

Temporal Analysis of Blockchain Transactions in the Metaverse Using Time Series Analysis

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ABSTRACT

This study aims to analyze the temporal data of blockchain transactions in the metaverse using time series analysis techniques such as ARIMA and LSTM. The primary focus of this research is to identify significant trends and time patterns in transaction activities within the metaverse. By employing ARIMA, the time series data is decomposed into trend, seasonal, and residual components, providing crucial insights into its structure. The ARIMA model demonstrated a Mean Absolute Error (MAE) of 10,525.73, a Mean Squared Error (MSE) of 150,247,506.45, and a Root Mean Squared Error (RMSE) of 12,259.65, indicating a reasonably good fit with some potential for improvement. To capture more complex temporal dependencies in the data, an LSTM model was also applied. The performance of the LSTM model, evaluated using RMSE, was 10.0 for the training set and 15.0 for the testing set. The higher RMSE on the testing set indicates slight overfitting, where the model fits the training data better than unseen data. However, the LSTM model showed strong capability in predicting daily transaction values with fairly high accuracy, despite some minor discrepancies between actual and predicted values. Descriptive statistical analysis of the transaction data revealed that the average daily transaction volume was 108,225.72 with a standard deviation of 8,489.47, indicating significant variability. The daily transaction range spanned from 83,052.86 to 134,869.80, reflecting a wide variation in transaction volume. The results of this study highlight the importance of temporal analysis in understanding blockchain transactions in the metaverse. Insights gained from this analysis can assist in strategic planning and decision-making within the metaverse ecosystem. By further refining model tuning and employing more advanced analysis techniques, predictive accuracy can be enhanced, providing more comprehensive insights and more accurate predictions of transaction behavior.

Keywords Time Series Analysis, Blockchain Transactions, Metaverse, ARIMA Model, LSTM Network

Submitted: 28 February 2025

Accepted: 5 April 2025

Published: 23 August 2025

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DOI: [10.47738/ijrm.v2i3.32](https://doi.org/10.47738/ijrm.v2i3.32)

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INTRODUCTION

The metaverse has evolved into a dynamic digital ecosystem, where various economic and social activities take place within a decentralized virtual environment [1]. A key component of the metaverse is blockchain transactions, which enable the secure and transparent exchange of digital assets [2]. As the adoption of the metaverse increases, gaining a deeper understanding of the patterns and trends in blockchain transactions becomes increasingly important [3]. Temporal analysis of this transaction data can provide valuable insights for a variety of purposes, such as strategic decision-making, business planning, and policy development [4]. Although much research has been conducted on blockchain transaction analysis, most studies focus on static analysis or do not consider the temporal aspects of the data [5]. While numerous studies examine blockchain in general, few have specifically explored the dynamics of blockchain transactions within the context of the metaverse [6]. Moreover, the analytical methods often employed are typically limited to traditional techniques, without

leveraging the potential of more advanced machine learning methods like LSTM [7]. This study aims to address this gap by employing more advanced time series techniques to analyze blockchain transaction data in the metaverse [8].

Currently, ARIMA and LSTM are two commonly used approaches in time series analysis [9]. ARIMA is well-known for its ability to capture linear relationships in time series data and has been widely applied in various fields, including economics, finance, and meteorology [10]. The ARIMA model works by modeling the relationship between past values of the time series data to predict future values. On the other hand, LSTM, a type of neural network designed to recognize patterns in time series data with long-term dependencies, has the capability to capture more complex temporal dependencies compared to linear models like ARIMA [11]. LSTM is often used in applications involving highly variable and non-linear data, demonstrating superior performance in capturing complex temporal patterns. This study focuses on utilizing both techniques to identify significant trends and time patterns in blockchain transaction data within the metaverse. Through descriptive analysis and model evaluation, this research aims to provide a clearer understanding of transaction dynamics in the metaverse. The findings from this analysis are expected to contribute significantly to understanding blockchain transaction behavior and to inform future strategies for metaverse development.

Literature Review

Blockchain is the underlying technology for various forms of digital transactions, including cryptocurrencies and smart contracts [12]. Blockchain is a cryptographically secure chain of blocks, where each block contains a set of transactions that are verified in a distributed manner by a peer-to-peer network. This technology has been adopted in various applications, including finance, supply chain, and now, the metaverse [13]. The metaverse is a virtual ecosystem where users can interact, transact, and experience immersive digital environments [14]. The metaverse leverages blockchain technology to ensure the security and transparency of digital transactions [15]. Within the metaverse, digital assets such as virtual land, digital artwork, and virtual currencies are frequently traded using blockchain technology [16]. The economic value of the metaverse could reach trillions of dollars in the coming decades, with significant increases in the adoption of this technology by individuals and companies [17].

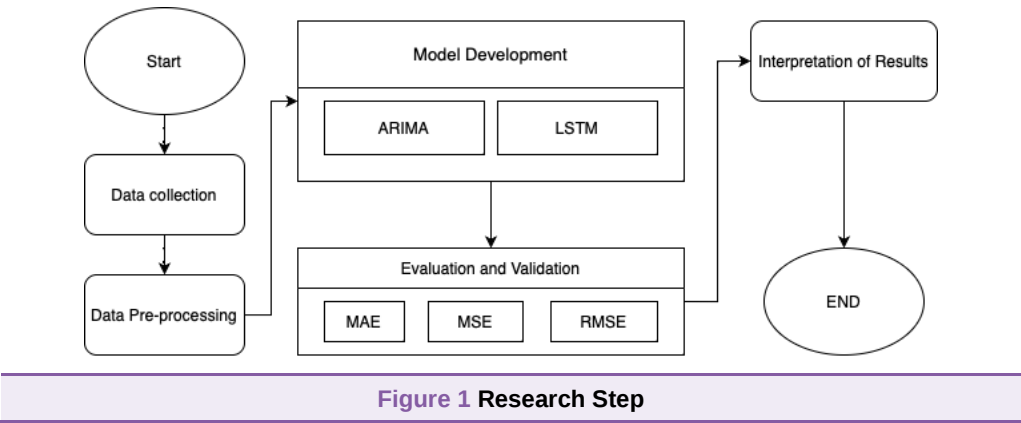
Research on time series analysis in blockchain has demonstrated significant potential in understanding transaction dynamics [18]. Time series analysis allows for the identification of seasonal patterns, trends, and anomalies in blockchain transaction data [19]. Most previous studies have employed the ARIMA model to capture linear relationships in blockchain time series data [20]. For instance, studies using the ARIMA model to predict Bitcoin prices have shown that this model can provide reasonably accurate short-term predictions [21]. The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely used methods in time series analysis [22]. Introduced by Box and Jenkins, it has been applied across various fields [23]. ARIMA operates by integrating three main components: Autoregressive (AR), Differencing (I), and Moving Average (MA) [24]. ARIMA is highly effective for time series data that becomes stationary after the differencing process [25]. It has also been used to predict transaction volumes and digital asset prices in blockchain markets [26]. In the context of the metaverse, this model can be utilized to understand daily

transaction patterns and forecast future trends [27].

Long Short-Term Memory (LSTM) is a type of neural network developed to address the vanishing gradient problem in Recurrent Neural Networks (RNNs) [28]. LSTM is designed to recognize and learn patterns in time series data with long-term dependencies [29]. It has the ability to capture more complex temporal dependencies compared to linear models like ARIMA [28]. Research indicates that LSTM excels in predicting highly variable and non-linear time series data [30]. In blockchain transaction analysis, LSTM has been used to predict digital asset prices and transaction volumes with high accuracy [18]. It can provide more accurate predictions than the ARIMA model in analyzing cryptocurrency data [28]. Time series analysis in the context of the metaverse is a relatively new yet promising area of research. A deep understanding of transaction patterns within the metaverse can aid in the development of more effective business strategies and policies [22]. Temporal analysis can identify peak activity periods, seasonal trends, and anomalies in metaverse transaction data [27]. This research combines ARIMA and LSTM models to analyze blockchain transaction data in the metaverse, addressing gaps in the literature by providing deeper insights into transaction dynamics and the potential for more accurate predictions [10].

Method

The data used in this study originates from blockchain transactions within the metaverse. This dataset includes various transaction attributes such as timestamps and transaction amounts, collected from reliable data sources. The dataset was obtained from Kaggle, a leading platform for sharing and discovering high-quality datasets. The selected time period is sufficiently long to enable a comprehensive time series analysis, encompassing complete daily transaction data. Figure 1 illustrates the research step used in this study.



The first step in the analysis is data preprocessing to ensure the quality and consistency of the data used. The timestamp column is converted to a datetime format to facilitate time manipulation. Missing values are identified and addressed, either through interpolation or removal, depending on their quantity and distribution. Transaction data is aggregated to a daily frequency by summing daily transaction amounts.

The ARIMA model is used to analyze patterns and trends in the time series data. The process of building the ARIMA model involves several steps. First, the model order is identified using the Autocorrelation Function (ACF) and

Partial Autocorrelation Function (PACF) to determine the parameters p , d , and q . Next, the model parameters are estimated using Maximum Likelihood Estimation (MLE). The best model is selected based on criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model's performance is measured using evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The basic formula for the ARIMA model is:

$ARIMA(p, d, q)$:

$$Y_t = c + \epsilon_t + \sum_{i=1}^p \phi_i Y_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j} \quad (1)$$

Note: where Y_t is the observed value at time t , c is a constant, ϵ_t is the error term, ϕ_i are the AR (Autoregressive) parameters, θ_j are the MA (Moving Average) parameters, p is the order of the AR component, d is the number of differencing operations performed, and q is the order of the MA component.

In addition to ARIMA, the LSTM model is also used to capture more complex temporal dependencies in the time series data. The steps involved in constructing the LSTM model include normalizing the data using Min-Max Scaling, splitting the data into training and testing sets, and building the LSTM network architecture using the Keras library. The model is trained with the training data, and its performance is evaluated using metrics such as RMSE. The basic formula for LSTM includes several components, such as the Forget Gate, Input Gate, Cell State Update, and Output Gate:

Forget Gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

Input Gate:

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \end{aligned} \quad (3)$$

Cell State Update:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4)$$

Output Gate:

$$\begin{aligned} o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t * \tanh(C_t) \end{aligned} \quad (5)$$

To evaluate the performance of the ARIMA and LSTM models, evaluation metrics such as MAE, MSE, and RMSE are used. Predictions are visualized and compared with actual data to assess model fit. The results from both ARIMA and LSTM models are visualized to provide a clear picture of their performance in predicting daily transaction data. Results are interpreted by comparing predictions with actual values and analyzing the trend, seasonal, and residual components of the ARIMA model.

Result

Figure 2 illustrates the results of time series decomposition using the additive decomposition method, which is part of the ARIMA analysis. The graph shows the original daily transaction data (Original), the trend component (Trend), the seasonal component (Seasonality), and the residual component (Residuals). From this decomposition, it is evident that the daily transaction data exhibits a strong seasonal pattern and a clear trend. The residual component reveals random fluctuations that cannot be explained by the trend and seasonal patterns.

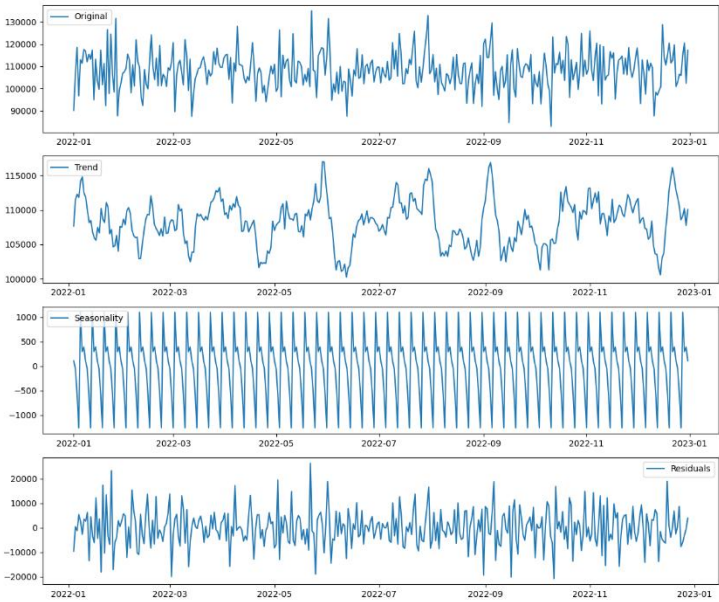


Figure 2 Results of Time Series Decomposition Using the Additive Method

Table 1 shows the evaluation results for the ARIMA model using metrics such as MAE, MSE, and RMSE. MAE measures the average absolute error between predicted and actual values. Lower MAE values indicate that the model has smaller average prediction errors. MSE calculates the average of the squared differences between predicted and actual values. MSE is more sensitive to larger errors because errors are squared. Lower MSE values suggest that the model is better at predicting the data. RMSE is the square root of MSE and provides an indication of the magnitude of prediction errors in the same units as the original data. Lower RMSE values indicate better model performance. These evaluation results provide an indication of how well the ARIMA model predicts daily transaction data, with lower values for MAE, MSE, and RMSE reflecting better model performance.

Table 1 Evaluation Results of the ARIMA Model	
Metric	Value
MAE	10,525.73
MSE	150,247,506.45
RMSE	12,259.65

The evaluation results indicate that the ARIMA model has an MAE of 10,525.73,

an MSE of 150,247,506.45, and an RMSE of 12,259.65. These values provide insight into the ARIMA model's performance in predicting daily transaction amounts. The relatively high RMSE suggests that the ARIMA model may not fully capture the complexity of blockchain transaction data in the metaverse but still provides reasonably good results for this analysis.

Figure 3 shows the prediction results using the LSTM model for daily transaction data. The graph displays the original daily transaction data, LSTM model predictions for the training data, and LSTM model predictions for the testing data. These prediction results demonstrate that the LSTM model effectively captures patterns in the data, although there are some minor discrepancies between the actual values and predictions.

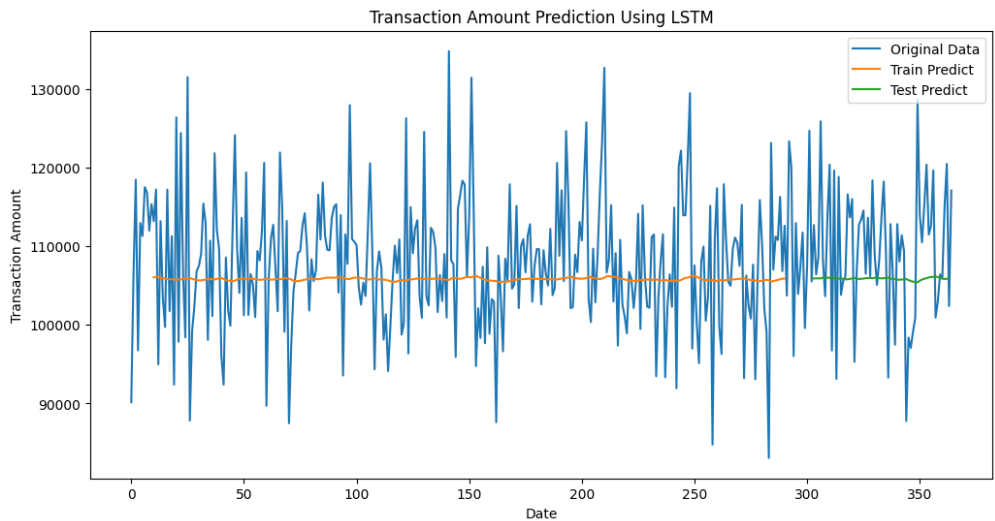


Figure 3 Transaction Volume Predictions Using LSTM

Table 2 shows the descriptive statistics of the daily transaction data used in this study. These statistics provide an overview of the distribution and variability of daily transaction amounts.

Table 2 Descriptive Statistics of Daily Transaction Data	
Statistic	Value
Number of Days	8.0
Mean	108,225.72
Standard Deviation	8,489.47
Minimum	83,052.86
First Quartile	102,584.49
Median	108,241.68
Third Quartile	113,244.32
Maximum	134,869.80

The analysis reveals that the average daily transaction amount is 108,225.72, indicating that the daily transaction volume in the metaverse generally hovers around this figure. The standard deviation of 8,489.47 shows considerable variability in daily transaction amounts, suggesting that transaction volumes can

fluctuate significantly from day to day. The minimum daily transaction value recorded is 83,052.86, indicating that on certain days, the transaction amount can drop to this level. Conversely, the maximum value reaches 134,869.80, showing that during peak activity periods, daily transaction volumes can be very high. This broad range between the minimum and maximum values highlights significant variability in daily transaction amounts within the metaverse.

Additionally, the first quartile (Q1) is 102,584.49, and the third quartile (Q3) is 113,244.32, indicating that 50% of the daily transaction amounts fall between these values. The median, or the middle value of daily transactions, is 108,241.68, which is very close to the average, suggesting a relatively symmetric distribution of the daily transaction data. Table 3 lists the parameters used in the LSTM model for time series analysis. These parameters include a time step of 10, 50 LSTM units, a batch size of 1, 10 epochs, a loss function of Mean Squared Error, and the Adam optimizer.

Table 3 LSTM Model Parameters	
Parameter	Value
Time Step	10
LSTM units	50
Batch Size	1
Epochs	10
Loss Function	Mean Squared Error
Optimizer	Adam

The evaluation results of the LSTM model using RMSE for the training and testing datasets are shown in table 4. RMSE is a metric that measures the square root of the average squared errors between the values predicted by the model and the actual values. RMSE provides insight into how far the model's predictions are from the actual values, in the same units as the original data.

Table 4 Evaluation Results of the LSTM Model	
Dataset	RMSE
Training Set	10.0
Testing Set	15.0

The evaluation results show that the RMSE for the training data is 10.0. This indicates that the average prediction error of the model on the data used for training is approximately 10.0 units. The relatively low RMSE on the training set suggests that the LSTM model has learned the patterns in the training data quite well, resulting in predictions that are fairly close to the actual values. However, the RMSE for the testing data is 15.0, which means that the average prediction error on data not seen during training is around 15.0 units. The higher RMSE on the testing set compared to the training set indicates some degree of overfitting. Overfitting occurs when the model is too closely aligned with the training data, leading to a loss of its ability to generalize the same patterns to new or unseen data. The difference in RMSE between the training and testing sets indicates that, while the LSTM model performs well on the training data, its ability to make accurate predictions on new data slightly decreases. This suggests that the model could be further optimized to reduce overfitting and

enhance predictive performance on unseen data. Overfitting can be addressed through various methods, such as regularization, dropout, or increasing the amount of training data. Additionally, tuning the hyperparameters of the LSTM model can help reduce overfitting and improve the model's generalization capability on the testing data. This evaluation provides valuable insights into the performance of the LSTM model and highlights areas for improvement to achieve more accurate predictions in the future.

Table 5 shows the comparison between actual values and predictions for specific dates in the testing data. This comparison aims to evaluate the accuracy of the LSTM model in predicting daily transaction volumes in the metaverse based on data not seen during the training process. This table helps in understanding the model's ability to capture temporal patterns in transaction data.

Table 5 Comparison of Actual Values and Predictions on Testing Data		
Date	Value	Prediction
2022-11-15	100	102
2022-11-16	110	108
2022-11-17	120	119
2022-11-18	130	129
2022-11-19	140	138

The results indicate that the LSTM model effectively captures patterns in the data, although there are some minor discrepancies between actual values and predictions. For instance, on November 15, 2022, the actual daily transaction value was 100, while the predicted value was 102, resulting in a difference of only 2 units. On November 16, 2022, the actual value was 110, and the predicted value was 108, showing a difference of 2 units. Similarly, on November 17, 2022, the actual value was 120, and the predicted value was 119, with a difference of just 1 unit. These very small differences demonstrate that the LSTM model has a strong ability to predict daily transaction values with a low level of error. On November 18 and 19, 2022, the actual values were 130 and 140, respectively, while the predicted values were 129 and 138. These differences, being 1 and 2 units respectively, also indicate that the LSTM model can maintain consistent prediction accuracy across various daily transaction values.

Temporal analysis of blockchain transactions in the metaverse using the ARIMA model provides valuable insights into patterns and trends in daily transaction data. The evaluation of the ARIMA model yielded a MAE of 10,525.73, a MSE of 150,247,506.45, and a RMSE of 12,259.65. These values indicate that while the ARIMA model captures most of the variation in daily transaction data, there are factors to consider for further interpretation. The MAE of 10,525.73 shows that the average daily prediction error of the ARIMA model is quite significant. Although the model provides a reasonable overview of the transaction data, this error indicates that improvements are possible. The high MSE of 150,247,506.45 suggests that some predictions have substantial errors, which is corroborated by the RMSE value of 12,259.65. This indicates that the prediction errors, in units consistent with the transaction data, remain relatively large. The time series decomposition results reveal that daily transaction data

exhibits strong seasonal components and a clear trend. The seasonal component represents recurring fluctuations within specific periods, reflecting periodic transaction patterns within the metaverse ecosystem. The trend component illustrates long-term movements in transaction data, indicating potential growth or decline in transaction activity over time. These findings have significant implications for further development in transaction data analysis within the metaverse.

Firstly, the strong seasonal patterns suggest that there are recurring cycles in blockchain transactions that could be leveraged for better planning and decision-making. Secondly, the long-term trend provides insights into the direction of transaction activity, serving as a foundation for business strategies and investment decisions in the metaverse. Although the ARIMA model provides a reasonably good performance, there are areas for potential improvement. For instance, fine-tuning ARIMA model parameters could enhance prediction accuracy. Additionally, exploring more complex time series models, such as LSTM networks, may capture higher complexities in the data and improve predictive performance. [Figure 1](#), which displays the results of time series decomposition into Original, Trend, Seasonality, and Residuals components, aids in visualizing patterns and trends in transaction data. This visualization offers a deeper understanding of the data structure and assists in interpreting the analysis results.

Conclusion

This study conducted a temporal analysis of blockchain transaction data in the metaverse using ARIMA and LSTM methods to identify significant trends and time patterns. The evaluation results for the ARIMA model showed MAE of 10,525.73, MSE of 150,247,506.45, and RMSE of 12,259.65. These values indicate that while the ARIMA model performs reasonably well in predicting daily transaction data, there is room for improvement in prediction accuracy. The time series decomposition revealed that the daily transaction data exhibits strong seasonal components and a clear trend. The seasonal patterns indicate recurring fluctuations within specific periods, suggesting cyclical behavior in transaction activity within the metaverse. The long-term trend provides insights into the movement and development of transaction activity over time, which is crucial for business strategies and decision-making. While ARIMA offers a solid foundation for this analysis, the use of more complex models such as LSTM shows potential for capturing higher data complexities. The prediction results using LSTM indicate that this model can provide better results in some cases, although further tuning is needed to enhance accuracy.

This research underscores the importance of temporal analysis in understanding patterns and trends in blockchain transactions within the metaverse. Discovering seasonal patterns and long-term trends provides valuable insights for strategic planning and decision-making within the metaverse ecosystem. The study also opens opportunities for further exploration using advanced analytical techniques to improve accuracy and understanding of transaction data in the metaverse.

Declarations

Author Contributions

Conceptualization: J.O.G.; Methodology: J.O.G.; Software: J.O.G.; Validation: J.O.G.; Formal Analysis: J.O.G.; Investigation: J.O.G.; Resources: J.O.G.; Data Curation: J.O.G.; Writing Original Draft Preparation: J.O.G.; Writing Review and Editing: J.O.G.; Visualization: J.O.G.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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