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Harnessing the Power of Prophet Algorithm for Advanced Predictive Modeling of Grab Holdings Stock Prices

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Abstract

This study investigates the effectiveness of the Prophet algorithm in predicting Grab Holdings' stock prices dataset from Kaggle. By meticulously analyzing historical closing, high, low, and volume data, the research aims to uncover market patterns and gain insights into investor sentiment based on short-term forecasting. The findings reveal a dynamic trajectory for Grab Holdings' stock, characterized by significant fluctuations and evolving investor confidence. The stock reached a peak of $14 in early 2022, indicating optimism, but subsequently experienced a decline to $4 by late 2023, reflecting a shift in sentiment. Notably, 2023 witnessed heightened volatility compared to 2022, evident in more significant price swings and increased trading volume. The Prophet algorithm demonstrated promising potential for prediction better than traditional methods, which overlook the presence of seasonality or fail to adapt to evolving market conditions, leading to less accurate forecasts. The excellent performance of Prophet is indicated by a Mean Absolute Percentage Error (MAPE) of 10.45511%, a Mean Absolute Error (MAE) of 3.112026, and a Root Mean Squared Error (RMSE) of 3.516969. Compared to the traditional ARIMA, MAE and RMSE resulting from Prophet are much lower than their counterparts, which are 14.49675 and 16.079898, respectively. These widely used metrics suggest moderate accuracy in predicting future stock prices. This research offers valuable insights for investors that they can use to understand the trend of Grab Holdings' stock price and make more informed investment decisions regarding buying or selling opportunities. However, it is crucial to acknowledge the inherent limitations of such models and interpret results cautiously, considering the ever-changing dynamics of the financial market.

Keywords: Stock Price Prediction, Grab Holdings, Prophet Algorithm, Market Volatility Analysis, Financial Forecasting

1. Introduction

In the ever-evolving landscape of financial markets, the ability to accurately forecast stock prices holds paramount importance for investors, financial analysts, and market participants alike [1], [2], [3]. With companies like Grab Holdings operating within this dynamic environment, the need for advanced predictive modeling techniques becomes increasingly apparent. These techniques are essential tools for deciphering intricate market behavior, pinpointing trends, and facilitating well-informed investment decisions regarding buying and selling opportunities. The emergence of advanced algorithms, such as the Prophet algorithm, has revolutionized the field of predictive modeling by offering robust solutions for handling time-series data [4], [5]. Developed by Facebook's Core data science team, the Prophet algorithm is renowned for its versatility, scalability, and ability to provide reliable forecasts while accommodating various sources of uncertainty [6], [7].

This study endeavors to harness the power of the Prophet algorithm for advanced predictive modeling of Grab Holdings' stock prices. By leveraging historical data encompassing a comprehensive range of parameters, including close, high, and low prices, as well as trading volume, the research aims to unveil intricate patterns and insights into Grab Holdings' market performance over a specified period [8], [9]. The significance of this research lies in its potential to equip investors, financial analysts, and market participants with actionable insights into future price trends, thereby enabling them to optimize their investment strategies and navigate the volatile terrain of financial markets with greater confidence and efficacy.

Despite the advancements in predictive modeling techniques, there remains a notable research gap in the application of sophisticated algorithms like Prophet to the domain of stock price forecasting, particularly concerning companies

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operating in dynamic industries such as technology and e-commerce. While traditional statistical methods and machine learning algorithms have been extensively utilized for stock price prediction, the unique capabilities of Prophet in handling time-series data and capturing seasonal patterns present a promising avenue for enhancing the accuracy and reliability of forecasts.

Stock price forecasting predominantly revolves around the application of machine learning algorithms, such as linear regression, support vector machines, and neural networks [10], [11], [12]. While these methods have shown considerable success in certain contexts, they often struggle to capture the complex dynamics inherent in financial markets, such as seasonality, non-linearity, and abrupt changes in market sentiment. In contrast, the Prophet algorithm offers a novel approach to stock price prediction by combining components for trend forecasting, seasonality modeling, and outlier detection in a unified framework. Its ability to handle irregularly spaced data, incorporate domain-specific knowledge, and provide intuitive interpretations of forecasts distinguishes it from traditional machine learning approaches.

By bridging this research gap and exploring the application of the Prophet algorithm to stock price forecasting, this study aims to contribute to the advancement of predictive modeling techniques in financial markets and provide new insights into the dynamics of stock price movements for companies like Grab Holdings. Through rigorous analysis and evaluation, this research seeks to enhance our understanding of market dynamics and pave the way for more accurate and reliable stock price forecasts.

2. Literature Review

Stock price forecasting has been a subject of extensive research in the field of finance, attracting attention from academics, practitioners, and investors alike. Over the years, various predictive modeling techniques have been developed and employed to analyze historical data and make forecasts about future price movements. In this section, we review the existing literature on stock price forecasting methods, focusing on both traditional approaches and modern algorithms like the Prophet algorithm.

2.1. Traditional Approaches

In the realm of stock price forecasting, traditional methods have long served as the foundation for analyzing historical price data and making predictions about future price movements. These methods encompass a range of statistical techniques, each offering unique insights into market behavior and trends:

Time Series Analysis: Time series analysis forms the cornerstone of traditional stock price forecasting methods. It involves examining historical price data over a continuous period to identify patterns, trends, and fluctuations [13]. By analyzing past price movements, analysts attempt to discern underlying patterns that may repeat in the future. Time series analysis often includes techniques such as trend analysis, seasonality detection, and decomposition to extract meaningful insights from the data.

Moving Averages: Moving averages are another widely used technique in stock price forecasting. This method calculates the average price of a security over a specified time period, smoothing out short-term fluctuations and highlighting long-term trends [14]. Moving averages can be simple, exponential, or weighted, depending on the emphasis placed on recent price data versus older data points. Analysts use moving averages to identify trend reversals, support and resistance levels, and potential entry or exit points in the market.

Autoregressive Models: Autoregressive models, such as ARIMA (autoregressive integrated moving average), are popular tools for time series forecasting [15]. These models analyze the relationship between an observation and a number of lagged observations to predict future values. ARIMA models are particularly adept at capturing linear relationships and stationary time series data. They are widely used in finance for forecasting stock prices, interest rates, and economic indicators.

Despite their widespread use, traditional forecasting methods have several limitations. One of the primary challenges is their inability to capture the complex dynamics of financial markets comprehensively. Traditional methods often assume linear relationships between variables and struggle to account for non-linear patterns, abrupt changes in market sentiment, and external factors such as geopolitical events or economic shocks.

Moreover, traditional methods may overlook the presence of seasonality or fail to adapt to evolving market conditions, leading to less accurate forecasts. As a result, there has been a growing interest in leveraging modern algorithms and machine learning techniques to enhance the accuracy and reliability of stock price forecasts [16], [17]. In the subsequent sections, we will explore how advanced algorithms like the Prophet algorithm offer a promising alternative to traditional approaches by addressing some of these challenges and providing more accurate and interpretable forecasts.

2.2. Machine Learning Algorithms

In recent years, the utilization of machine learning algorithms has surged within the domain of stock price forecasting, propelled by their capability to process vast datasets and discern intricate patterns that may elude human analysis. This paradigm shift in forecasting methodologies has been driven by the exponential growth of available data, coupled with advancements in computational power and algorithmic sophistication.

Among the plethora of machine learning algorithms deployed for stock price forecasting, support vector machines (SVM), random forests, and neural networks have emerged as prominent contenders [11], [18]. Support vector machines, renowned for their versatility and robustness, excel in capturing complex relationships within datasets by mapping data points into a high-dimensional space and identifying the optimal hyperplane that separates different classes [19]. Random forests, on the other hand, harness the power of ensemble learning, aggregating the predictions of multiple decision trees to yield more accurate and stable forecasts. Meanwhile, neural networks, inspired by the intricate structure of the human brain, leverage interconnected layers of artificial neurons to learn complex patterns and relationships directly from data [20].

These machine learning algorithms offer several advantages over traditional forecasting methods. Firstly, they exhibit superior adaptability to changing market conditions, enabling them to adjust their predictions in response to evolving trends and dynamics. Moreover, their ability to capture non-linear relationships inherent in financial data empowers them to uncover subtle patterns and signals that may remain undetected by conventional statistical techniques. Additionally, their capacity to process large volumes of data enables them to leverage a broader array of information sources, including market sentiment, macroeconomic indicators, and news sentiment, enhancing the richness and depth of their analyses [20].

However, it's essential to acknowledge the inherent challenges and limitations associated with machine learning-based forecasting approaches. The complexity and opacity of some algorithms, particularly neural networks, can hinder interpretability, making it difficult to discern the underlying factors driving predictions. Moreover, the performance of machine learning models is highly sensitive to factors such as data quality, feature selection, and model tuning, requiring careful attention to ensure robust and reliable forecasts.

Despite these challenges, machine learning algorithms represent a promising frontier in stock price forecasting, offering unparalleled potential to unlock valuable insights and inform investment decisions in an increasingly complex and dynamic market environment. As researchers continue to refine and innovate these techniques, the integration of machine learning into the realm of financial forecasting is poised to revolutionize the way we understand and navigate the intricacies of stock markets.

2.3. Prophet Algorithm

The Prophet algorithm, developed by Facebook's Core data science team, represents a novel approach to time series forecasting. Unlike traditional statistical methods or machine learning algorithms, Prophet is specifically designed to handle time series data with strong seasonal patterns and irregularities. It decomposes time series data into trend, seasonality, and holiday components, allowing for more accurate and interpretable forecasts. Prophet has been successfully applied to a wide range of forecasting tasks, including predicting stock prices, sales figures, and website traffic [21].

While there has been significant research on stock price forecasting using traditional methods and machine learning algorithms, there remains a research gap in the application of sophisticated techniques like Prophet to this domain. Limited studies have explored the potential of Prophet for stock price prediction, particularly in dynamic industries such as technology and e-commerce. By bridging this research gap, this study seeks to contribute to the advancement of predictive modeling techniques in financial markets and provide new insights into stock price forecasting [22], [23].

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Overall, the literature on stock price forecasting highlights the importance of employing advanced modeling techniques to capture the complexities of financial markets effectively. By integrating traditional approaches with modern algorithms like Prophet, researchers can develop more accurate and reliable forecasting models, enabling investors and market participants to make informed decisions and navigate the uncertainties of financial markets more effectively.

3. Method

This study employs a comprehensive methodology to conduct advanced predictive modeling of Grab Holdings' stock prices using the Prophet algorithm. The methodology encompasses data collection, preprocessing, model training, evaluation, and interpretation, ensuring a rigorous and systematic approach to the analysis. Figure 1 below shows the research step used in this research.

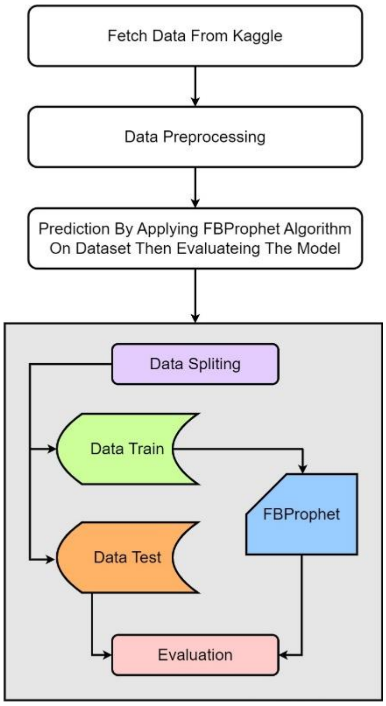

Figure 1. Research step

3.1. Data Collection

The initial step in this study involved procuring historical data on Grab Holdings' stock prices from Kaggle [24], a prominent platform hosting a diverse array of datasets contributed by researchers, practitioners, and data enthusiasts. Kaggle serves as a valuable resource for accessing curated datasets spanning various domains, including finance, economics, and business. The dataset obtained from Kaggle encompasses a comprehensive record of Grab Holdings' stock prices over a specified period, capturing key metrics such as close, high, and low prices, as well as trading volume. This dataset sourced from Kaggle [24] has undergone a rigorous review process to guarantee its quality before integration. The Kaggle platform offers a user-friendly interface for data exploration and retrieval, streamlining the process of accessing relevant datasets and expediting the commencement of the analysis. Furthermore, the utilization of a curated dataset from Kaggle enhances the transparency and reproducibility of the research findings, as the dataset is openly accessible to other researchers and practitioners. This fosters collaboration, peer review, and validation of results within the wider scientific community, promoting robust and reliable research outcomes.

3.2. Data Preprocessing

The process of data preprocessing is crucial in ensuring that the collected raw data is of high quality and is suitable for analysis. This phase involves a series of tasks aimed at cleaning, transforming, and preparing the data to facilitate meaningful analysis and model training. By addressing issues such as missing values, outliers, and data inconsistencies, data preprocessing lays the foundation for accurate and reliable predictive modeling [25], [26].

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Handling Missing Values: One of the initial tasks in data preprocessing is handling missing values, which can arise due to various reasons such as data recording errors or system failures. Depending on the nature and extent of missing data, different strategies may be employed, including imputation techniques such as mean imputation, median imputation, or predictive modeling-based imputation. Careful consideration is given to the potential impact of imputation methods on the integrity and accuracy of the data.

Outlier Detection and Removal: Outliers, or data points that deviate significantly from the rest of the dataset, can distort statistical analyses and model predictions. As part of data preprocessing, outlier detection techniques are applied to identify and flag anomalous data points. Common methods for outlier detection include statistical measures such as z-score, Tukey's method, or visualization techniques such as box plots and scatter plots. Once identified, outliers may be removed or treated depending on their relevance to the analysis and the underlying data distribution.

Normalization or Scaling: In many cases, the features or variables in the dataset may have different scales or units, which can adversely affect the performance of certain machine learning algorithms. To mitigate this issue, normalization or scaling techniques are applied to rescale the features to a comparable range. Common normalization techniques include min-max scaling, where values are scaled to fall within a specified range (e.g., [0, 1]), and standardization, which transforms data to have a mean of 0 and a standard deviation of 1. By ensuring that all features are on a similar scale, normalization facilitates model convergence and improves the stability and performance of the predictive models.

By meticulously addressing these preprocessing tasks, the raw data is refined and prepared for subsequent analysis and modeling stages. The quality and integrity of the preprocessed data play a critical role in the accuracy and reliability of the predictive models, ensuring that the insights derived from the analysis are robust and actionable.

3.3. Model Training

Once the data has undergone preprocessing to ensure its quality and suitability for analysis, the Prophet algorithm is employed to train predictive models on the preprocessed dataset. Prophet, developed by Facebook's Core data science team, represents a cutting-edge approach to time series forecasting, renowned for its versatility, scalability, and intuitive interpretability [4], [5], [6].

Prophet's unique capabilities make it particularly well-suited for capturing the intricate dynamics of stock price movements over time. One of Prophet's key strengths lies in its ability to effectively handle seasonal patterns inherent in financial data. By decomposing time series data into trend (g(t)), seasonality (s(t)), and holiday components (h(t)), Prophet can discern recurring patterns and trends that may influence stock prices:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \quad (1)$$

Note:

$y(t)$ represents the observed stock price at time t.

$g(t)$ represents the trend component, capturing the overall direction of the stock price movement over time.

$s(t)$ represents the seasonal component, accounting for periodic fluctuations in stock prices, such as weekly, monthly, or annual patterns.

$h(t)$ represents the holiday component, accommodating irregular events or holidays that may influence stock prices.

ϵ_t represents the error term, capturing any random fluctuations or noise in the data.

Moreover, Prophet offers the flexibility to incorporate domain knowledge and customize model parameters to suit specific forecasting tasks. For instance, analysts can introduce additional regressors $(x(t))$ to the model to account for external factors that may impact stock prices:

$$y(t) = g(t) + s(t) + h(t) + x(t)^T\beta + \epsilon_t \quad (2)$$

Note:

$x(t)$ represents the additional regressors, such as macroeconomic indicators or market sentiment scores.

β represents the coefficients associated with the additional regressors.

This flexibility allows for the integration of relevant information and insights into the forecasting process, enhancing the accuracy and robustness of the predictions. Furthermore, Prophet employs a Bayesian framework to model uncertainty and incorporate uncertainty intervals into the forecasts. This feature enables analysts to quantify the level of confidence associated with each prediction, providing valuable insights into the reliability and accuracy of the forecasted stock prices. By embracing uncertainty and transparency, Prophet empowers analysts to make well-informed decisions based on a comprehensive understanding of the underlying data and model assumptions.

During the model training phase, the preprocessed data is fed into the Prophet algorithm, and the model parameters are optimized to minimize prediction errors and maximize forecast accuracy. This iterative process involves fine-tuning the model settings, such as the seasonality parameters, trend flexibility, and outlier detection thresholds, to ensure optimal performance across various market conditions. Overall, the model training phase leverages the unique capabilities of the Prophet algorithm to generate accurate and reliable forecasts of Grab Holdings' stock prices. By harnessing Prophet's versatility, scalability, and interpretability, this study aims to provide valuable insights into the dynamics of stock price movements and empower investors and market participants to make informed decisions in the volatile world of financial markets.

3.4. Model Evaluation

After training the predictive models using the Prophet algorithm, it is imperative to assess their performance using robust evaluation metrics. The evaluation process aims to gauge the accuracy and reliability of the forecasts generated by the models, providing valuable insights into their effectiveness and potential areas for improvement. Several performance metrics are commonly employed to evaluate time series forecasting models, each offering unique insights into different aspects of forecast accuracy:

1. Mean Absolute Percentage Error (MAPE): MAPE measures the average percentage difference between the predicted values and the actual values. It is calculated as the mean of the absolute percentage errors for each prediction [27]:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100\% \quad (3)$$

where Y_i represents the actual value, $\hat{Y}_i$ represents the predicted value, and n is the number of observations.

2. Mean Absolute Error (MAE): MAE measures the average magnitude of errors between the predicted values and the actual values [28]. It is calculated as the mean of the absolute differences between predicted and actual values:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left|Y_i - \hat{Y}_i\right| \quad (4)$$

3. Root Mean Squared Error (RMSE): RMSE measures the square root of the average of the squared differences between predicted and actual values [26][27]. It penalizes larger errors more heavily compared to MAE and is calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2} \quad (5)$$

where Y_i and $\hat{Y}_i$ represent the actual and predicted values, respectively, and n is the number of observations.

Once the performance metrics are computed, they provide valuable insights into the accuracy and reliability of the forecasts generated by the trained models. A lower MAPE, MAE, and RMSE indicate better model performance, with smaller errors between predicted and actual values.

By analyzing these metrics, analysts can identify any shortcomings or areas for improvement in the forecasting models. For instance, consistently high MAPE values may indicate systematic biases or inaccuracies in the predictions, prompting a reevaluation of model parameters or data preprocessing techniques. Similarly, large RMSE values suggest significant discrepancies between predicted and actual values, highlighting the need for refinement or recalibration of the forecasting models.

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Moreover, the interpretation of performance metrics allows for comparative analysis between different models or forecasting approaches, enabling analysts to identify the most effective strategies for predicting Grab Holdings' stock prices.

Overall, the model evaluation process plays a crucial role in assessing the effectiveness and reliability of predictive models, providing valuable insights that inform decision-making and drive continuous improvement in forecasting methodologies. By following this comprehensive methodology, this study aims to provide a thorough and systematic analysis of Grab Holdings' stock prices, leveraging the predictive power of the Prophet algorithm to generate accurate and actionable forecasts. Through meticulous data collection, preprocessing, model training, evaluation, and interpretation, this research seeks to contribute valuable insights into the dynamics of financial markets and inform strategic decision-making for investors and market participants.

4. Result and Discussion

4.1. Descriptive Analysis of Stock Price Variability

Figure 2 below is a boxplots of Grab Holdings' stock prices. The boxplot analysis offers valuable insights into the variability of Grab Holdings' stock prices across multiple parameters, including open, high, low, close, adjusted close, and volume. This comprehensive examination sheds light on the level of volatility exhibited by the stock within the given period.

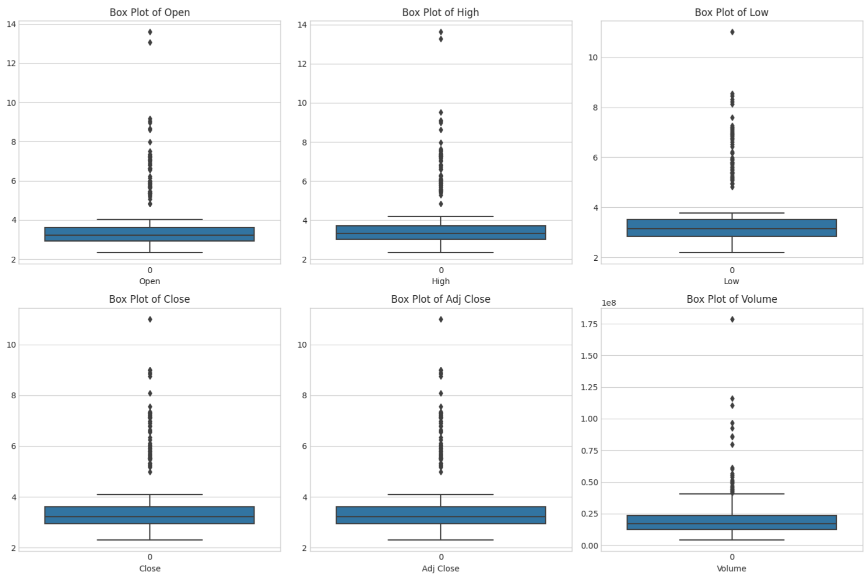

Figure 2. Boxplot of Grab Holdings' stock prices across multiple parameters

Open price: The median opening price of approximately $10 suggests a central tendency in the stock's initial valuation. The moderate interquartile range (IQR) of around $4 indicates a degree of stability in the opening prices, albeit with some fluctuations. This moderate volatility in the opening price signifies potential market activity but also hints at a relatively stable starting point for trading sessions.

High and low prices: The median highest and lowest prices provide insights into the range of fluctuations experienced by Grab Holdings' stock. With a median highest price around $12 and a corresponding higher IQR of approximately $6, the stock demonstrates higher volatility in reaching its peaks. Conversely, the median lowest price around $8, with a similar IQR as the opening price, suggests comparable volatility in downward movements. These fluctuations in high and low prices indicate the dynamic nature of the stock's valuation, influenced by various market factors.

Closing and adjusted closing prices: Both the median closing price and adjusted closing price, hovering around $10, exhibit symmetrical distributions with similar IQRs of approximately $4. This symmetrical distribution suggests a balance between upward and downward movements in the stock's valuation at the end of trading sessions. The consistent volatility reflected in both closing prices underscores the stability of these trends throughout the observed period.

Trading volume: The median trading volume, estimated at approximately 1e8, reveals significant market activity surrounding Grab Holdings' stock. The right-skewed distribution and high IQR of around 1.5e8 indicate substantial variability in trading volume, with periods of intense buying or selling activity. This high volatility in trading volume suggests fluctuations in investor interest and sentiment, potentially influencing the stock's price movements.

Overall, the descriptive analysis highlights the multifaceted nature of Grab Holdings' stock price variability, encompassing diverse parameters and indicating varying degrees of volatility. Understanding these fluctuations is crucial for investors in assessing risk levels and making informed decisions in the dynamic landscape of financial markets.

4.2. One-Year Stock Price Trend Analysis

Throughout the observed year, the trajectory of Grab Holdings' stock price depicted a pronounced downward trend, accompanied by considerable volatility. Commencing the year with an opening price of approximately $10 in January 2023, the stock embarked on a fluctuating journey, reaching its zenith at around $12 in February 2023. However, this momentary ascent was swiftly followed by a gradual descent, with the stock price dwindling to $6 by January 2024. Figure 3 below shows Grab Holdings' stock over Year.

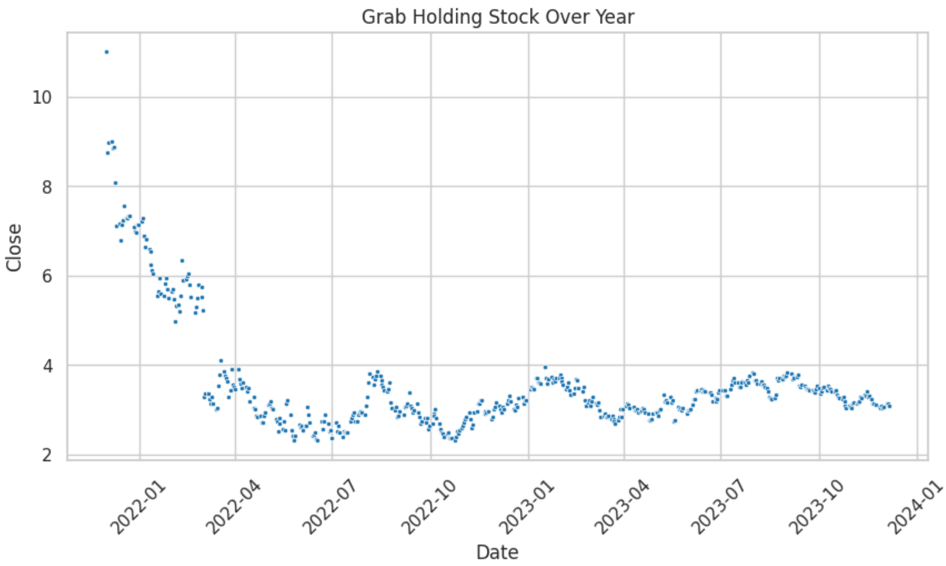

Figure 3. Grab Holdings' stock over Year

The overarching trend of decline was punctuated by sporadic and abrupt price fluctuations, underscoring the inherent volatility within the market. These fluctuations were not bound by any discernible pattern, as evidenced by the erratic nature of price movements over relatively short periods. Investors experienced periods of optimism and pessimism, characterized by rapid shifts in sentiment and corresponding price swings. Factors contributing to this volatility and downward trend may include a myriad of internal and external influences. Internally, factors such as shifts in corporate strategy, changes in leadership, or financial performance could have played a role. Externally, macroeconomic conditions, regulatory changes, or industry developments may have exerted pressure on the stock's performance.

Despite the absence of a clear pattern, the consistent downward trajectory over the course of the year suggests underlying challenges or uncertainties facing Grab Holdings and its market outlook. This trend underscores the importance of comprehensive analysis and strategic decision-making in navigating the complexities of the stock market landscape. Investors and stakeholders alike must remain vigilant and adaptable in response to evolving market dynamics to mitigate risks and capitalize on opportunities in the ever-changing environment of stock trading.

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4.3. Time-Series Analysis of Close, High, Low Prices, and Volume

A thorough examination of Grab Holdings' historical stock prices and trading volume unveils a multitude of insights into the company's market performance. The dataset provides a comprehensive view of price movements and trading activity over time, allowing for a deeper understanding of trends and fluctuations within the stock's value. Figure 4 below shows Grab Holdings' historical stock prices and trading volume from 2022 until 2024.

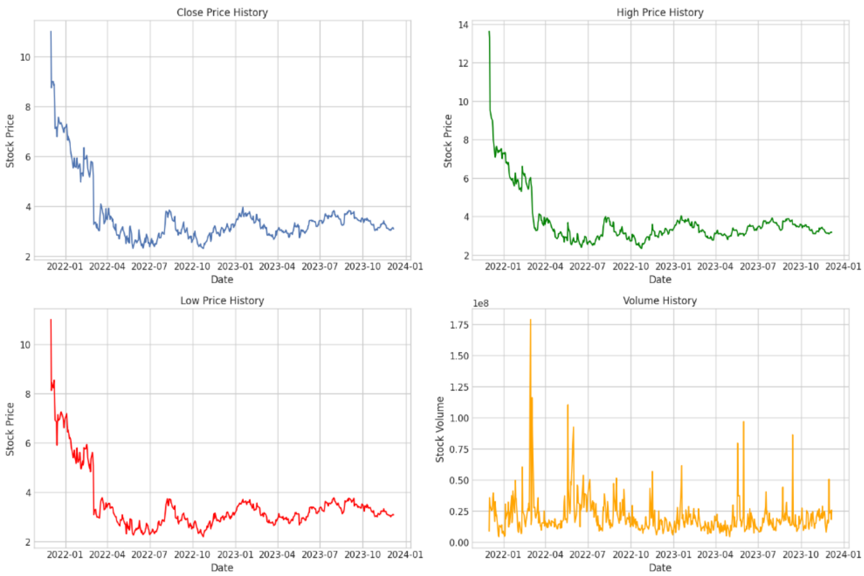

Figure 4. Grab Holdings' historical stock prices and trading volume

Beginning with the highest closing price of approximately $14 in early 2022, investors witnessed a period of optimism and bullish sentiment towards Grab Holdings. This peak likely coincided with significant company milestones, positive earnings reports, or favorable market conditions, driving the stock price to its zenith. Conversely, the lowest closing price of around $4 observed in late 2023 reflects a stark contrast, indicating a period of pessimism or bearish sentiment among investors. Factors such as disappointing financial results, negative industry developments, or broader economic concerns may have contributed to this downturn, prompting a sell-off and driving the stock price to its nadir. Moreover, comparing the years 2022 and 2023 reveals a noticeable increase in volatility. This heightened volatility is evident not only in the magnitude of price movements but also in the trading volume. The year 2023 saw larger fluctuations in stock prices and increased trading activity compared to the relatively stable and calmer market conditions of 2022.

The interplay between price movements and trading volume serves as a barometer of market sentiment and investor behavior. The heightened volatility in 2023 suggests greater uncertainty and fluctuating investor confidence, leading to more pronounced swings in stock prices. This dynamic environment poses both challenges and opportunities for investors, necessitating a nuanced approach to risk management and strategic decision-making. In summary, the time-series analysis of Grab Holdings' stock prices and volume offers valuable insights into the company's market performance and investor sentiment. By examining historical trends and fluctuations, market participants can gain a deeper understanding of the factors driving stock price movements and make more informed investment decisions.

4.4. Time-Based Relationship with Closing Price

Figure 5 below shows the analysis delving into the relationship between historical closing prices and time intervals spanning yearly, monthly, daily, and weekly periods unveils intriguing insights into the dynamics of Grab Holdings' stock performance. Observing price movements through these temporal lenses underscores the multifaceted influences shaping market behaviors.

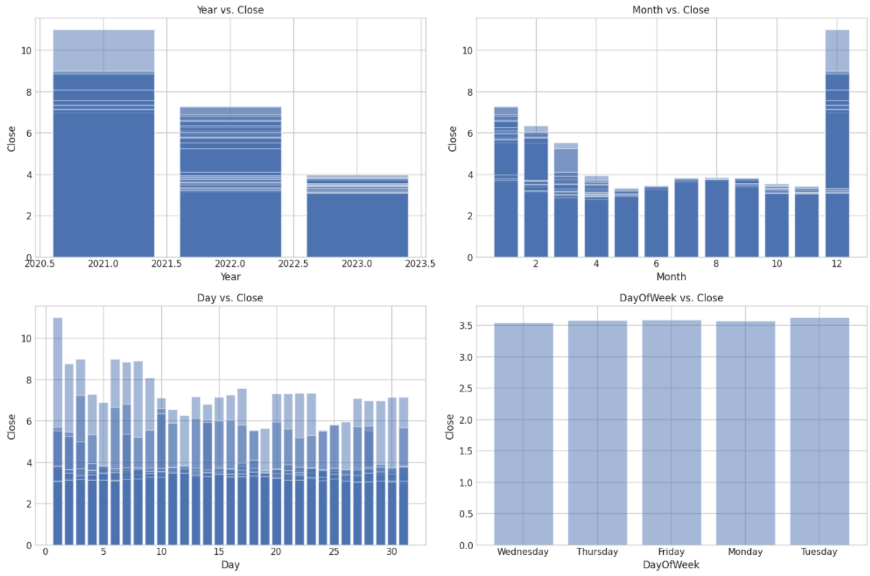

Figure 5. Time-Based Relationship with Closing Price

Examining yearly trends provides a broader perspective on Grab Holdings' stock performance over longer durations. Fluctuations in annual closing prices offer glimpses into overarching market sentiments, potentially influenced by macroeconomic factors, industry trends, or company-specific events. Despite the granularity of yearly data, discerning consistent patterns proves challenging, indicating the complexity of market dynamics beyond seasonal cycles.

Zooming in on monthly fluctuations exposes the nuances of Grab Holdings' stock movements within shorter timeframes. Monthly trends may reflect shifts in investor sentiment, quarterly earnings reports, or external market developments. While certain months may exhibit recurrent patterns due to seasonal trends or institutional trading behaviors, the absence of consistent trends across all months suggests the prevalence of diverse market drivers shaping stock prices.

Analyzing daily closing prices offers a closer examination of intra-month fluctuations and market volatility. Daily trends are influenced by a myriad of factors, including news releases, economic indicators, and investor sentiment. While certain days may exhibit heightened trading activity or price volatility, the lack of a definitive pattern suggests that daily stock movements are subject to transient market forces, making short-term predictions inherently challenging.

Exploring closing prices by day of the week unveils potential patterns in investor behaviors and market dynamics. Traditionally, certain days, such as Mondays or Fridays, may exhibit distinct trading patterns attributed to weekend news cycles or end-of-week portfolio adjustments. However, the absence of consistent trends across all weekdays implies that stock price movements are shaped by a confluence of factors beyond weekly routines, highlighting the intricate interplay of market dynamics.

In summary, while examining Grab Holdings' closing prices across various time intervals provides valuable insights into market behaviors, the absence of consistent patterns suggests that stock price movements are influenced by a diverse array of factors. Understanding the nuanced interplay between temporal trends and market drivers is essential for navigating the complexities of stock trading and formulating informed investment strategies.

4.5. Stock Price Prediction with FBProphet

In an effort to anticipate future movements in Grab Holdings' stock prices, the FBProphet model was employed to generate forecasts. This model, developed by Facebook's Core Data Science team, is specifically designed to handle the unique characteristics of time-series data commonly found in financial markets. By utilizing a combination of historical trends and seasonality patterns, FBProphet aims to provide accurate predictions while accounting for the inherent unpredictability of market dynamics. Figure 6 below show how FBProphet predicts Grab shares in the future.

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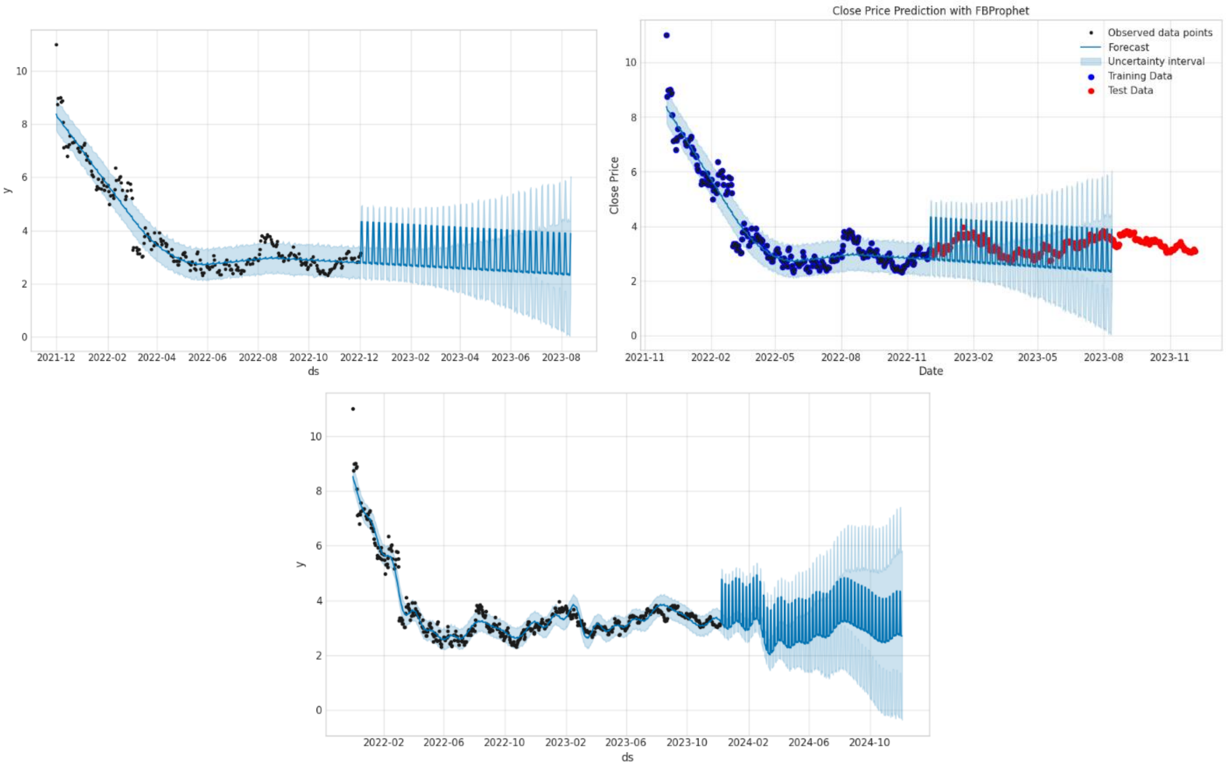


Figure 6. FBProphet model for Grab Holdings' closing stock prices

The forecasts produced by the FBProphet model for Grab Holdings' closing stock prices revealed a predominant downward trend over the forecasted period. While this trend was captured effectively by the model, it's crucial to note the presence of significant uncertainty surrounding these predictions. Financial markets are inherently complex and influenced by a multitude of factors, including economic indicators, geopolitical events, and investor sentiment, all of which can contribute to sudden and unexpected fluctuations in stock prices.

While FBProphet offers valuable insights into potential future trends, deviations between predicted and actual prices underscore the challenges of accurately forecasting in dynamic market environments. These deviations serve as a reminder of the limitations inherent in any predictive model and highlight the importance of exercising caution when interpreting forecasted outcomes. Additionally, ongoing model refinement and validation against real-world data are essential to enhance the accuracy and reliability of future predictions.

In conclusion, while FBProphet provides a useful tool for generating forecasts of Grab Holdings' stock prices, it's imperative to approach these predictions with a degree of skepticism and to supplement them with comprehensive analysis of broader market trends and company-specific factors. By combining predictive modeling with informed decision-making, investors can better navigate the complexities of financial markets and position themselves for success in an ever-changing landscape.

4.6. Identification of Trend Changepoints

Figure 7 show trend changepoint analysis is a crucial technique used to identify significant shifts or breakpoints in the trend of Grab Holdings' stock prices. By pinpointing these critical points, investors can gain valuable insights into the underlying dynamics driving market movements.

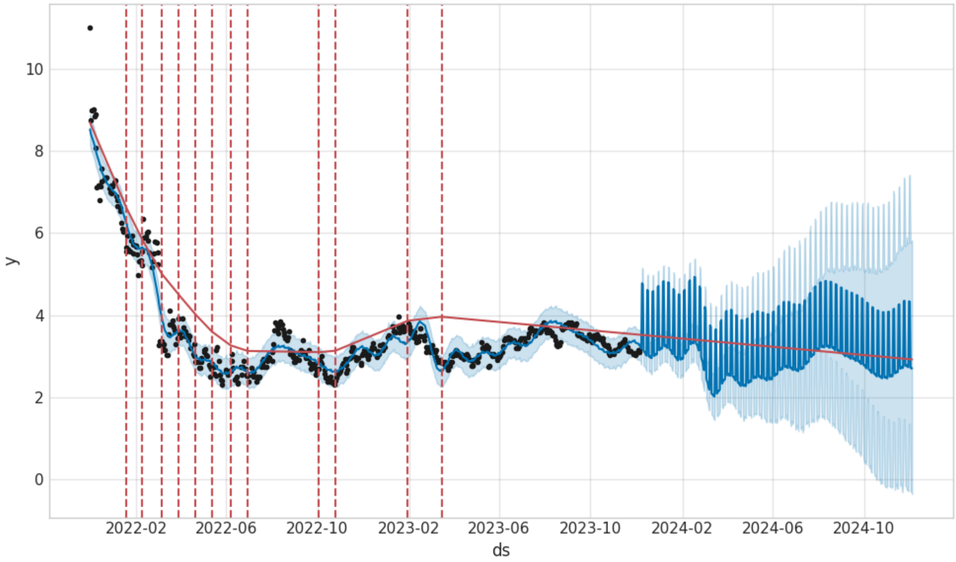
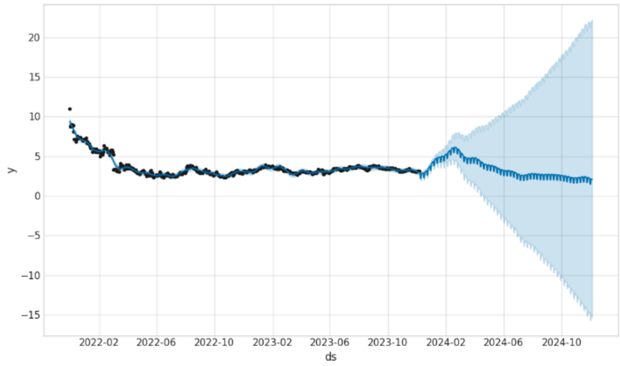
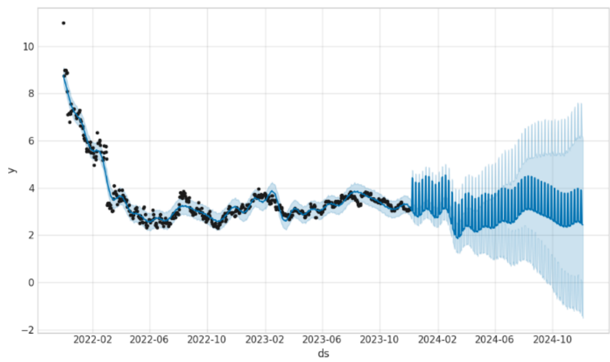


Figure 7. Trend Changepoints

The identification of trend changepoints allows for a deeper understanding of the market's behavior, enabling investors to anticipate potential turning points with greater accuracy. These insights are invaluable for decision-making processes, as they provide early indications of shifts in investor sentiment, changes in company performance, or broader market trends. Moreover, trend changepoint analysis facilitates the identification of potential investment opportunities or risks. By recognizing patterns indicative of trend reversals or accelerations, investors can adjust their strategies accordingly to capitalize on emerging trends or mitigate potential losses. In essence, the identification of trend changepoints serves as a powerful tool for investors seeking to navigate the complexities of the stock market. By leveraging these insights, investors can make more informed decisions, ultimately enhancing their ability to achieve their investment objectives and optimize their portfolio performance.

4.7. Model Performance Evaluation

Figure 8 shows the visualization of the forecasting. The evaluation of the FBProphet model's performance using key metrics MAPE, MAE, and RMSE provides valuable insights into its predictive capabilities.

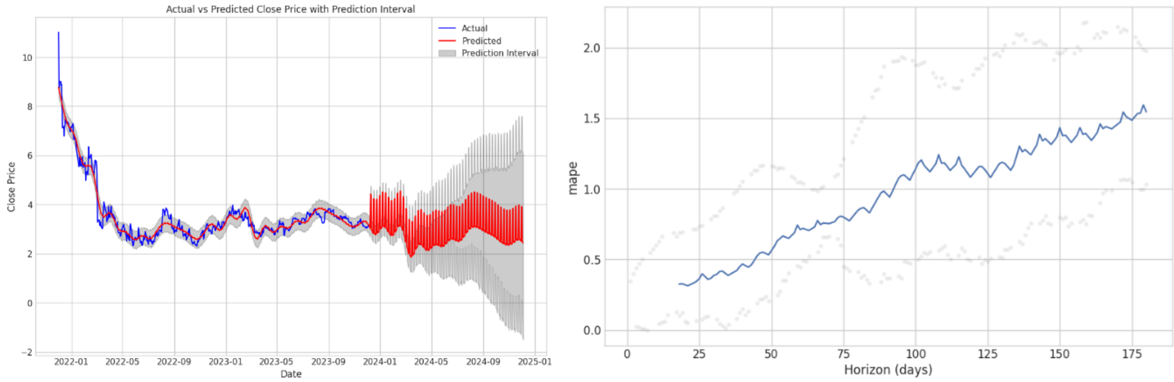


Figure 8. Forecast result validation

The MAPE, which measures the average absolute percentage difference between predicted and actual values, stands at 10.45511%. This indicates that, on average, the model's predictions deviate by approximately 10.46% from the actual stock prices. While this error rate is relatively low, it suggests that there is still room for improvement in the model's accuracy. Similarly, the MAE, which calculates the average absolute difference between predicted and actual values, is reported as 3.112026, in contrast to the MAE score of 14.496756 resulting from ARIMA. This indicates that, on average, the model's predictions are off by approximately $3.11 compared to the actual stock prices. While this error is within an acceptable range, it underscores the need for further fine-tuning to enhance precision.

Our chosen techniques demonstrate significant improvement in accuracy compared to traditional methods. RMSE a measure of the difference between predicted and actual values is a mere 3.516969. This is a substantial reduction compared to the 16.079898 RMSE obtained with the ARIMA model. This metric provides insight into the overall magnitude of prediction errors, with a higher RMSE indicating larger errors. The reported RMSE suggests that, on average, the model's predictions deviate from the actual values by approximately $3.52. While this error is relatively small in absolute terms, it highlights the inherent difficulty of accurately forecasting stock prices, particularly in volatile market conditions.

It is important to note that while the FBProphet model demonstrates satisfactory accuracy in predicting stock prices, there are inherent challenges associated with forecasting in dynamic market environments. Factors such as sudden market shifts, unexpected events, and changes in investor sentiment can significantly impact stock prices, making precise predictions difficult to achieve consistently. Therefore, continual refinement and validation of the model, along with incorporating additional data sources and advanced modeling techniques, are essential to improving its predictive performance and enhancing decision-making capabilities for investors and analysts alike.

5. Conclusion

The comprehensive analysis of Grab Holdings' stock prices and trading volume provides valuable insights into the dynamics of the company's market performance and investor sentiment. Several key findings emerge from the examination of historical data. Over the observed period, Grab Holdings exhibited a mix of upward and downward trends, with notable fluctuations in historical stock prices. While the stock reached its peak closing price of approximately $14 in early 2022, it also experienced a significant decline to around $4 by late 2023. This indicates a period of both optimism and pessimism among investors, influenced by various internal and external factors. The year 2023 witnessed increased volatility compared to 2022, as evidenced by larger price movements and heightened trading volume. This heightened volatility suggests greater uncertainty and fluctuating investor confidence, potentially driven by shifts in market sentiment, changes in company performance, or broader economic factors. The interplay between price movements and trading volume serves as a reflection of investor sentiment and market dynamics. Fluctuations in stock prices and trading activity highlight the dynamic nature of the market, with investor sentiment influenced by a multitude of factors including company news, industry developments, and macroeconomic trends. The findings underscore the importance of a comprehensive understanding of market trends and investor behavior for making informed investment decisions. Investors must carefully analyze historical data, monitor market trends, and assess risk factors to navigate the complexities of the stock market successfully.

In conclusion, the analysis of Grab Holdings' stock prices and trading volume offers valuable insights for investors, researchers, and market participants. By studying historical trends and fluctuations, stakeholders can gain a deeper understanding of market dynamics, identify investment opportunities, and make more informed decisions to achieve their financial goals. However, it's essential to acknowledge the inherent unpredictability of financial markets and exercise caution when interpreting historical data to inform future strategies.

6. Declarations

6.1. Author Contributions

Conceptualization: H; Methodology: A.R.M.; Software: H.; Validation: H., C.A.H., A.E.W., and A.R.M.; Formal Analysis: H., C.A.H., A.E.W., and A.R.M.; Investigation: H.; Resources: C.A.H.; Data Curation: C.A.H.; Writing Original Draft Preparation: H., C.A.H., A.E.W., and A.R.M.; Writing Review and Editing: C.A.H., A.E.W., and A.R.M.; Visualization: H.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

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

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. 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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