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Electric load forecasting using LSTM and Bi-LSTM: a systematic literature review

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ABSTRACT

Future electricity load forecasting plays a critical role in modern power systems to ensure operational efficiency, planning, and grid stability. Conventional statistical methods used for forecasting often fail to capture nonlinear and temporal fluctuations in electricity demand, especially under high variability conditions. Deep learning methods are widely used for forecasting, especially long short-term memory (LSTM) and bidirectional LSTM (Bi-LSTM) methods, which are strong alternatives for forecasting due to their superior sequence modeling capabilities compared to others. This literature review identifies key research gaps, including the lack of standard benchmarks, the underutilization of contextual features, poor model interpretability, and challenges in real-time deployment. This literature review analyzes key datasets, model architectures, evaluation metrics, and performance comparisons with mean absolute percentage error (MAPE) as the primary benchmark. The analysis results from various sources show that Bi-LSTM generally outperforms standard LSTM in capturing forward and backward dependencies, albeit with higher computational demands. Future research directions are expected to be able to overcome the limitations of forecasting models and improve the adaptability and transparency of LSTM-based forecasting models in smart grid applications.

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1. INTRODUCTION

The development of electricity system technology today continues to grow rapidly. The development of electricity systems is directed at increasing efficiency, reliability, and integration of renewable energy sources into the electricity network [1]. One of the developments in electricity technology is in the field of electric load forecasting (ELF) because it is an essential component for planning the operation of the electricity system, regulating energy supply, and managing the overall electricity network infrastructure [2]. The accuracy of electricity load prediction can directly affect system stability, generator optimization, and operational cost efficiency, especially in dealing with short-term and long-term electricity load fluctuations [3]. Traditional forecasting methods that are often used, such as autoregressive integrated moving average (ARIMA) [4], exponential smoothing, and regression-based techniques, are widely used because of their simplicity and interpretability [5]. In their use, traditional forecasting methods have limitations in capturing long-term temporal dependencies and complex non-linear patterns of historical data [6]. These methods generally assume linearity and stationarity of time series [7], thus limiting their effectiveness in understanding

complex temporal dependencies, non-linear consumption behavior [8], and high load fluctuations due to exogenous variables such as temperature, holidays, weather, and socio-economic factors of users [9].

In response to the limitations of traditional forecasting methods, in recent years, the development of machine learning (ML) and deep learning (DL) models has become the latest solution to overcome the weaknesses of traditional forecasting methods [10]. One of the forecasting models that is currently being developed is the recurrent neural network (RNN) and its development branches, such as long short-term memory (LSTM) and bidirectional LSTM (Bi-LSTM) [11]. The LSTM model is designed to be used to capture long-term dependencies in sequential data and can overcome the vanishing gradient problem inherent in RNN [12].

The Bi-LSTM model is a development of LSTM that extends the forecasting pattern with the concept of two-way checking in the past and the future [13]. Several studies explain that the use of forecasting methods using Bi-LSTM, especially when combined with hybrid methods such as convolutional neural networks (CNN) [14], wavelet transform [15], and attention mechanisms, significantly increases forecasting accuracy and reduces errors [16]. Furthermore, although the progress of forecasting with LSTM and Bi-LSTM methods has high accuracy, there are several challenges. LSTM-based prediction models have challenges and weaknesses such as dependence on accuracy and data quality [17], preprocessing complexity [18], computational complexity and training time [19], overfitting and poor generalization [20]. and difficulties in long-term forecasting [21]. This paper presents a comprehensive literature review related to electricity load forecasting using LSTM and Bi-LSTM models. The authors analyze the research works that have been carried out systematically, evaluate the performance of the models using standard metrics, and discuss research trends, challenges, and open issues. Through this literature review, the authors review the use of LSTM and Bi-LSTM models in short-term and long-term electricity load prediction, compare the performance, advantages, and limitations of each prediction model based on the evaluation results of various studies.

2. METHOD

2.1. Literature selection criteria

The selection of literature sources used in this review paper is based on a structured methodology that is useful for ensuring high-quality, relevant, and up-to-date study sources that focus on electricity load forecasting using LSTM and Bi-LSTM models. The overall procedure is presented in Figure 1; literature selection is based on the criteria of the year of publication (2019-2025) and publication sources from international journals such as IEEE Access, Energy, Energies, Applied Sciences, Energy Reports, Sustainable Cities and Society, and International Journal of Energy Research. In addition, the relevance to the main topic is related to the application of LSTM and Bi-LSTM models to predict future electricity loads, either alone or in a hybrid form, for short-, medium-, and long-term electricity load forecasting. The last is the availability of evaluation metrics that use one or more generally accepted forecast evaluation metrics such as MAPE, root mean squared error (RMSE), mean absolute error (MAE), or coefficient of determination (R^2).

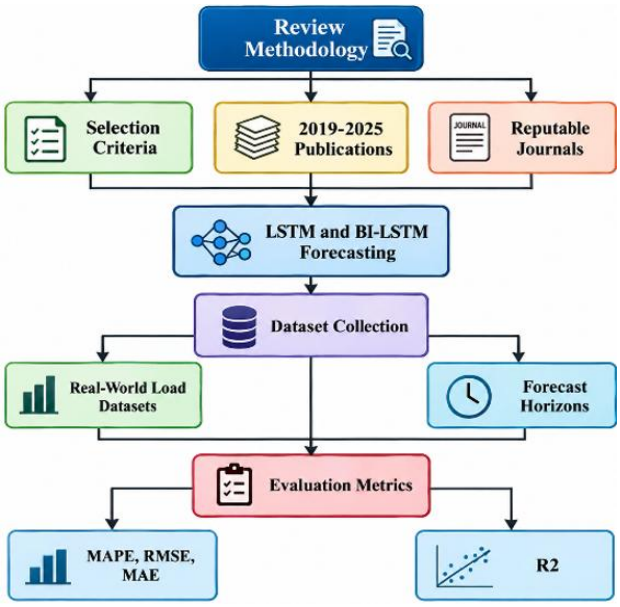

Figure 1. Block diagram literature review

2.2. Dataset characteristics

The characteristics of the data sets used in this review paper are reviewed using various electricity load data sets that can be categorized based on data sources, where data is collected from various smart meters, utility companies, and open repositories. In addition, the temporal resolution category is also used to determine the granularity of data variations between minute, hourly, and daily intervals. The forecast coverage category is also included, such as very short-term load forecasting (VSTLF), which forecasts the next seconds and minutes, short-term load forecasting (STLF), which forecasts the next minutes to hours, medium-term load forecasting (MTLF), which forecasts the next days to weeks, and long-term load forecasting (LTLF), which forecasts the next months to years.

2.3. Evaluation matrix

The evaluation matrix used, based on the references used, is mean absolute percentage error (MAPE), RMSE, and R^2. Table 1 presents a comparative evaluation matrix of selected studies on electricity-load forecasting using LSTM and Bi-LSTM-based models. The reviewed approaches include standalone Bi-LSTM and hybrid architectures such as CNN–Bi-LSTM, EMD–Bi-LSTM, CEEMDAN–RF-LSTM, LSTM–GA, and LightGBM–Bi-LSTM. The use of hybrid architectures indicates a growing trend toward combining recurrent networks with feature extraction, signal decomposition, and optimization techniques to improve forecasting performance.

Table 1. Evaluation matrix

Ref.	Year	Model type	Dataset type	Metrics used
[2]	2023	EMD + Bi-LSTM	Smart grid load	MAPE, RMSE
[16]	2020	CNN + Bi-LSTM	Residential load	MAPE, RMSE
[4]	2022	CEEMDAN + RF-LSTM	Building dataset	MAPE, RMSE
[7]	2019	CNN + Bi-LSTM	Aggregated grid data	MAPE
[22]	2024	Bi-LSTM	Regional grid load	MAPE
[19]	2024	CNN + Bi-LSTM	Building load profile	MAPE
[18]	2022	LSTM + GA	Smart meter readings	MAPE, R^2
[23]	2024	AC-Bi-LSTM	Load forecasting dataset	MAPE
[24]	2021	LightGBM + Bi-LSTM	Household electricity	MAPE, MAE
[25]	2025	InMetra Boost + BiLSTM	Smart grid city load	MAPE, RMSE

The datasets include residential, household, building, smart-meter, smart-grid, and regional load profiles, demonstrating the applicability of LSTM-based models across different electricity-demand characteristics. MAPE and RMSE are the most frequently reported evaluation metrics, while MAE and R^2 are used as complementary indicators in several studies. MAPE measures relative forecasting error, RMSE emphasizes larger errors, MAE represents the average absolute error, and R^2 indicates the model's ability to explain variations in actual load.

3. RESULTS AND DISCUSSION

Electric load forecasting studies continue to grow rapidly, and many studies are conducted by combining LSTM and Bi-LSTM with other modules such as CNN [26], attention mechanisms [27], or optimization algorithms [28]. Variations in combining these architectures aim to capture temporal and spatial patterns more efficiently.

3.1. Datasets utilized in electric load forecasting

Most studies aimed at forecasting electric loads utilize data from electricity providers and publicly available data [1]. As explained in Table 2, for example, ISO/NE, PJM [16], and NYISO data - widely used for comparing forecasting models due to their hourly and sub-hourly accuracy [20]. In addition, the UCI machine learning repository data [5] provides residential load consumption data [12]. Specific utility data obtained from regional electricity companies in China, the United States, and Europe [29]. Smart grid-based data, which often combines renewable energy generation and weather inputs [17]. Furthermore, in addition to using electricity load data from various open sources, many studies also use weather and temporal variables such as temperature [4], humidity [19], wind speed [30], and holiday indicators [25]. Based on the literature study that has been conducted, it was found that most studies focus on STLF with hourly resolution. This is due to its application relevance in real-time energy management systems [31].

Table 2. Datasets utilized in electric load forecasting

Reference	Dataset source	Resolution	Range	Region
[16]	ISO-NE	Hourly	2 years	United States
[5]	UCI Smart Grid	15-minute	6 months	Eropa
[23]	PJM Interconnection	Hourly	4 years	United States (Mid-Atlantic)
[32]	Chinese Utility Company	Daily	5 years	Tiongkok
[33]	Korean Electric Power Corp	Hourly	1 year	South Korea

3.2. Model architecture used

The electrical load forecasting studies obtained from the results of this review paper mostly use LSTM and BI-LSTM models. As shown in Table 3, this prediction model is superior to other conventional models because of its ability to overcome vanishing gradients and remember long-term information. The LSTM model is generally used as a baseline, while Bi-LSTM is often combined with additional layers such as CNN or attention to improve the accuracy of the prediction results.

Table 3. Prediction model architecture

Ref	Model	Components	Special architecture	Advantages
[1]	LSTM	2 hidden layers	Standar time series	Stable, handles long-term dependencies
[16]	CNN-BiLSTM	CNN + Bi-LSTM	Feature extraction & memory	Leverages past and future information
[34]	Attn-BiLSTM	Attention + Bi-LSTM	Temporal feature focus	Spatial feature extraction
[23]	AC-BiLSTM	Auto-Correlation + Bi-LSTM	Lag-dependency modeling	Focuses on important data in sequence
[35]	EMD-BiLSTM	Empirical Mode Decomp + Bi-LSTM	Multi-scale decomposition	Suitable for multistep prediction

LSTM is widely used to perform sequence prediction because of its ability to capture long-term data dependencies through cell state memory and gating mechanisms [36]. Meanwhile, Bi-LSTM improves the LSTM method in the prediction process by processing data in two directions, namely forward and backward, so that it can capture past and future contexts [36]. Bi-LSTM can show improved performance in data sets with seasonal patterns or multiple variations of external factors [21]. Many studies have also proposed hybrid architecture methods for the prediction process that combine LSTM or Bi-LSTM with other methods such as CNN [4], Attention [8], EMD [7], or transformer methods to extract spatial-temporal patterns more effectively [33], details are presented in Table 4.

Table 4. Hybrid architecture of prediction models

Reference	Architecture	Components
[37]	CNN–BiLSTM	CNN for feature extraction, BiLSTM for sequential modeling
[24]	Attention–BiLSTM	Attention mechanism before or after BiLSTM
[6]	CEEMDAN–LSTM	Signal decomposition + LSTM
[38]	NeuralProphet–BiLSTM	Trend + seasonality + deep learning

3.3. Performance comparison and results evaluation

Comparison of performance and evaluation of the results of the prediction system process generally use MAPE, RMSE, and MAE. Based on several literature studies, such as those summarized in Table 5, forecasting model architectures that use a hybrid system such as CNN-Bi-LSTM and Attn-Bi-LSTM have the best performance compared to models that use LSTM or Bi-LSTM independently or other hybrid combinations, especially in the context of short-term STLF forecasting [17]. Based on the data obtained, the MAPE results from the hybrid model are below 2% [39]. In addition, studies that have been conducted [35] show that the integration of the attention mechanism allows the model to give more weight to time steps that are relevant to the prediction value and is proven to reduce MAPE by ~1% compared to without attention.

Table 5. Prediction model evaluation results

Ref	Model	MAPE (%)	RMSE	MAE
[1]	LSTM	3.12	2.51	2.04
[16]	CNN-BiLSTM	1.52	1.21	1.05
[32]	Attn-BiLSTM	1.74	1.42	1.26
[23]	AC-BiLSTM	2.10	1.82	1.54
[35]	EMD-BiLSTM	1.83	1.55	1.41

3.4. Discussion

The development of studies related to forecasting future electricity loads using LSTM and Bi-LSTM continues to grow rapidly over time [40]. Based on several studies in the literature, several important insights regarding the strengths and limitations of forecasting with these models, as well as current research gaps and directions for future research developments, are revealed [41]. This section will present an in-depth discussion divided into several core discussions, starting from the main findings, advantages, and disadvantages of the model, to future challenges.

Based on studies of the literature studied in Table 6 [42], [43], the LSTM and Bi-LSTM forecasting models consistently have advantages in forecasting accuracy compared to other traditional forecasting techniques such as ARIMA, support vector regression (SVR) [44], and simple feedforward neural networks in terms of accuracy which is validated using MAPE, RMSE, and MAE. In one study [36], the LSTM-based model can improve the MAPE value that was previously forecasted using the basic RNN method from 7.62% to 2.87%. In addition, the research conducted revealed that the Bi-LSTM model is able to achieve superior accuracy in the forecasting process with a MAPE value of 1.92% compared to 2.34% from the unidirectional LSTM [6].

Table 6. Performance comparison of forecasting models based on multiple metrics

Ref	Model	Dataset used	Horizon	MAPE (%)
[32]	ARIMA	ISO-NE (United States)	STLF	6.15
[30]	ANN	PJM dataset	STLF	5.32
[31]	SVR	Ontario load data	STLF	4.88
[38]	LSTM	United Kingdom National grid	STLF	2.94
[42]	Bi-LSTM	ISO New England + weather data	STLF	2.32
[43]	Hybrid LSTM+CNN	Smart grid Australia	STLF	1.81

LSTM and Bi-LSTM forecasting models have become commonly used models in electric load forecasting (ELF) due to their ability to perform sequential data processing and capture long-term dependencies [20]. The validation method using MAPE is used as an evaluation metric for the forecasting results of LSTM and Bi-LSTM [13]. Based on the MAPE evaluation results [31], forecasting using LSTM and Bi-LSTM generally has a value ranging from 1% to 5% in the ELF scenario [21]. LSTM-based forecasting models have high accuracy values in ELF tasks due to their ability to reduce the vanishing gradient problem found in traditional RNN methods [19]. Meanwhile, the Bi-LSTM forecasting model is able to process data sequences in two directions [8], namely forward and backward [30], and can improve prediction accuracy by performing two-way checks on the load profile data carried out in the prediction process [6].

Based on empirical evaluations in various studies in Table 7, the Bi-LSTM prediction model tends to outperform the LSTM prediction model by 5%–15% in terms of accuracy using the MAPE validation model [45]. This advantage is especially true for datasets with high temporal variability, such as smart meter data and residential hourly loads [33]. In addition, hybrid models that integrate LSTM with other forecasting models such as CNN [5], attention mechanisms [35], and wavelet transforms [24] can further improve the accuracy of forecasting performance.

Table 7. Comparison of LSTM and Bi-LSTM models

Feature	LSTM	Bi-LSTM
Temporal dependency	Captures past dependencies	Captures both past and future dependencies
Model complexity	Moderate	Higher (twice the LSTM size)
Accuracy (MAPE)	2–5% [31]	1.5–4% [6]
Training time	Lower [36]	Higher [29]
Interpretability	Medium	Lower due to dual directionality
Best use case	STLF, MTLF	STLF, sequence modeling with contextual info

Based on the literature review conducted in Table 8, it was found that LSTM networks outperform traditional machine learning models and shallow neural networks [3], especially in STLF due to their capacity to mitigate the vanishing gradient problem and retain relevant historical information in long sequences [20]. The gate architecture of the LSTM model consists of input, forget, and output gates that allow selective memory updates [45], thereby improving prediction stability under highly fluctuating load conditions [45]. Several studies, such as [33], have shown that LSTM models consistently achieve lower MAPE and RMSE compared to feedforward neural networks or autoregressive models [13]. Despite its

advantages, LSTM models also have certain limitations, including the fact that they tend to require large computational resources and large training datasets to avoid overfitting and ensure generalization [23]. In addition, LSTM prediction models only perform unidirectional predictions that allow for missing data processes, making them less than optimal for datasets that have both past and future information [4]. LSTM training models are also often sensitive to hyperparameter settings and require careful tuning [21].

Table 8. Comparative strengths and weaknesses of LSTM and Bi-LSTM models

Aspect	LSTM	Bi-LSTM
Memory capability	Captures long-term dependencies via gating mechanisms [36]	Captures both past and future dependencies [19]
Accuracy in STLF	High accuracy in short-term predictions [20]	Improved accuracy, especially for multi-day/multi-hour forecasts [18]
Model complexity	Moderate; less complex than Bi-LSTM [4]	Higher due to dual-layer structure [42]
Training requirements	Requires tuning and large data [23]	Longer training time and more resources needed [43]
Applicability to real-time data	Suitable for real-time processing [7]	Less practical for real-time use without adaptation [6]
Generalization	May overfit small datasets [37]	More robust with sufficient data [46]

The Bi-LSTM forecasting model improves the LSTM forecasting model by introducing a bidirectional mechanism where one LSTM direction processes the forward sequence, and at the same time the other LSTM processes the backward sequence [11]. This bidirectional structure enhances the ability to capture and process data in two directions, namely past and future, resulting in higher accuracy in the medium- and long-term forecasting process [22]. Based on literature studies [43], data on performance improvements in terms of MAPE reduction of 5–15% were obtained compared to unidirectional LSTM in various regional and industrial data sets. The disadvantage of the Bi-LSTM forecasting model is that it is computationally more expensive than standard LSTM in Table 9 [17], often doubling the parameter size and training time [32]. In addition, in real-time forecasting scenarios where future data is not available [32], the Bi-LSTM model is less practical unless adapted through real-time data fusion or streaming techniques [6].

Table 9. Summary of key research challenges and proposed future solutions

Challenge	Description	Future Direction	References
Data quality & scarcity	Incomplete or noisy data affects learning and accuracy	Data preprocessing, GAN-based augmentation	[35]
Model interpretability	Black-box nature limits trust and adoption in practice	Explainable AI, attention visualization	[39]
Real-time inference	High latency and memory usage of Bi-LSTM	Model compression, edge AI deployment	[42]
Domain transferability	Poor generalization across regions/sectors	Transfer learning, domain adaptation	[33]
Hyperparameter sensitivity	Performance varies significantly with parameter settings	Automated tuning, Bayesian optimization	[23]
Long-term forecast degradation	Accuracy drops in long-term forecasts due to compounding errors	Hybrid LSTM + Transformer or statistical fusion	[47]

Despite substantial progress in electricity load forecasting using LSTM and Bi-LSTM models [48], based on the results of the reference studies conducted [49], there are still critical research gaps that limit the scalability, generalization, and implementation of the approach in the real world [50]. Several areas that are underexplored or inadequately addressed have been identified. These gaps highlight several opportunities for future research to improve the robustness, comparability, and generalizability of load forecasting models. Key issues include the lack of standardized benchmark datasets and evaluation frameworks, limited use of multivariate and contextual variables such as weather, holidays, and socio-economic factors, and insufficient exploration of LTLF. These limitations reduce reproducibility and make objective comparisons between LSTM-based models difficult. Further gaps concern model interpretability, regional adaptability, and real-time implementation. The limited application of explainable AI (XAI), such as SHAP and attention mechanisms, reduces transparency and operator trust, while models trained in specific regions may not generalize well to different networks or consumer patterns. In addition, the computational complexity of Bi-LSTM models presents challenges for real-time and edge deployment, highlighting the need for lightweight approaches such as pruning, quantization, attention distillation, and transfer learning, as further explained in Figure 2.

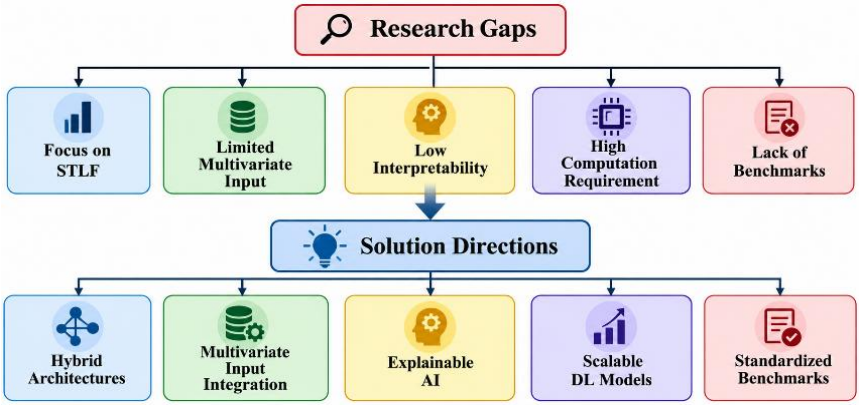

Figure 2. Mapping of research gaps and solution directions

4. CONCLUSION

This systematic literature review examined the application of LSTM and Bi-LSTM models for electricity load forecasting and found that both architectures are capable of representing nonlinear temporal dependencies in electricity-demand data, while hybrid configurations such as convolutional neural network-bidirectional long short-term memory (CNN-BiLSTM), attention-BiLSTM, attention-based convolutional (AC)-BiLSTM, and EMD-BiLSTM have demonstrated promising performance under specific experimental conditions; for example, the reviewed results report MAPE values of 1.52% for CNN-BiLSTM, 1.74% for Attention-BiLSTM, 2.10% for AC-BiLSTM, and 1.83% for empirical mode decomposition (EMD)-BiLSTM, compared with 3.12% for the evaluated standalone LSTM model. However, these results should not be interpreted as evidence of universal superiority of Bi-LSTM or deep-learning models because cross-study comparisons are constrained by differences in datasets, temporal resolution, forecasting horizons, input variables, preprocessing procedures, model configurations, and evaluation metrics; moreover, the literature is predominantly focused on short-term load forecasting, limiting conclusions regarding medium- and long-term applications.

The synthesis further identifies six major challenges comprising the absence of standardized benchmark datasets, limited integration of contextual variables, insufficient model interpretability, limited cross-regional transferability, computational requirements for real-time deployment, and degradation of forecasting reliability over longer horizons. From a practical perspective, LSTM and Bi-LSTM models should therefore be selected according to forecasting objectives, data characteristics, accuracy requirements, and computational constraints rather than architecture alone. Future research should emphasize standardized benchmarking, multivariate contextual inputs, explainable artificial intelligence, transfer learning and domain adaptation, and lightweight architectures through model compression or pruning to improve reproducibility, generalization, interpretability, and real-time applicability in smart-grid and modern power-system operations.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY

The data used to support the research findings are available from the corresponding author upon request.

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