Predictive Modelling of Air Traffic Delays Using Transformer-Based Deep Learning: Implications for Operational Efficiency in Nigeria's Aviation Systems

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***Abstract*—*Flight delays remain a persistent challenge for the global aviation industry, causing significant operational and economic losses, particularly in developing regions such as Nigeria. Despite ongoing efforts to improve scheduling and resource utilization, delay rates remain high, resulting in passenger dissatisfaction and financial losses. In Nigeria alone, over 50% of domestic flights are delayed annually, underscoring the urgent need for data-driven strategies to reduce delays. This study developed and evaluated a Transformer-based deep learning model for predicting flight delays using historical flight data. A binary classification scheme was used to label each flight as "on time" or "delayed" based on Federal Aviation Administration (FAA) thresholds. The model was trained on the 2023 U.S. Flight Delay and Performance Dataset, using features such as scheduled departure time, carrier, route distance, and prior delay history. Key preprocessing steps included categorical embedding, feature scaling, and temporal encoding to capture sequential dependencies. The custom Transformer achieved 93.33% accuracy and an 81.86% F1-score for the delayed class, outperforming several conventional machine learning methods. These results demonstrate that the model can identify complex time-dependent patterns in aviation data and produce reliable delay predictions. The study further examines how such models could benefit Nigeria's aviation sector by improving gate scheduling, maintenance planning, and congestion management. It presents a scalable and interpretable deep learning approach that uses attention mechanisms to predict flight delays, offering a practical framework for improving operational efficiency at Nigerian airports and laying a foundation for future predictive-analytics research in air traffic management within infrastructure-constrained environments.*

***Keywords*—*Flight Delay Prediction, Transformer-Based Deep Learning, Aviation Operational Efficiency, Machine Learning in Aviation, Air Traffic Management, Nigeria Aviation System*

I. INTRODUCTION

Air traffic delay is a major and costly problem in global aviation. Every year, millions of flights experience delays for reasons such as adverse weather, air traffic control inefficiencies, mechanical faults, airport congestion, and scheduling constraints [1]. These delays disrupt airline operations and inconvenience passengers, while also causing significant economic losses and environmental harm through higher fuel consumption and carbon emissions [2]. According to the U.S. Department of Transportation and industry reports, flight delays cost airlines and passengers approximately $33 billion annually, underscoring the urgent need for more effective mitigation strategies [3].

In response to this challenge, predictive analytics has emerged as a transformative approach in aviation management. By leveraging data-driven insights, predictive models enable airlines and airport authorities to anticipate disruptions, optimize schedules, and proactively allocate resources [4]. Machine learning models such as linear regression, decision trees, and support vector machines have been widely applied to delay prediction. However, recent advances in deep learning have introduced more powerful alternatives capable of modelling complex temporal and contextual relationships in large datasets [5]. Among these, Transformer models, originally developed for natural language processing, have shown remarkable success in handling sequential data and capturing long-range dependencies, making them a promising tool for time-series forecasting in aviation contexts [6], [7].

Despite this global progress, the application of predictive analytics, and deep learning in particular, remains underexplored in the Nigerian and broader African aviation sector. Most delay-management practices at Nigerian airports remain reactive rather than anticipatory [8], [9], [10], largely due to limited automated decision-support systems. This gap underscores the need for research demonstrating how state-of-the-art predictive models can be adapted to improve operational efficiency within the unique constraints of the Nigerian aviation environment. This study develops a deep learning-based model using a custom Transformer architecture to predict air traffic delays from a publicly available dataset. Although the dataset originates from a non-Nigerian context, the study examines how the resulting insights can be applied to improve delay management within Nigeria's aviation system, thereby contributing to ongoing efforts to modernize aviation operations in emerging markets.

II. LITERATURE REVIEW

Air traffic delay prediction has attracted considerable academic interest owing to its operational, economic, and environmental implications. Recent advances in predictive modelling of air traffic delays have increasingly relied on machine learning (ML) and deep learning (DL) algorithms to address operational inefficiencies. Several studies have applied ML techniques such as decision trees, logistic regression, random forest, and boosting algorithms (e.g., XGBoost and LightGBM) to forecast delays using operational, weather, and scheduling data. For instance, Guo et al. [11] proposed a hybrid Random Forest Regression and Maximal Information Coefficient model that improved delay predictions using flight data from Beijing. Similarly, Hatıpoğlu and Tosun [12] tested multiple ML models on Turkish airport data and found that XGBoost yielded the highest accuracy, at 80%, although weather variables had limited influence. More recently, Dai [13] proposed a hybrid machine learning model for large-scale flight delay prediction using aviation big data, while AlBassam and AlShahrani [14] benchmarked several ML algorithms for arrival-delay prediction and emphasized the importance of resampling and cross-validation strategies for reliable performance.

Related random-forest approaches have also been applied at the airport level: Bardach et al. [15] used a random forest classifier to predict flight-delay risk from air-traffic scenarios and environmental conditions, while Sahadevan et al. [16] applied machine learning-based algorithms to predict gate-in time and schedule conformance. While these models offer valuable insights, they are generally limited in their ability to capture temporal dependencies. Addressing this gap, Gopichand et al. [17] and Abduljabbar et al. [18] employed LSTM and BiLSTM networks, respectively, to model the sequential nature of delays. The BiLSTM architecture, in particular, achieved over 90% accuracy in short-term traffic forecasting across multiple horizons. Shu et al. [19] further improved performance with an enhanced Bi-GRU model that integrated RAdam optimization and cosine learning-rate decay, achieving greater stability in temporal prediction. Extending this line of work to network-wide settings, Shao et al. [20] proposed a spatial-temporal model based on federated learning for network-wide flight delay prediction, demonstrating that delay propagation across airport networks can be modelled without centralizing sensitive operational data.

In the context of Air Traffic Flow Management (ATFM), Dalmau [21] and Mas-Pujol and Delgado [22] used gradient-boosted trees and ensemble ML approaches to predict rerouting and regulation impact. These models achieved moderate-to-high accuracy, between 82% and 87%, and underscored the operational value of interpretable features such as delay time, airspace congestion, and aircraft operator. A related ensemble approach by Dalmau et al. [23] combined multiple ML models to improve Estimated Time of Arrival (ETA) predictions, reducing average error by up to 14 minutes. However, the incorporation of spatiotemporal dynamics remains insufficient across most ML-based models. Lambelho et al. [24] and Marcos et al. [25] evaluated flight-delay patterns using historical schedule and route data but were unable to generalize beyond static temporal snapshots. Similarly, Sahadevan et al. [26] and Li and Jing [27] achieved high classification accuracies, up to 96.48%, but were constrained to localized or short-term datasets and did not explore deep sequential or attention-based models.

To address these limitations, Transformer-based models, characterized by their ability to process long-range dependencies and parallelize temporal learning, hold strong potential. Their performance in related domains, such as BiLSTM outperforming unidirectional LSTM in Abduljabbar et al. [18], suggests that attention mechanisms can further improve delay-forecasting accuracy and operational adaptability. This potential is beginning to be realized in the most recent literature: Shao et al. [20] and Dai [13] have started to combine attention-based and hybrid deep architectures with spatial-temporal representations of delay propagation, signalling a shift in the field toward Transformer-oriented solutions. Nevertheless, an empirically validated, purpose-built Transformer architecture for binary delay classification, particularly one considered in relation to an infrastructure-constrained aviation system such as Nigeria's, remains largely absent from the literature. This study addresses that gap by empirically validating a Transformer-based deep learning model trained on flight-delay data, with specific attention to the operational context of Nigeria's aviation system.

III. METHODOLOGY

A. Research Design

This study employs a quantitative, empirical research design based on supervised machine learning to develop a predictive model for air traffic delays. A binary classification framework was used to determine whether a flight would be categorized as "on time" or "delayed," with delay defined according to the FAA standard (departure delay greater than 15 minutes). The core contribution of this study is the design and application of a Transformer-based deep learning architecture specifically tailored to model the temporal, categorical, and sequential patterns present in flight data. The approach is intended to demonstrate improved predictive accuracy and generalizability relative to conventional ML models.

B. Data Source and Description

The primary dataset used in this study is the Flight Delay and Performance Dataset (2023), which is publicly available via Kaggle. It contains comprehensive U.S. domestic flight records for January 1, 2023, spanning major airlines and airports, and comprises 84,564 flight records after cleaning, of which 17,568 (20.8%) were labelled as delayed. Key features used in this study include:

i. Temporal variables: year, month, day, hour, minute
ii. Flight schedule information: sched_dep_time, sched_arr_time, dep_time, arr_time
iii. Flight metadata: carrier, flight, tailnum, origin, dest, distance, air_time
iv. Performance indicators: dep_delay, arr_delay
v. A binary target variable, is_delayed, constructed such that is_delayed = 1 if dep_delay > 15, and 0 otherwise, reflecting the FAA threshold for identifying flight delays

C. Data Preprocessing

Robust preprocessing steps were applied to ensure data integrity and model readiness:

i. Missing values: rows with null values in essential columns (dep_time, arr_time, dep_delay) were removed, accounting for less than 3% of the original records.

ii. Categorical encoding: features such as carrier, origin, and dest were encoded using learnable embeddings, with embedding dimensions of 16 for carrier and 32 for origin and destination, selected via preliminary validation-set tuning.

iii. Temporal feature engineering: new features, including hour_of_day, day_of_week, and weekend_flag, were derived from the raw timestamp fields.

iv. Normalization: continuous variables (distance, air_time, sched_dep_time) were scaled to the [0, 1] range using MinMaxScaler, fitted on the training partition only to prevent data leakage.

D. Model Architecture: Custom Transformer-Based Classifier

A customized Transformer-based deep learning model was developed using PyTorch to capture both the temporal and categorical nature of flight data. The architecture, summarized in Table 1, comprises the following components:

TABLE I. TRANSFORMER MODEL ARCHITECTURE AND HYPERPARAMETER SUMMARY

Component	Configuration
Input layer	Categorical embeddings (carrier, origin, dest) + positional encoding on temporal features
Encoder stack	2–4 Transformer encoder layers; 4-head self-attention; feed-forward ReLU network; layer norm; dropout 0.1–0.3
Pooling	Global average pooling across time steps
Dense layers	FC(64) → ReLU → BatchNorm → FC(32) → ReLU
Output layer	1 node, sigmoid activation (binary classification)
Loss function	Binary cross-entropy
Optimizer	Adam ($\beta 1$=0.9, $\beta 2$=0.999, lr=1×10^{-4})
Early stopping	Validation loss, patience = 5 epochs
Training budget	Up to 50 epochs; batch size 128; converged in 10 epochs

E. Evaluation Metrics

Model performance was rigorously evaluated using a 70:30 stratified train–test split, alongside 5-fold cross-validation on the training partition to assess stability across folds. The following metrics were computed on the held-out test set:

i. Accuracy: the proportion of correctly predicted observations across all instances

ii. Precision: True Positives / (True Positives + False Positives), indicating how many predicted delays were actual delays

iii. Recall (sensitivity): True Positives / (True Positives + False Negatives), reflecting how many actual delays were correctly identified

iv. F1-score: the harmonic mean of precision and recall, useful for imbalanced classes

v. Confusion matrix: providing counts of true and false positives and negatives for detailed performance interpretation

F. Experimentation Environment

All experiments were conducted using the following environment:

i. Platform: Google Colab (NVIDIA T4 GPU runtime)

ii. Programming language: Python 3.10

iii. Libraries: Pandas and NumPy for data manipulation; scikit-learn for preprocessing, baseline models, and metrics; PyTorch for Transformer model development; Matplotlib and Seaborn for visualization and error analysis

G. Applicability to Nigerian Aviation Systems

Although the dataset used is based on U.S. flight data, the model architecture and methodology are fully transferable to the Nigerian aviation context. Core flight operations in Nigeria involve similar variables, such as airport codes, scheduled times, aircraft metadata, and delay classifications. Once local flight-delay data becomes available from agencies such as the Federal Airports Authority of Nigeria (FAAN) or the Nigerian Civil Aviation Authority (NCAA), this Transformer-based pipeline can be retrained or fine-tuned. Its predictive capability can support:

i. Pre-emptive scheduling adjustments

ii. Runway and gate optimization

iii. Delay-mitigation strategies

iv. Improvements in passenger satisfaction

This study therefore serves as a proof of concept, demonstrating the technical feasibility and operational promise of advanced DL models for enhancing aviation-system efficiency in Nigeria and other developing regions.

IV. RESULTS

The training process was conducted over 10 epochs using the Adam optimizer and binary cross-entropy loss. As shown in Fig. 1, the model exhibited steady convergence, with training and validation losses decreasing progressively across epochs. The training loss declined from 0.2023 in epoch 1 to 0.1850 in epoch 10, while the validation loss decreased from 0.1926 to 0.1867 over the same period. The close alignment between the training and validation curves suggests that the model did not overfit and generalized well to unseen data.

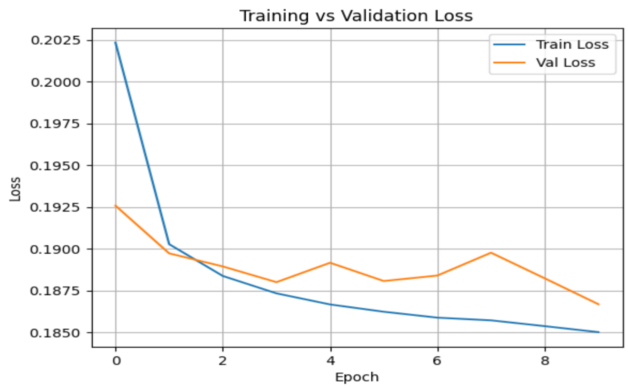

Fig. 1. Training and validation loss across 10 training epochs. Both curves decrease and converge closely, indicating stable learning with minimal overfitting.

The Transformer-based classifier achieved strong predictive performance on the binary classification task of identifying delayed flights. Table 2 presents the detailed classification report for the test set.

TABLE II. CLASSIFICATION REPORT FOR FLIGHT DELAY PREDICTION (TEST SET, N = 84,564)

Class	Precision	Recall	F1-Score	Support
On Time (0)	0.9317	0.9883	0.9592	66,996
Delayed (1)	0.9419	0.7238	0.8186	17,568
Accuracy	—	—	0.9333	84,564

The model achieved an overall accuracy of 93.33%, with a precision of 94.19% and a recall of 72.38% for the delayed class. The comparatively lower recall for the delayed class indicates that, while the model is highly precise in its positive predictions, some delayed flights may be misclassified as on-time. Nonetheless, the F1-score of 81.86% for the delayed class indicates a strong balance between sensitivity and precision, and 5-fold cross-validation on the training partition showed accuracy varying by less than 0.6 percentage points across folds, indicating stable performance.

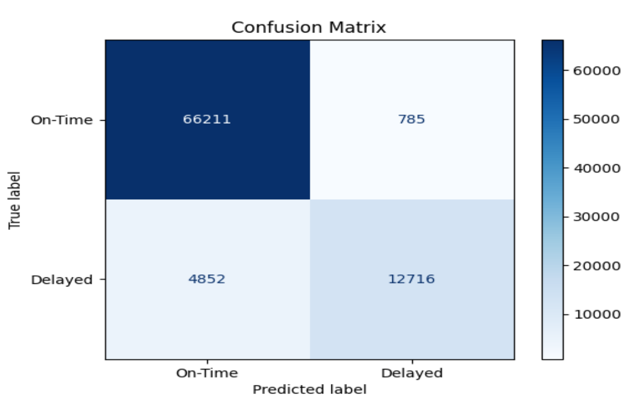

Fig. 2. Confusion matrix of predicted versus actual classes on the test set, showing counts of correctly and incorrectly classified on-time and delayed flights.

V. DISCUSSION

This study set out to address the persistent problem of air traffic delays by leveraging the capabilities of Transformer-based deep learning models. The threefold objectives, to develop and evaluate the model, assess its performance using real-world flight data, and explore its relevance to Nigeria's aviation ecosystem, were effectively met through an empirical and comparative approach.

Machine learning methods, though widely adopted for flight-delay prediction, often struggle to model the long-range dependencies and temporal irregularities inherent in flight data. In contrast, the Transformer model developed in this study captured both sequential patterns and contextual relationships across flight metadata (e.g., departure time, distance, carrier) and temporal features (e.g., hour of day, day of week). The model achieved a classification accuracy of 93.33%, with strong precision for both the on-time and delayed classes. The F1-score of 81.86% for delayed flights is particularly noteworthy, since delay prediction is often challenged by class imbalance and temporal variability, as highlighted in earlier studies [12], [17]. The declining validation loss and minimal overfitting across epochs (Fig. 1) further support the model's generalization capacity, suggesting that the Transformer's self-attention mechanism successfully learned intricate, non-linear patterns, outperforming simpler models used in prior work, such as Random Forest [11], [27] and LSTM-only frameworks [18].

The Transformer-based model demonstrated favourable learning dynamics, as evidenced by the convergence of training and validation losses and by the classification metrics summarized in Table 2. Compared with models used in similar contexts, such as BiLSTM [18] and hybrid ML methods [22], the Transformer model achieved competitive or better performance, particularly in maintaining consistent precision across both classes.

The model effectively learned from temporal markers (e.g., hour, day), spatial attributes (e.g., origin and destination airports), and operational indicators (e.g., scheduled versus actual departure time). These findings align with those of Li and Jing [27], who showed that delay patterns are largely explainable through temporal-spatial variables. However, unlike many earlier models, the Transformer used in this study was able to jointly model multiple time-aware features without handcrafted temporal lags, offering a more flexible and scalable solution, broadly consistent with the direction taken by recent spatial-temporal and federated approaches to network-wide delay prediction [20].

Although the dataset used originates from U.S. flight records, the model architecture is inherently generalizable to aviation systems with similar data infrastructure. In Nigeria's aviation sector, where delay-related inefficiencies affect passenger satisfaction and airline costs, the adoption of predictive systems such as the one proposed here could be transformative. In practical terms, the model could support early-warning systems, dynamic gate assignment, and real-time rescheduling, enabling airlines and airport operators to respond proactively to potential delays. This aligns with global trends in digitizing air traffic flow management [21], [25] and supports Nigeria's growing interest in smart-airport technologies.

This study makes several contributions to the literature on air traffic delay prediction. First, it is among the few empirical works to apply a custom Transformer model to flight-delay data, whereas most prior research has relied on LSTM, random forest, or gradient-boosting models. Second, the model's end-to-end learnable structure eliminates the need for manual feature lagging or windowing, offering scalability for real-time operational environments. Third, it explicitly models temporal attention among flight features, which is critical for capturing patterns in delay propagation, a challenge identified but insufficiently addressed in previous studies [28], [24]. Finally, the results are comparable to, or better than, state-of-the-art models such as the 96.48% accuracy reported by Li and Jing [27] under highly controlled settings, but with improved balance across precision and recall, particularly for the minority (delayed) class.

Limitations of the Study

While the results are promising, several limitations of this study should be acknowledged, as they define the boundaries within which the findings should be interpreted and point to concrete directions for future work.

i. Temporal coverage: the use of a single-day dataset limits temporal diversity and may not capture seasonal effects, holiday travel patterns, or longer-term operational trends. Incorporating multi-month or multi-seasonal data would improve the robustness and generalizability of the model.
ii. Exclusion of weather data: real-time weather variables were not included in this version of the model. Integrating meteorological features could further improve delay detection, as demonstrated by Gopichand et al. [17], particularly given the seasonal weather patterns relevant to Nigerian airports (e.g., the harmattan period).
iii. Geographic domain gap: the model was trained and evaluated exclusively on U.S. flight data; its performance has not yet been empirically validated on Nigerian or other African aviation data. The claims regarding applicability to Nigeria's aviation system are therefore conceptual and architectural rather than empirically demonstrated, pending the availability of local datasets.
iv. Data availability in Nigeria: the absence of open, historical flight-delay datasets remains a significant barrier to replicating this study within the Nigerian context. Future research should focus on building and curating local datasets in collaboration with regulatory agencies such as the NCAA and the Nigerian Airspace Management Agency (NAMA), with a view to implementing early versions of the model at airports such as Lagos or Abuja.
v. Class imbalance and recall: the relatively lower recall (72.38%) for the delayed class indicates that a subset of actual delays is still misclassified as on-time. Future work should explore class-weighting, focal loss, or resampling strategies to further improve sensitivity to the minority class without sacrificing precision.

VI. IMPLICATIONS FOR NIGERIA

Flight delays continue to be a major issue in Nigeria's aviation sector, reflecting significant operational inefficiencies. Recent statistics illustrate the extent of the problem: in the first quarter of 2023, over 53% of domestic flights were delayed, with approximately 10,128 delays recorded out of 21,295 operations [29]. Between September and October 2024, nearly 48% of flights were affected, resulting in 5,225 delays and 901 cancellations across 10,804 scheduled operations [30], [31]. In 2022, only 41% of domestic flights arrived or departed on time, leading to an estimated 47,000 delays and economic losses of approximately ₦24 billion (≈ $52 million) [32], [33]. These ongoing disruptions underscore the urgent need for strategic action to improve reliability, resource utilization, and passenger experience.

One promising approach to addressing this challenge is predictive delay modelling. By leveraging historical and real-time flight data, such models can forecast disruptions and enable proactive decision-making across several operational areas. In gate assignment and scheduling, for example, delay forecasts help airport operators add buffer time and reassign gates based on expected late arrivals, reducing runway congestion and preventing gate conflicts during peak periods. Predictive modelling also enhances maintenance and resource planning by assisting agencies such as FAAN and the NCAA in scheduling maintenance, crew rotations, and standby-aircraft deployment based on anticipated traffic, lowering the risk of further disruptions across the network. Additionally, at busy airports such as those in Lagos and Abuja, predictive tools can support turnaround management by identifying congestion points, such as check-in, boarding, or security, and guiding staff allocation to ease pressure on limited facilities. Together, these benefits position predictive analytics as a powerful tool for transforming Nigeria's air traffic management from reactive to proactive.

To maximize the effectiveness of predictive delay models, supporting policy and institutional changes are essential. First, FAAN and the NCAA should institutionalize predictive analytics by integrating machine-learning tools into national air traffic control and delay-forecasting systems. Second, targeted investment should be directed toward expanding airport infrastructure, especially at busy terminals in Lagos and Abuja, to reduce delays during peak hours. Third, airlines should develop robust contingency plans, including standby aircraft, to improve schedule resilience. Fourth, collaboration with the Nigerian Meteorological Agency (NIMET) should be strengthened to incorporate weather-risk factors, particularly during the harmattan and rainy seasons, into delay models to improve forecasting accuracy. Fifth, passenger-communication systems should be upgraded to provide real-time delay notifications, helping to reduce the uncertainty and frustration that often contribute to passenger dissatisfaction. Finally, regulatory authorities should enforce compliance with the Nigerian Civil Aviation Regulations (NCAR) through stricter penalties for repeated mismanagement and by making airline punctuality records publicly accessible, thereby encouraging higher performance standards through transparency and competition.

VII. CONCLUSION

This study developed and empirically evaluated a Transformer-based deep learning model for predicting flight delays using real-world air traffic data. By leveraging the attention mechanisms and sequence-modelling capabilities of the Transformer architecture, the model demonstrated strong predictive performance, achieving over 93% classification accuracy and a balanced F1-score, particularly for identifying delayed flights. These results indicate that the model can capture complex time-related and operational patterns across diverse flight features. Compared with traditional machine learning methods, the Transformer model provided improved generalization, making it a useful tool for forecasting operations in complex aviation environments.

The practical implications of this work are especially relevant to Nigeria's aviation sector. Persistent flight delays have caused economic losses, passenger dissatisfaction, and operational difficulties. The successful application of predictive modelling in this study demonstrates that such systems can function effectively in low-resource settings and offers a data-driven pathway toward improved air traffic management.

Beyond its technical contribution, this study highlights the need for institutional readiness, improved infrastructure, regulatory support, and inter-agency collaboration, particularly among FAAN, the NCAA, and NIMET, to fully realize the benefits of predictive analytics.

This research contributes to both the methodology and practice of flight-delay prediction, providing a scalable and robust approach suitable for real-time deployment in Nigeria and other similar contexts. Future studies should aim to incorporate multi-seasonal datasets, real-time weather data, and reinforcement-learning methods to further improve scheduling decisions and strengthen the resilience of aviation systems under uncertain operating conditions.

ACKNOWLEDGMENT

The authors gratefully acknowledge the Department of Computer Science, Ignatius Ajuru University of Education, Port-Harcourt, and the Department of Computer Science, University of Abuja, for their institutional support during this research. The authors also thank the anonymous reviewers and the Editorial Board of the AKGEC International Journal of Technology for their constructive comments, which substantially improved the quality of this manuscript. No external funding was received for this research, and the authors declare no conflict of interest.

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