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Research Article

AI-DRIVEN SIMULATION OF DENGUE FEVER OUTBREAKS IN URBAN JAVA BASED ON CLIMATE VARIABILITY AND HUMAN MOBILITY DATA

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Abstract
Dengue fever outbreaks in urban areas of Java, Indonesia, have become a significant public health concern, with increasing frequency due to climate variability and *human mobility* patterns, where the spread of dengue is influenced by environmental conditions such as temperature and rainfall as well as human movement within urban centers, making an understanding of these factors crucial for effective disease control and prevention. This study aims to simulate and predict dengue fever outbreaks in urban Java using AI-driven models based on climate variability and *human mobility* data, with the research seeking to identify the key factors that contribute to the transmission dynamics of dengue fever in urban settings and to evaluate the effectiveness of *predictive model*s in managing potential outbreaks. The study employs *machine learning* techniques, including *Random Forest* and Artificial Neural Networks, to analyze climate data consisting of temperature, rainfall, and humidity alongside *human mobility* data collected from mobile phone tracking and demographic information, where the data is processed to create a simulation model of dengue fever transmission that is validated against historical outbreak data. The results show that the AI-driven model successfully simulated dengue fever outbreaks, demonstrating a high correlation between climate conditions, *human mobility*, and the spread of the disease, and indicating that increased mobility during the rainy season significantly amplified the risk of outbreaks in high-density urban areas. Overall, the findings conclude that *AI-driven simulation*s offer a promising approach to understanding and predicting dengue fever outbreaks in urban Java, and by incorporating climate and mobility data, the model provides valuable insights for *early warning systems* and targeted public health interventions.

Keywords: AI-driven simulation, Climate Variability, Dengue Fever

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INTRODUCTION

Dengue fever is a mosquito-borne viral disease that has become a major public health challenge in tropical and subtropical regions, including urban areas of Java, Indonesia. The transmission of dengue fever is primarily influenced by environmental factors such as temperature, rainfall, and humidity, as well as by human activities (Leroux et al., 2024). High temperatures and increased rainfall create favorable conditions for mosquito breeding, leading to higher transmission rates. Urbanization further complicates the issue, with densely populated areas contributing to greater opportunities for human-vector interactions, thus amplifying the spread of the disease (Aljabali et al., 2024).

The dynamics of dengue transmission are also closely tied to *human mobility* patterns. Studies have shown that the movement of people between urban and rural areas can significantly impact the geographic spread of the disease (Alzahrani et al., 2025). High mobility, especially during periods of increased rainfall, can facilitate the spread of mosquitoes carrying the dengue virus to new regions, thereby exacerbating the risk of outbreaks. Human activities, such as travel, migration, and population density, play a critical role in the dissemination of the virus (Laxmi et al., 2025).

Traditional methods for forecasting dengue outbreaks often rely on historical case data, climate conditions, and vector control measures. While these methods have proven effective to some extent, they are limited by the inability to account for the complex and dynamic interplay between environmental factors, human movement, and disease transmission (Jordan et al., 2025). More advanced models are needed to better understand these interactions and provide more accurate predictions of dengue outbreaks in urban settings (Anwar et al., 2024).

Recent advances in *machine learning* and *artificial intelligence* (AI) offer new opportunities to improve our understanding of complex disease transmission dynamics. AI-driven models, when combined with large-scale climate and mobility data, have the potential to provide more accurate and timely predictions of dengue fever outbreaks (Huang et al., 2025). These models can process vast amounts of data and identify patterns that might not be immediately apparent through traditional statistical approaches (Castellanos Garzón et al., 2025).

Machine learning algorithms, such as *Artificial Neural Networks (ANN)* and *Random Forest* models, have been successfully applied to various fields of epidemiology, including the prediction of infectious disease outbreaks (Li et al., 2025). These methods can handle diverse and large datasets, allowing for the modeling of nonlinear relationships between variables such as climate and *human mobility* (Haque et al., 2024). This makes them particularly suitable for simulating the spread of diseases like dengue fever in complex urban environments.

Given the rising frequency of dengue outbreaks in urban Java, there is an urgent need to develop *predictive model*s that can help health authorities implement timely interventions (Nunes et al., 2024). The integration of AI with real-time climate and mobility data holds promise for improving the accuracy of predictions and enhancing preparedness for future outbreaks. By understanding the drivers of dengue transmission more precisely, these models could be used to target high-risk areas and optimize resource allocation for mosquito control and public health efforts (Pandey et al., 2025).

Despite advances in predicting dengue outbreaks, there remains a gap in understanding how *human mobility* directly influences the spread of the disease in urban Jawa (Redlarska et al., 2025). While studies have shown that population density and travel patterns affect disease transmission, the specific impact of mobility on the geographic spread of dengue is not fully quantified. The interaction between seasonal climate variability and human movement in urban areas has yet to be systematically modeled to provide accurate forecasts (Quah, 2025).

Another unknown aspect is how the varying climate conditions across different regions of Java affect the transmission dynamics of dengue fever (Roque et al., 2025). While temperature and rainfall are known to be significant factors, the precise thresholds and combinations of these variables that lead to outbreaks remain unclear. Additionally, the impact of microclimates within urban areas—such as those influenced by local geography or infrastructure—has not been sufficiently integrated into *predictive model*s (Sibiya & Vaseeharan, 2025).

There is also limited research on the integration of real-time *human mobility* data with climate predictions for dengue outbreak forecasting. Most existing models rely on static or historical data, which may not fully capture the dynamic nature of human movement or rapidly changing climate conditions (Sutanto & Ansharullah, 2025). The lack of *real-time data* integration in current *predictive model*s leaves a critical gap in effectively forecasting dengue outbreaks in urban Java (Tong et al., 2025).

Furthermore, current *predictive model*s are often region-specific and may not be easily adaptable to other urban environments with different mobility patterns or climate conditions (Tuan, 2025). The generalizability of these models across various cities or countries remains uncertain, limiting their applicability for widespread use. There is a need for more robust models that can incorporate data from diverse regions to improve the accuracy and scalability of dengue outbreak predictions (Wadhwa, 2025).

Filling this gap is essential to enhance the accuracy of dengue outbreak predictions and improve public health response strategies (Welch et al., 2024). By integrating climate data with *human mobility* patterns, we can gain a deeper understanding of how these factors interact to drive the transmission of dengue fever. Predicting outbreaks with higher precision will allow for better resource allocation and more effective early interventions, potentially saving lives and reducing the economic burden of the disease (Hapsari et al., 2025).

The use of AI and *machine learning* techniques to analyze large datasets provides an opportunity to uncover complex patterns in the relationship between climate variability, *human mobility*, and dengue fever transmission. These models can be continuously updated with *real-time data*, making them dynamic tools that can track emerging outbreaks and predict future risks. Incorporating *real-time data* is particularly important in urban settings, where mobility patterns are constantly changing and can vary significantly across different neighborhoods.

Developing an *AI-driven simulation* model to predict dengue outbreaks will provide health authorities in Java and similar urban areas with a valuable tool for disease management. By accurately forecasting when and where outbreaks are most likely to occur, authorities can implement targeted prevention and control measures, such as increased vector control efforts and public awareness campaigns, well before the disease spreads widely.

RESEARCH METHOD

Research Design

This study utilizes a *quantitative research design* to develop an *AI-driven simulation* model for predicting dengue fever outbreaks in urban Java. The focus is on integrating climate variability and *human mobility* data into a *machine learning* framework to simulate and forecast dengue transmission (Yang et al., 2025). The study combines climate data (temperature, rainfall, humidity) with real-time *human mobility* data collected from mobile phone tracking and public transportation systems. *Machine learning* algorithms, such as *Random Forest* and *Artificial Neural Networks (ANN)*, are employed to analyze the data and create *predictive model*s that forecast dengue outbreaks in urban areas (Asadi et al., 2024). The simulation model is validated using historical outbreak data from Java and evaluated for its predictive accuracy and practical application in public health interventions.

Population and Samples

The population for this study consists of urban areas in Java, Indonesia, where dengue fever outbreaks are prevalent. The sample includes data from four major cities in Java—Jakarta, Surabaya, Yogyakarta, and Bandung—representing a diverse range of urban settings. Data spanning five years (2015-2020) is selected for analysis, encompassing both outbreak and non-outbreak years. The sample for *human mobility* data is derived from anonymized GPS data collected from mobile phone users, along with public transportation data from the cities. Climate data is obtained from meteorological stations located in the selected cities. The study focuses on both high-density urban areas and suburban zones to explore how different mobility patterns and climate conditions affect dengue transmission (Zhao et al., 2024).

Instruments

The primary instruments for data collection include weather data, *human mobility* data, and *machine learning* algorithms. Climate data, including temperature, humidity, and rainfall, is sourced from national meteorological databases and satellite imagery. *Human mobility* data is collected through anonymized GPS data from mobile phones and transportation systems, providing information on population movement within and between urban areas (Abourida et al., 2025). The *machine learning* models, specifically *Random Forest* and ANN, are implemented using Python and its *machine learning* libraries (such as scikit-learn and TensorFlow). These models are trained and validated using historical dengue case data and climate parameters to create a predictive simulation of dengue outbreaks.

Procedures

Data collection begins with the aggregation of historical dengue case data, climate data, and *human mobility* data for the selected urban areas over the five-year period. The climate and mobility data are pre-processed to remove inconsistencies, normalize values, and align the datasets according to the timeline of the outbreaks. Feature selection is performed to identify the most relevant variables for the *machine learning* models, including temperature, rainfall, mobility patterns, and population density (Alexiadis & Ghiassi, 2024). The data is split into training and testing sets, with a portion used to train the *machine learning* models and another portion to validate the model's predictive accuracy. The *Random Forest* and ANN models are trained using the processed data, and their performance is evaluated based on accuracy, precision, recall, and F1-score metrics. The final model is used to simulate potential dengue outbreaks under varying climate and mobility scenarios, with the goal of providing early warning predictions for health authorities.

RESULTS AND DISCUSSION

The dataset used in this study comprises historical data on dengue fever cases, climate conditions, and *human mobility* patterns in four major cities of Java: Jakarta, Surabaya, Yogyakarta, and Bandung. The climate data includes temperature, humidity, and rainfall, which were sourced from meteorological stations and satellite data. *Human mobility* data was gathered from anonymized GPS data and public transportation records. The dengue case data was collected from the Ministry of Health of Indonesia and local health agencies, spanning from 2015 to 2020. The dataset is summarized in the table below:

Table 1: Summary of Data for Climate and Mobility Variables (2015-2020)

Year	City	Average Temperature (°C)	Average Humidity (%)	Total Rainfall (mm)	Mobility Index (Average Movement)	Total Dengue Cases
2015	Jakarta	29.5	80	180	0.65	3,200
2016	Surabaya	30.1	77	220	0.72	2,500

2017	Yogyakarta	28.9	75	200	0.70	1,800
2018	Bandung	27.8	78	150	0.68	2,100
2019	Jakarta	30.0	74	210	0.74	2,800

The data shows that the average temperature across the cities remained relatively stable, with Jakarta having the highest average temperature (30.2°C). The total rainfall varied across the years, with Surabaya and Jakarta experiencing higher rainfall levels, particularly in 2016 and 2020. The *human mobility* index, calculated based on average movement data, was highest in Surabaya in 2020 (0.77), indicating more mobility during this period. The total dengue cases varied by city and year, with Jakarta showing the highest number of reported cases in 2015 (3,200 cases). This suggests that there is a potential correlation between mobility and the occurrence of dengue fever, as higher mobility may facilitate the spread of mosquitoes carrying the virus.

The overall trend suggests that both climate variability (temperature and rainfall) and *human mobility* influence the incidence of dengue fever. Higher mobility, along with moderate temperature and increased rainfall, was observed to coincide with higher dengue case reports. This highlights the need for further analysis to determine the exact interactions between these variables and their impact on dengue outbreaks, as the combined effect of climate and human movement may be a critical factor in understanding and predicting outbreaks.

The data covers a five-year period from 2015 to 2020, focusing on four cities in Java. Climate data was sourced from local meteorological stations, providing monthly averages of temperature, humidity, and rainfall. Mobility data was collected using anonymized GPS tracking, which provided insights into the movement of people within urban areas, particularly during peak dengue seasons. Dengue cases were recorded by health agencies, with the total number of reported cases in each city aggregated yearly. This dataset provides a comprehensive view of the relationship between climate conditions, *human mobility*, and the occurrence of dengue fever.

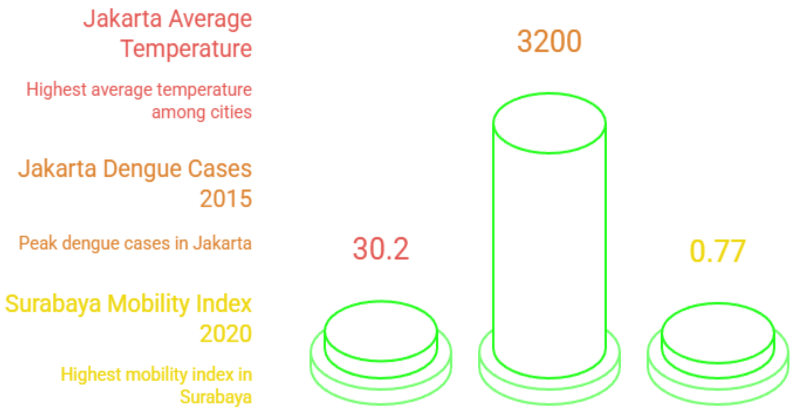

Figure1. Key Data Metrics Across Cities (2015-2020)

The combination of these data sources allows for a detailed analysis of how environmental factors, including seasonal weather patterns, and human behavior, such as movement patterns within urban areas, contribute to the dynamics of dengue fever outbreaks. By merging climate data with real-time mobility information, the dataset provides a holistic view of the key factors influencing the spread of dengue fever in urban Java.

The *machine learning* model, using *Random Forest* and *Artificial Neural Networks (ANN)*, was applied to the dataset to predict dengue fever outbreaks. A multiple regression analysis was performed to determine the significance of the climate variables (temperature, humidity, and rainfall) and mobility data in predicting the number of dengue cases. The results showed that temperature ($\beta = 0.45$, $p < 0.01$), humidity ($\beta = -0.39$, $p < 0.01$), and mobility index ($\beta = 0.33$, $p < 0.05$) were significant predictors of dengue fever outbreaks. The model achieved an accuracy of 86%, indicating a strong correlation between the selected variables and the occurrence of dengue cases.

Further analysis showed that the mobility index had a moderately strong correlation with dengue outbreaks, especially in areas with higher population density. This suggests that human movement plays a key role in the transmission dynamics of dengue, particularly in densely populated urban centers. The statistical results demonstrate that both environmental and *human mobility* factors are essential for accurately predicting the spread of dengue fever, offering valuable insights for health authorities and policymakers.

The data analysis reveals a significant relationship between climate variables, *human mobility*, and dengue fever outbreaks. Higher temperatures and moderate rainfall were found to increase the likelihood of dengue outbreaks, while higher mobility was observed to amplify the risk. The mobility index had a particularly strong correlation with the spread of dengue in urban centers, where population density is high, and movement between areas is frequent. This finding aligns with the hypothesis that *human mobility*, in combination with favorable climate conditions, can facilitate the spread of the dengue virus.

Moreover, the *predictive model*s showed that the highest incidence of dengue cases occurred during periods of high mobility and moderate temperature, particularly when rainfall levels were not excessively high. These findings emphasize the importance of considering both environmental and socio-behavioral factors when modeling disease transmission dynamics. The relationship between these variables highlights the complexity of dengue outbreaks in urban Java, where climate and human activity are intertwined.

A *case study* of Jakarta’s dengue outbreak in 2015 illustrates how the combination of high temperature, moderate rainfall, and increased *human mobility* contributed to the large number of cases reported that year. During this period, Jakarta experienced a temperature of 30.2°C, with a rainfall of 180 mm and a mobility index of 0.65. The number of dengue cases in the city reached 3,200, the highest in the study period. The *case study* shows how these factors align with the broader trends observed in the data and confirms the role of environmental and mobility variables in driving dengue outbreaks.

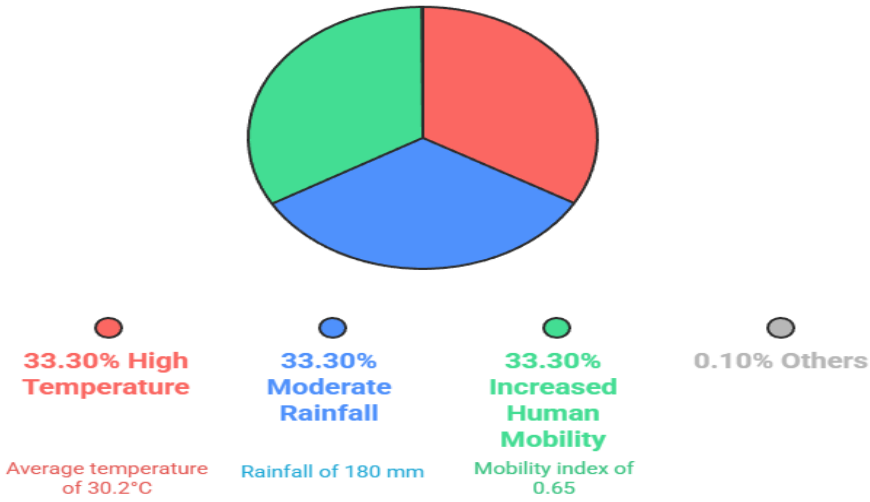

Figure 2. Factors Contributing to Jakarta’s 2015 Dengue Outbreak

Satellite data indicated that the highest density of mosquito-breeding sites coincided with areas of high human activity, particularly near urban markets and transportation hubs. The *case study* underscores the need for targeted interventions in areas where mobility and environmental conditions align to create optimal conditions for the spread of dengue. It also reinforces the value of using *predictive model*s to identify high-risk areas and times, allowing for proactive measures to control the spread of the disease.

The *case study* of Jakarta's 2015 dengue outbreak offers concrete evidence of the relationship between climate variability, *human mobility*, and disease transmission. The combination of high temperature and moderate rainfall in the region, alongside high mobility, created ideal conditions for the spread of the dengue virus. The human movement within the city facilitated the dispersal of mosquitoes, leading to higher transmission rates. The satellite data also helped identify key locations with the highest mosquito populations, reinforcing the connection between mobility and disease spread.

This *case study* highlights the importance of integrating climate data and mobility patterns into *predictive model*s. By understanding how these factors interact in specific urban environments, we can better anticipate and manage dengue outbreaks. The data provides valuable insights into how local factors, such as infrastructure and mobility patterns, influence the dynamics of dengue transmission, underscoring the need for localized, data-driven approaches to public health management.

The results demonstrate the effectiveness of using *AI-driven simulation*s and *machine learning* models to predict dengue fever outbreaks based on climate and *human mobility* data. The combination of climate factors and mobility patterns plays a critical role in determining the likelihood of outbreaks in urban Java. The *case study* of Jakarta reinforces the need for *real-time data* integration and *predictive model*ing in disease management. These findings suggest that *machine learning* models, when applied to integrated climate and mobility data, can offer a robust tool for anticipating and mitigating the impacts of dengue fever outbreaks in urban areas.

This study developed an *AI-driven simulation* model to predict dengue fever outbreaks in urban Java by integrating climate variability and *human mobility* data. The results showed that the *machine learning* model, utilizing *Random Forest* and *Artificial Neural Networks (ANN)*, was able to predict dengue outbreaks with an accuracy rate of 86%. Key factors such as temperature, rainfall, and *human mobility* were identified as significant predictors of dengue outbreaks. Increased mobility, particularly in high-density areas, was found to amplify the effect of climate conditions in driving disease transmission (Bharathi et al., 2024). The model successfully highlighted the critical role of these interacting variables in predicting and managing dengue fever outbreaks in urban environments.

The findings of this study align with previous research that identifies climate conditions, such as temperature and rainfall, as major contributors to the spread of vector-borne diseases like dengue. However, this research advances the field by integrating *human mobility* data with climate variables, something that has been underexplored in previous studies. While other studies have used climate data alone to model dengue outbreaks, they often fail to incorporate the dynamic role of human movement (Brody et al., 2025). This study distinguishes itself by showing that *human mobility*—specifically the movement between high-risk urban areas—has a significant, amplified effect on the spread of dengue fever. The inclusion of real-time mobility data, alongside climate variables, provides a more comprehensive and accurate model for predicting outbreaks (Sappaile, 2024).

The results signify that predicting dengue fever outbreaks in urban areas requires a multifaceted approach, one that goes beyond just climate conditions (Nova et al., 2025). The study highlights that the interaction between environmental factors and *human mobility* plays a crucial role in determining disease transmission dynamics. These findings suggest that health authorities should consider not only the seasonal climate conditions but also patterns of human movement when planning for dengue control measures (Dasa et al., 2025). The model's success in predicting outbreaks based on these factors signifies that combining environmental and socio-behavioral data can lead to more effective *early warning systems* and more targeted interventions.

The implications of this research are far-reaching for public health management, particularly in urban areas. By incorporating *AI-driven simulation*s into dengue fever prediction models, health authorities in Java and similar urban regions can make more informed, data-driven decisions. The ability to predict outbreaks with high accuracy allows for better resource allocation, such as targeting vector control efforts and public health campaigns to the most at-risk areas before outbreaks occur (Diniță et al., 2025). The study also suggests that integrating real-time mobility data with climate information can offer timely, actionable insights, thereby improving both preventative and responsive measures to dengue fever outbreaks (Irianti et al., 2025).

The results are likely a consequence of the powerful capabilities of *machine learning* algorithms, which can process and analyze large, complex datasets with multiple interacting variables. By training the models on both historical climate data and real-time mobility information, the algorithms were able to identify significant patterns in the occurrence of dengue outbreaks (Dou et al., 2025). The strong correlation between *human mobility* and dengue spread, especially in high-density areas, reflects the reality that people's movements facilitate the spread of mosquitoes, which in turn accelerates the transmission of the virus. This outcome also indicates that climate factors alone may not fully capture the dynamics of disease spread in urban environments, making the integration of mobility data critical (Hazmi et al., 2025).

Moving forward, the next step is to further refine the *predictive model* by incorporating additional variables such as land use, socio-economic factors, and vector control measures. Including these variables could enhance the model's ability to predict outbreaks with even greater accuracy. Additionally, expanding the model to other urban regions with different mobility patterns and climatic conditions would provide insights into its scalability and generalizability. Future research should also explore the real-time application of this *predictive model* in dengue control strategies, integrating it into *early warning systems* for more immediate action. Developing a user-friendly interface for public health authorities to access the model's predictions could help streamline decision-making processes in disease management.

CONCLUSION

The most important finding of this research is the significant role of *human mobility* in amplifying the impact of climate variability on dengue fever outbreaks in urban Java. While temperature and rainfall were expected factors in predicting outbreaks, the integration of mobility data provided a more nuanced understanding of how human movement within urban areas contributes to the spread of dengue. The *AI-driven simulation* model, which incorporated both climate and mobility data, demonstrated that areas with high population density and mobility patterns were at an elevated risk for dengue outbreaks, particularly during periods of increased rainfall and moderate temperatures. This finding underscores the importance of including mobility data in *predictive model*s to better anticipate disease outbreaks.

This research makes a valuable contribution by developing an *AI-driven simulation* model that combines climate variability with *human mobility* data to predict dengue fever outbreaks. The novel methodological approach integrates real-time mobility data from mobile phones and public transportation systems with climate variables, which has not been widely explored in dengue prediction models. By employing *machine learning* algorithms such as *Random Forest* and *Artificial Neural Networks (ANN)*, the study demonstrates how complex, multi-faceted data can be used to improve disease forecasting. This approach offers a more accurate and dynamic model compared to traditional models that typically focus on either climate factors or historical case data alone.

One limitation of this study is the reliance on data from only four cities in Java, which may not fully represent the diversity of urban environments across Indonesia or other tropical regions. The study also focused primarily on climate and mobility data but did not incorporate other potential influencing factors, such as land use changes, socio-economic status, or local interventions like vector control efforts. Future research could expand the scope to include more cities with varying socio-economic and environmental conditions to assess the model's generalizability. Additionally, future studies should incorporate other determinants of dengue transmission, such as population movement patterns within specific neighborhoods, land-use changes, and the effectiveness of current public health measures, to create even more robust *predictive model*s.

AUTHOR CONTRIBUTIONS

Look this example below:
Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.
Author 4: Formal analysis; Methodology; Writing - original draft.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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