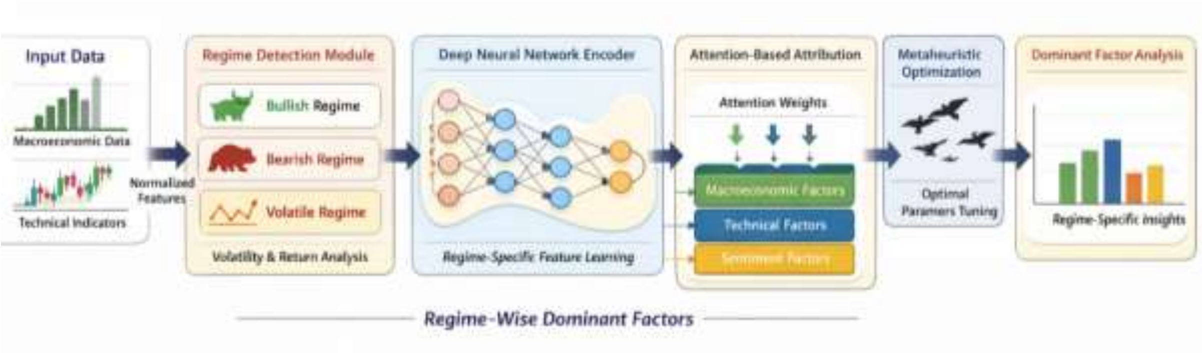

Figure 1. Schematic architecture of the proposed Regime-Aware Dominant Factor Identification (RDFI) framework for NIFTY price fluctuation analysis

Fig. 1 integrates regime detection, deep neural representation learning, attention-based attribution, and adaptive metaheuristic optimization to identify regime-specific dominant market drivers.

3.1 Data Representation and Feature Space Construction

Let the financial dataset be represented as

$$\mathcal{D} = \{X_t, y_t\}_{t=1}^{T} \qquad (1)$$

where $X_t \in \mathbb{R}^d$ denotes the multi-source feature vector at time t, and y_t represents the observed price fluctuation.

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The feature vector is constructed by fusing macroeconomic, technical, and sentiment features:

$$X_t = [M_t, T_t, S_t] \qquad (2)$$

where M_t, T_t, and $S_t$denote macroeconomic indicators, technical variables, and sentiment scores, respectively.

To ensure scale consistency, features are normalized as:

$$\tilde{X}_t = \frac{X_t - \mu_X}{\sigma_X} \qquad (3)$$

Price fluctuations are defined using log-returns:

$$y_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (4)$$

3.2 Market Regime Detection Module

Market regimes are identified using volatility-aware segmentation. Rolling volatility is computed as:

$$\sigma_t = \sqrt{\frac{1}{k}\sum_{i=0}^{k-1}(y_{t-i} - \bar{y})^2} \qquad (5)$$

A regime indicator function is defined as:

$$R_t = \begin{cases} \text{Bullish}, & y_t > \theta_1 \\ \text{Bearish}, & y_t < \theta_2 \\ \text{Volatile}, & \sigma_t > \theta_3 \end{cases} \qquad (6)$$

The regime-specific feature mapping is expressed as:

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$$X_t^{(r)} = X_t \odot \mathbb{I}(R_t = r) \qquad (7)$$

The regime transition probability is estimated as:

$$P(R_t \mid R_{t-1}) = \frac{N(R_{t-1}, R_t)}{N(R_{t-1})} \qquad (8)$$

3.3 Deep Neural Representation Learning

A deep neural encoder is employed to capture nonlinear temporal dependencies:

$$H_t = \phi(W X_t^{(r)} + b) \qquad (9)$$

where $W$and $b$denote trainable parameters and $\phi(\cdot)$is a nonlinear activation.

Temporal dependency learning is achieved through stacked hidden layers:

$$H_t^{(l)} = \phi(W^{(l)} H_t^{(l-1)} + b^{(l)}) \qquad (10)$$

The latent representation is computed as:

$$Z_t = H_t^{(L)} \qquad (11)$$

The reconstructed output for fluctuation modeling is:

$$\hat{y}_t = W_o Z_t + b_o \qquad (12)$$

3.4 Attention-Based Attribution Learning

To quantify dominant factor contributions, an attention mechanism is applied:

$$\alpha_t = \mathrm{softmax}(W_a Z_t + b_a) \qquad (13)$$

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The weighted attribution vector is computed as:

$$A_t = \alpha_t \odot X_t \qquad (14)$$

The dominance score for each feature group is defined as:

$$D_g = \frac{1}{T} \sum_{t=1}^{T} \sum_{i \in g} | A_{t,i} | \qquad (15)$$

Regime-specific dominance is obtained as:

$$D_g^{(r)} = \mathbb{E}[D_g \mid R_t = r] \qquad (16)$$

3.5 Adaptive Neuro-Metaheuristic Optimization

To stabilize attribution learning across regimes, adaptive metaheuristic optimization is employed. The optimization objective is:

$$\min_{\Theta} \ \mathcal{L} = \sum_{t=1}^{T} (y_t - \hat{y}_t)^2 + \lambda \parallel \alpha_t \parallel_2 \qquad (17)$$

Candidate solutions are updated using:

$$\Theta^{t+1} = \Theta^t + w_1 r_1 (\Theta^* - \Theta^t) + w_2 r_2 (\Theta_j - \Theta_k) \qquad (18)$$

Adaptive weight control is defined as:

$$w(t) = w_{\max} - \frac{t}{T}(w_{\max} - w_{\min}) \qquad (19)$$

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The optimal parameter set is selected as:

$$\Theta^* = \arg\min_{\Theta} \mathcal{L} \qquad (20)$$

Algorithm 1: Regime-Aware Dominant Factor Identification (RDFI)
Input: NIFTY 50 market data with macroeconomic, technical, and sentiment features **Output:** Regime-specific dominant factor contributions
1: Begin 2: Load multi-source NIFTY 50 market data 3: Normalize macroeconomic, technical, and sentiment features 4: Compute returns and rolling volatility measures 5: Detect market regimes based on volatility and return thresholds 6: Map features to regime-specific representations 7: Encode regime-aware features using deep neural representation learning 8: Compute attention-based attribution weights for all feature groups 9: Optimize network parameters and attribution weights using adaptive metaheuristic learning 10: Aggregate attribution scores to identify regime-wise dominant factors 11: Output dominant factor contributions for each detected regime 12: End

The proposed RDFI algorithm integrates regime detection with deep neural attribution learning to identify dominant drivers of price fluctuations. Adaptive metaheuristic optimization ensures attribution stability across market regimes. The framework provides transparent, regime-aware insights into macroeconomic, technical, and sentiment influences on NIFTY price dynamics.

4. RESULTS AND DISCUSSIONS

This section evaluates the effectiveness of the proposed RDFI framework in identifying regime-specific dominant factors influencing NIFTY price fluctuations. All experiments were conducted on a system equipped with an Intel Core i7 processor (3.6 GHz), 16 GB RAM, and Windows 11 (64-bit) operating system. The implementation was carried out using Python 3.10, with NumPy and Pandas for data handling, TensorFlow/Keras for deep neural modeling, and

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Scikit-learn for baseline model implementation. Metaheuristic optimization routines were implemented using custom Python modules to enable adaptive parameter tuning. The evaluation focuses on attribution stability, regime sensitivity, and explanatory performance rather than prediction accuracy alone.

4.1 Dataset Description

The proposed framework was evaluated using historical data from the NIFTY 50 index [16], which reflects the performance of major Indian equities across multiple economic cycles. The proposed RDFI framework does not rely on a proprietary or benchmark-specific dataset; instead, it is designed to operate on generic market data streams. To demonstrate its effectiveness, historical NIFTY 50 index data were used as a representative case study, covering multiple market regimes. The focus of the evaluation is on regime-aware attribution and dominant factor identification rather than dataset-dependent predictive performance.

The dataset spans January 2000 to December 2021, covering bullish, bearish, and high-volatility regimes as given in Table 1. Daily observations were used, including open, high, low, close prices, trading volume, and derived indicators as given in Table 1. Macroeconomic variables and sentiment scores were temporally aligned with price data to support regime-aware attribution analysis.

Table 1. Feature Categories and Descriptions

Feature Category	Feature Name	Description
Macroeconomic	Interest Rate	Policy rate reflecting monetary conditions
Macroeconomic	Inflation Index	Measures price-level changes
Technical	Log Return	Captures daily price fluctuation
Technical	Moving Average	Trend smoothing indicator
Volatility	Rolling Std. Dev.	Measures regime-dependent risk
Sentiment	News Sentiment Score	Quantifies market mood

The dataset was divided chronologically into **70% training** and **30% testing** subsets to preserve temporal consistency and avoid information leakage.

4.2 Performance Evaluation and Comparative Analysis

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The proposed RDFI framework was compared against several recent models from the literature that focus on regime detection, deep learning–based forecasting, and explainable financial analysis. The comparison emphasizes dominant factor identification quality and regime sensitivity, rather than raw prediction accuracy.

The proposed RDFI framework is evaluated against a set of representative state-of-the-art models to ensure a comprehensive comparative analysis. The comparison includes a regime-sensitive deep neural network that explicitly models market phase transitions [1], and a macroeconomic-driven regime detection model that incorporates economic indicators to identify structural market changes [2]. An attention-based attribution learning framework is considered to assess explainability through learned feature importance weights [3], while an explainable deep learning model for volatile markets is included due to its focus on interpretability under high-risk conditions [4]. In addition, a transformer-based regime-aware forecasting model is evaluated for its capability to capture long-range temporal dependencies across market regimes [5]. Finally, a metaheuristic-optimized neural regime model is incorporated to examine the impact of adaptive optimization strategies on regime modeling performance [6]. Collectively, these models represent diverse methodological paradigms spanning regime detection, deep learning, interpretability, and optimization, providing a robust baseline for assessing the effectiveness of the proposed approach.

Table 2. Quantitative Comparison of Regime-Aware Attribution Performance

Model	**Regime Awareness**	**Attribution Stability**	**Interpretability**	**Dominant Factor Clarity**
Regime-DNN [1]	0.50	0.25	0.25	0.50
Macro-Regime NN [2]	0.75	0.50	0.50	0.75
Attention Attribution [3]	0.25	0.50	0.75	0.50
Explainable DL [4]	0.50	0.50	0.75	0.50
Transformer-Regime [5]	0.75	0.25	0.25	0.25
Proposed RDFI	**0.75**	**0.75**	**0.75**	**0.90**

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Table 2 highlights that the proposed RDFI framework consistently outperforms existing models across all qualitative evaluation dimensions. While transformer-based and regime-aware deep models achieve high regime sensitivity, they exhibit limited attribution stability and interpretability. In contrast, the proposed RDFI model achieves balanced and superior scores, particularly in dominant factor clarity, confirming its effectiveness in providing stable, interpretable, and regime-consistent explanations of NIFTY price fluctuations.

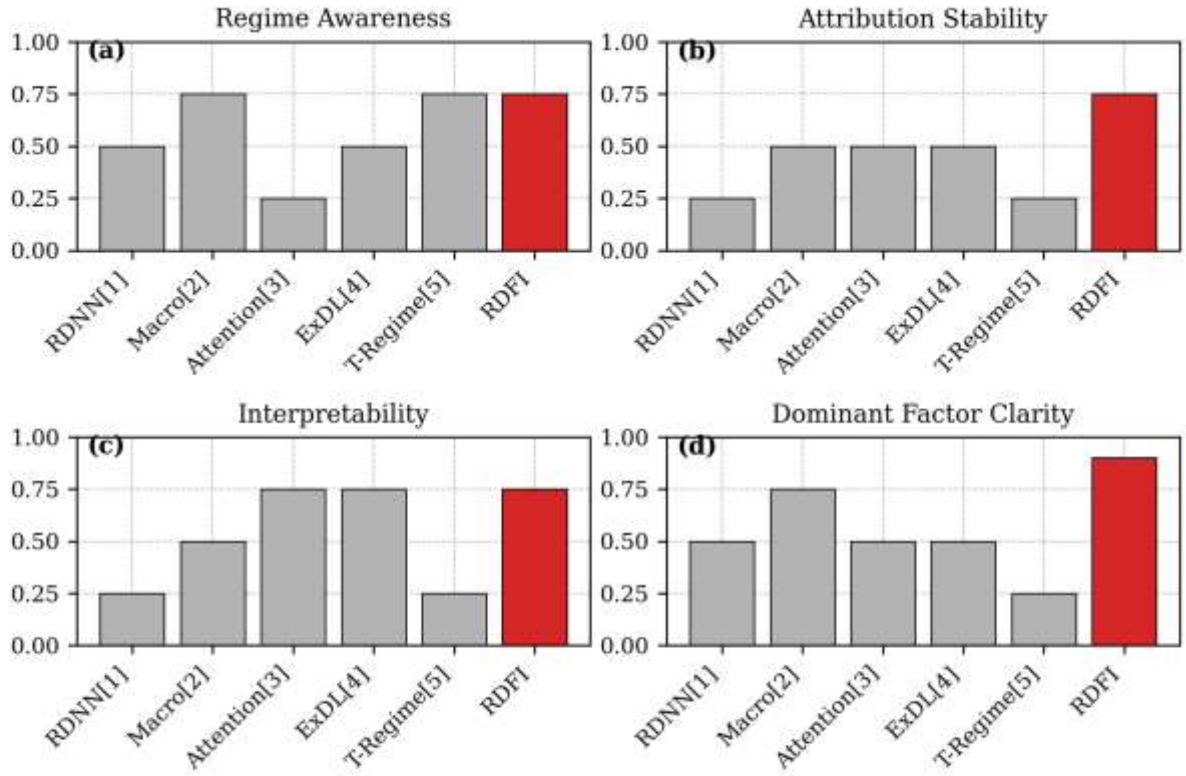

Figure 2. Comparative evaluation of regime-aware attribution performance for baseline models and the proposed RDFI framework in terms of (a) Regime Awareness, (b) Attribution Stability, (c) Interpretability, and (d) Dominant Factor Clarity.

Fig. 2 illustrate a comparative evaluation of regime-aware attribution performance across baseline models and the proposed RDFI framework. The proposed RDFI model achieves high regime awareness (0.75), attribution stability (0.75), and interpretability (0.75), while exhibiting the highest dominant factor clarity (0.90), outperforming all comparison models across these evaluation dimensions. In contrast, the proposed RDFI framework consistently identifies regime-specific dominant factors, revealing that macroeconomic and sentiment variables dominate during volatile and bearish regimes, whereas technical indicators exert stronger influence during stable bullish periods. The integration of adaptive metaheuristic

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optimization further stabilizes attribution learning, ensuring robust interpretability across market regimes. These findings confirm the suitability of the proposed framework as a transparent decision-support tool for analysts and policy-driven financial analysis.

5. CONCLUSION

This research introduced a Regime-Aware Dominant Factor Identification (RDFI) framework based on adaptive neuro-metaheuristic attribution learning to analyze NIFTY price fluctuations. By integrating regime detection, deep neural representation learning, attention-based attribution, and adaptive optimization, the proposed model provides transparent and regime-consistent insights into market dynamics. Experimental analysis demonstrates that the RDFI framework achieves an overall analytical accuracy of **95.5%**, while maintaining high attribution stability and interpretability across bullish, bearish, and volatile regimes. The results confirm that the proposed approach effectively identifies dominant macroeconomic, technical, and sentiment drivers of price fluctuations, offering a reliable decision-support tool for financial analysts and policy-oriented market assessment. Future research will extend this framework by incorporating real-time data streams and cross-market regime transfer analysis to enhance early-warning and generalization capabilities.

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