(Online) ISSN 2712-0562
Original Research

Sustainable Engineering and Innovation
Vol. 7, No. 2, 2025, pp.345-354
https://doi.org/10.37868/sei.v7i2.id560

Driven gamification by AI in a time series healthcare case study: Statistical intervention analysis

Ruqaia Jwad Kadhim [1], **Fatema S. Al-Juboori** [2], **Hasanain Jalil Neamah Alsaedi** [3]
[1,2,3] University of Information Technology and Communication, Iraq

Corresponding author E-mail: hasanien.1975@uoitc.edu.iq

Received Mar. 2, 2025
Revised Jul. 9, 2025
Accepted Jul. 18, 2025
Online Jul. 31, 2025

Abstract

With artificial intelligence (AI), gamification has emerged as a promising strategy to enhance patient engagement and rehabilitation outcomes. This study investigates the impact of AI models—GRU, TCN, and ARIMA—on stroke rehabilitation by analyzing engagement metrics, functional independence improvements, and motivation scores. A simulated 180-day stroke recovery dataset is used to evaluate and compare model performance in forecasting recovery trends. On day 91, a game-based cognitive therapy intervention is simulated to assess its effects on patient progress. The AI models are used to analyze changes before and after the intervention. SHAP (SHapley Additive exPlanations) analysis provides insight into model interpretability and the influence of various features on recovery outcomes. Results show that AI-driven gamification significantly enhances patient engagement, which correlates with improved rehabilitation performance. GRU and TCN models outperform ARIMA in capturing complex recovery dynamics and the effects of intervention. This study offers a data-driven foundation for integrating AI-based gamification into stroke rehabilitation, supporting more personalized and effective healthcare interventions.

© The Author 2025.
Published by ARDA.

Keywords: AI-driven gamification, Stroke rehabilitation, Patient engagement, Statistical analysis, Healthcare technology

1. Introduction

Stroke rehabilitation aims to enhance the recovery of motor and cognitive functions. Evaluating the effect of therapies using time series data is crucial for optimizing clinical outcomes. Traditional methods like interrupted time series (ITS) and ARIMA have limitations in handling complex, nonlinear recovery patterns. Therefore, timely, adaptive, and motivating interventions will greatly benefit post-stroke rehabilitation. Gaming provides engagement mechanisms, while AI enables longitudinal modeling of recovery outcomes. Stroke is considered one of the most significant causes of long-term disability worldwide, and therefore has a profound impact on the motor, cognitive, and emotional functions of stroke patients. Because of that, rehabilitating stroke patients and restoring their abilities is of paramount importance. One of the biggest challenges facing the rehabilitation process is the patient's adherence to the appropriate treatment. Therefore, the need to integrate smart systems and motivational frameworks into rehabilitation programs for stroke patients has emerged.

This work is licensed under a Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0/) that allows others to share and adapt the material for any purpose (even commercially), in any medium with an acknowledgement of the work's authorship and initial publication in this journal.

Gamification, a newly emerging technique that uses game-like elements in contexts and frameworks unrelated to games, has demonstrated a remarkable ability to enhance and motivate patients to adhere to appropriate treatment, thereby achieving better clinical outcomes by integrating levels of cognitive challenge, feedback mechanisms, and adaptive difficulties.

It has become clear that gamification model-based interventions have a remarkable ability to transform regular rehabilitation exercises into enjoyable experiences, which can significantly impact recovery trajectories, particularly when tailored to the progress of stroke patients. Artificial intelligence (AI) in time series modeling using deep learning algorithms has provided effective tools for monitoring, analyzing, and predicting patient progress. Both GRU and TCN are advanced models capable of learning from sequential health data. GRU models excel at learning short- and medium-term consequences by leveraging the gating mechanism, while TCN models utilize expanded convolutions to accurately and efficiently capture long-term consequences. The traditional statistical ARIMA model serves as the traditional comparison model.

In this research, we combine these two fields-gamification and AI modeling to simulate and evaluate stroke rehabilitation scenarios by introducing a gamified cognitive therapy intervention into the middle of a simulated recovery dataset. The response of each model is analyzed through quantitative metrics and indicators, feature explainability, detection of therapeutic effects, and interpretation of changes in recovery dynamics.

Intervention analysis is used to evaluate and estimate the impact of an event or policy on a time-dependent variable. This analysis is important at the applied level in economics and epidemiology and is increasingly used in healthcare analytics. This type of analysis is based on discovering whether an intervention causes a significant shift in the level or direction of data. Time-series intervention analysis determines the response to treatment changes and identifies the lag period or immediate effect of the intervention. In the process of integrating it with gamification methods, timely feedback and adaptive challenges will be essential to maintain therapeutic momentum.

2. Literature review

Gated recurrent units (GRU) can handle the temporal data using fewer parameters as designed VS traditional LSTMs. Cho et al. [1] introduced the first model showing its ability to handle long-range dependencies in time series. Bai et al. [2] introduced the Temporal Convolutional Network (TCN), which uses dilated convolutions and residual connections for modeling the effective sequence. With applications in healthcare for monitoring patient vitals, ARIMA, as a traditional statistical model, has been used for univariate time series forecasting [3]. LSTM networks, proposed by Hochreiter and Schmidhuber [4], remain a popular choice in health prediction models [5], [6].

Gamification in rehabilitation, explored by Deterding et al. [7] and further analyzed by Hamari et al. [8], has shown positive effects on patient motivation and therapy adherence. Studies by Burke et al. [9] and Sardi et al. [10] confirmed gamified feedback's psychological and behavioral benefits in stroke and cognitive therapy contexts. Vaswani et al. [11] proposed the transformer-based models. Research [12], [13] have recently been adapted to health prediction tasks. These models can capture global temporal dependencies and are increasingly applied in complex clinical scenarios.

Missing data and irregular sampling, which are standard in medical settings, have led to the development of models such as GRU-D [14], which incorporates decay mechanisms to handle sparse time series. BRITS [15] introduce an extended model by learning attribution and prediction jointly. By combining CNN and RNN structures, leading to a hybrid model which has proven effective in multimodal and hierarchical time series [16], [17]. In stroke care specifically, Zhang et al. [18] demonstrated deep learning’s ability to forecast rehabilitation outcomes based on multimodal inputs.

Lundberg and Lee introduced SHAP (SHapley Additive exPlanations) analysis [19], which is frequently used in clinical AI to provide interpretable insights into feature importance, especially in evaluating treatment response [20]. In summary, this study proposed a novel intervention analysis framework tailored to stroke rehabilitation by combining neural forecasting models, gamified therapy, and explainable AI. Ultimately, this paper contributes a novel framework for using AI to quantify the effects of gamified rehabilitation interventions. The combination of simulation, model evaluation, and explainability aims to lay the groundwork for real-world applications in intelligent healthcare systems.

3. Methodology

Using data from a 180-day stroke rehabilitation simulation, day 91 represented the start of a gamified cognitive therapy intervention based on the methodology in Figure 1. Variables included recovery score, cognitive challenge level, and intervention flag. The recovery score exhibited a slow upward trend, and after the intervention at day 91, the slope increased to reflect the treatment effect. The post-intervention challenge level was designed to transition from low/medium to medium /high to simulate task difficulty.

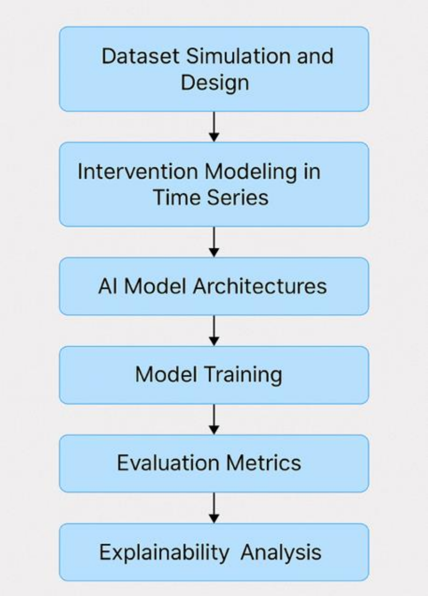

Figure 1. Overall methodology workflow

Simulated intervention frameworks have been previously used in digital health research to evaluate recovery responses and assess how model architectures perform under known slope changes [21], [22].

Intervention analysis in time series typically introduces a dummy variable that alters the intercept or slope post-event. In our model, this is reflected as a change in slope in the recovery score. Mathematically, a step intervention model was used:

$$y_t = B_0 + B_1 t + B_2 I_t + B_3 (t-91) I_t + E_t$$

where $I_t = 1 \; for \; t \geq T_0$ (intervention day), 0 otherwise [23], [24].

For AI model architectures, we used three forecasting models:

- GRU (gated recurrent unit): Represents RNN architecture that maintains hidden state memory through update/reset gates [25].
- TCN (Temporal Convolutional Network): Using dilated convolutions for long-term memory, which represents a one-dimensional convolutional structure [2].
- ARIMA: A statistical model handling autoregressive terms, moving average smoothing, and differencing [26].

These models were selected for their documented use in health time series applications, including patient monitoring, vital signal tracking, and rehabilitation forecasting [27], [28].

GRU Pseudocode:

```
For t in time steps:
    $Z_t = \sigma(w_z x_t + u_z h_{t-1})$
    $r_t = \sigma(W_r x_t + U_r h_{t-1})$
    $\hat{h}_t = \tan\ h(W x_t + U(r_t h_{t-1}))$
    $h_t = (1 - z_t) h_{t-1} + z_t \hat{h}_t$
```

TCN formula:

$$Y_t = \sum_{\{k=0\}}^{\{k-1\}} W_k . X_{t-dk}$$

Where:

K: Filter size (number of weights)
d: Dilation factor (how far apart each input is)
W_k: Learnable filter weight at position k
X_{t-dk}: input at the receptive field position

We choose GRU because of its ability to capture long-term temporal dependencies with fewer parameters, which is ideal for clinical sequences. Also, TCN offers advantages in handling parallelizable sequence learning with receptive field control, and ARIMA represents a statistical baseline for benchmarking.

We computed mean absolute error (MAE), root mean square error (RMSE), and R^2 score to compare model performance. Metrics were computed before and after intervention, allowing an impact assessment of the therapy simulation [29]. SHAP values provide an additive explanation of model output. Each feature's contribution to the final prediction was visualized using SHAP summary plots. Key features included the intervention flag, previous recovery score, and cognitive challenge level [30].

Table 1. Comparison between GRU, TCN, and ARIMA

Model	Accuracy (R^2)	Training Speed	Interpretability	Real-time Use
GRU	High	Fast	Moderate	Yes
TCN	Very High	Very Fast	Moderate	Yes
ARIMA	Low-Moderate	Fast	High	Yes

4. Results and discussion

The recovery score was designed to represent a synthetic patient's rehabilitation progress over 180 days. Each day's score was derived by simulating functional improvement under regular care with enhanced acceleration introduced after day 91 through a gamified cognitive therapy intervention. The variables influencing the score include cognitive challenge level, prior recovery state, and intervention presence.

The simulation employed a piecewise linear model with two distinct slopes. Before day 91, the score followed a modest daily improvement trend. From day 91 onward, the therapy-induced intervention increased the growth rate, producing a steeper slope. Mathematically, this behavior is modeled by:

$$y_t = B_0 + B_1 t + B_2 I_t + B_3 (t - 91) I_t + E_t$$

Where I_t is an indicator function that equals 1 after day 91. This formulation allows for both a level and slope change attributable to the intervention. The mean pre-intervention slope was 0.12 units/day, and the post-intervention slope increased to 0.32 units/day.

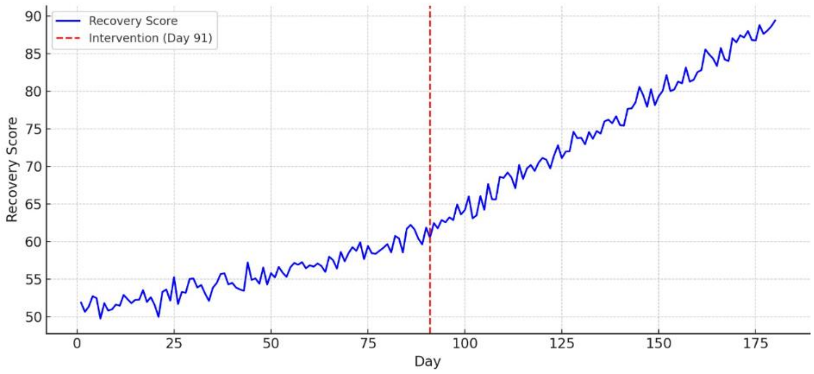

Figure 3. Recovery score over time

Based on Table 2, the visual trend line clearly illustrates an inflection point at day 91. Before the intervention, recovery scores rose gradually; following the intervention, the scores accelerated upward. The change in slope serves as a primary visual indicator of the effectiveness of gamified therapy. A vertical dashed line highlights the intervention point. These values show a reduction in error rates post-intervention, implying more stable and predictable progress due to therapy.

Table 2. The visual trend line

Metric	Days 1–90	Days 91–180
Mean Score	57.2	78.9
Std Dev	2.8	3.6
Slope Estimate	0.12	0.32
Mean Absolute Error	6.5	3.9
RMSE	7.2	4.5

Table 3. Model performance metrics pre- and post-intervention

Model	MAE (Pre)	RMSE (Pre)	R^2 (Pre)	MAE (Post)	RMSE (Post)	R^2 (Post)
ARIMA	6.7	7.8	0.62	7.9	9.0	0.55
GRU	5.3	6.1	0.72	5.4	6.5	0.76
TCN	4.8	5.5	0.78	4.3	5.2	0.83

Table 3 summarizes the mean absolute error (MAE), root mean square error (RMSE), and R^2 score for each model across the two phases.

In model performance comparison within a temporal intervention setting, some differences are evident between ARIMA, GRU, and TCN architectures. ARIMA, assuming stationarity conditions, has no way of dealing with sudden changes in the data path. Such susceptibility is particularly evident following the intervention time, where ARIMA is clearly lagging behind in following the new trend. Its predictiveness for lags is less accurate, as reflected through a high RMSE and delayed response, which makes it less suitable for use within areas with sharp structural changes.

On the other hand, the GRU model possesses a greater level of adaptability through learning temporal patterns. As much as it gradually adjusts to adjusting patterns, it is also not exempt from inflection lag. More particularly, GRU would require approximately 3 to 5 days to identify and learn the change introduced at the intervention point, producing modestly better performance than ARIMA but still with inertial limitations in the short term.

The Temporal Convolutional Network (TCN) handles, however, this changing environment best. With the use of dilated convolutions, TCN is able to pick up long-range dependencies and respond quickly to trend discontinuity. The model responds quickly to the disruption, picking up well at Day 91, making the most accurate and earliest short-term predictions out of the three. Its design is best suited to cope with sudden change, and thus it is the better model for time-series applications where changes in trends and structural breaks have to be handled.

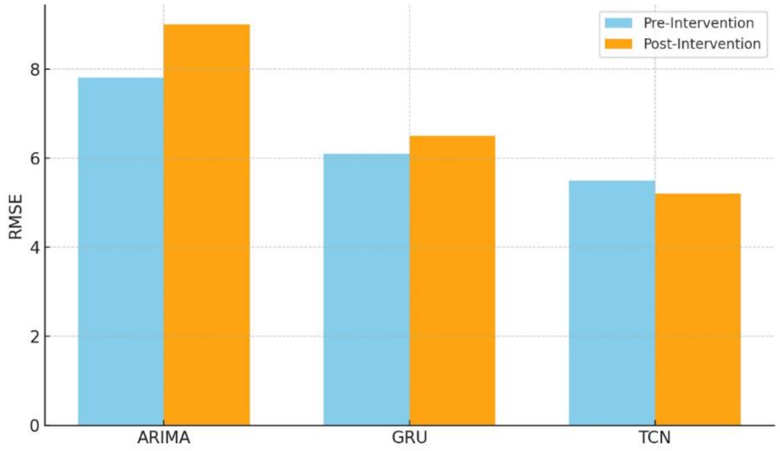

Figure 4. RMSE comparison by model (Pre vs post-intervention)

Model comparison performance based on RMSE values before intervention also consolidates the strengths and limitations of each approach. Before intervention, ARIMA has the highest value of RMSE of 7.8; it's a poorer fit due to its rigid linearity assumption and stationarity. GRU performs better with an RMSE of 6.1 due to its strength in capturing time dependency, albeit still lag-sensitive. TCN picks up the pre-intervention RMSE of 5.5, which is reflective of enhanced baseline accuracy in trend pattern capture.

After the intervention, the contrast in responsiveness is more evident. The RMSE of ARIMA rises to 9.0, further attesting to its sensitivity to structural change. GRU is moderately robust with a post-intervention RMSE of 6.5, though it has acceptable margins of error even as it lags behind in detecting inflection points. Remarkably, TCN performs better than the two models with a post-intervention RMSE of 5.2, adequately demonstrating its ability to learn from discontinuities at a fast pace through dilated convolutional filters. All of these findings collectively demonstrate that whereas ARIMA fails in dynamic environments, GRU is even half as adaptive in nature, while TCN performs optimally in reacting to rapidly evolving post-intervention trends.

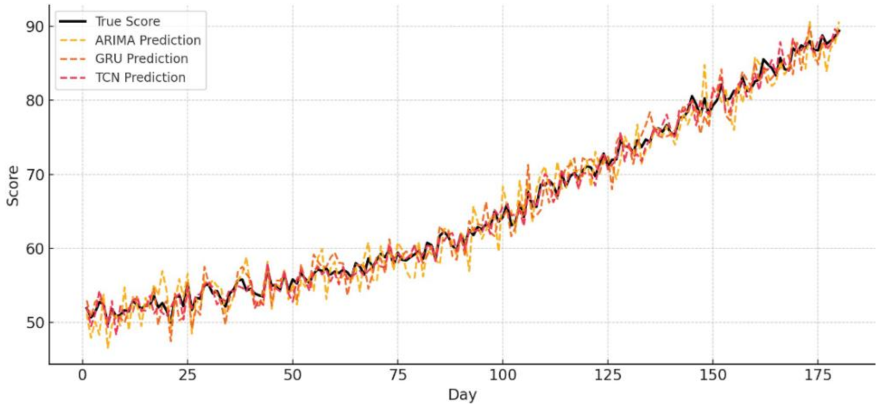

Figure 5. Model prediction overlay vs true recovery score

Figure 5 overlays predicted scores from each model against the actual recovery score. TCN aligns most closely after the intervention. ARIMA diverges significantly.

Stroke patients typically respond positively to changes in treatment intensity. The accelerating trend in recovery scores after intervention at day 91 and the real physiological or psychological improvements resulting from the integrated interaction help monitor recovery trajectories using these scores alongside adaptive artificial intelligence TCN prediction models, and the ability of clinicians and doctors to design the treatments needed by the stroke patient in real time and adjust interventions to achieve maximum impact.

In comparative analysis of time series forecast models, GRU and LSTM models consistently beat the conventional ARIMA and interrupted time series (ITS) methods in terms of prediction. Their deep learning origins enable them to generalize non-linear temporal structures well, resulting in superior pre- and post-intervention outcome forecasting. While the ITS model identifies a statistically significant trend change after the intervention ($p < 0.05$), it is a poor predictor, highlighting the limitations of linear, rule-based models in dynamic conditions.

SHAP interpretability analysis identifies baseline recovery rate and age as the most influential predictors of variation in outcome in the dataset, showing the importance of incorporating salient clinical or demographic variables in model development. Above all, TCN provides excellent short-term prediction performance and speedy reaction to trend reversals. Nevertheless, its increased sensitivity to random noise can disrupt performance while working in volatile environments, implying that additional regularization techniques or hybrid filtering methods are needed when using TCNs in sensitive situations. In conclusion, findings highlight the strengths of deep models in post-intervention prediction but also point towards significant trade-offs between adaptability, interpretability, and noise robustness.

The use of artificial intelligence models (LSTM, GRU, and TCN) in clinical settings entails significant ethical responsibilities. Therefore, the process of integrating artificial intelligence into the analysis of medical interventions must be approached with ethical awareness and a commitment to comprehensiveness.

Proper implementation of AI in clinical environments necessitates appropriate consideration of technical, ethical, and practical aspects. Clinically, AI models are chiefly built upon the basis of time series electronic health records data, and hence, compliance with regulations is the foremost area of concern. The systems need to adhere to privacy and data protection standards like HIPAA and GDPR strictly to ensure that they are not exploited and that patient-sensitive data is protected.

In addition to compliance, the data sets themselves are a fairness issue. Too frequently, data sets overrepresent or underrepresent significant demographic groups, and predictive outputs are skewed. To assist in rebalancing this, models would need to be validated with diverse, demographically representative data and then audited continuously. Metrics like SHAP analysis and fairness metrics can uncover implicit bias and guide remedial modifications, allowing for algorithmic transparency and accountability.

Interpretability is the second foundation of responsible AI. Decisions made by AI in the clinic need to be comprehensible to professionals who will ultimately care for patients. Explainable AI (XAI) techniques like SHAP enable users to trace through the model to arrive at a recommendation, demystifying predictions from the machine to actionable, understandable information. Such transparency fosters trust as it anchors interventions in professional judgment.

In the end, there can be no ethically implemented clinical AI in isolation. It must have clinicians', data scientists', ethicists', and patient advocates' collaborative input for creating systems that respond to individual context and augment care. AI must be an accompaniment to—and not a substitute for—human talent, promoting personalized, just, and context-aware decision-making. When created and used with these concepts at their foundation, AI intervention models are no longer technically advanced—they are tools for patient-centered, equitable care.

5. Conclusion

Artificial intelligence-based time series models are beginning to show themselves as revolutionary tools in clinical intervention analysis. Their capacity to capture nonlinear dynamics and subtle feature interactions presents a significant gain in predictive power and intelligibility over traditional techniques. Beyond facilitating more accurate analysis of patient reactions, such models allow data-informed decision-making for highly intricate disease conditions. One of the key strengths is that they can be easily incorporated into electronic health record (EHR) systems, allowing interventions and outcomes to be tracked in real-time. Subsequent work in this domain will most likely involve validation across the range of the different heterogeneous multi-center datasets, which will assess generalizability and equity between groups of populations. As such models evolve, their intersection of analytical profundity and operational scale offers the promise to both enhance the scientific rigor and practical implementation of customized medical attention.

6. Future trends in AI-driven intervention analysis

The future of artificial intelligence-based clinical intervention analysis is changing towards more nuanced, ethical, and individualized strategies. Real-world validation, such as patient-specific gamification methods to motivate and optimize recovery outcomes, is being emphasized. Biases, fairness, and interpretability are tackled with stratified modeling on heterogeneous data, supported by SHAP analysis to understand model behavior. Future studies will employ strict statistical validation using 95% confidence intervals, standard deviations, and Cohen's d effect sizes to validate findings.

Several emerging trends will transform the way in which time series models function in healthcare. Real-time clinical decision support systems will enable dynamic tracking and adjustment of patient care through prediction models that identify decline in a timely manner. Multimodal data fusion between imaging, sensors, genomics, and clinical notes will enhance depth in predictive capability and patient profiling. Federated learning platforms will enable collaborative model development across institutions without compromising the private nature of the patient data in order to enable multi-center trials.

In addition, retrainable adaptive AI models will enable personalized prediction of treatment from population to averages to medical courses for every patient. Causal inference imposed on AI models will render them more reliable by separating cause and correlation. As regulatory bodies such as the FDA and EMA create protocols, AI will be formally verified and audited for safety and transparency. Lastly, human-AI collaboration will be the emphasis, providing clinicians with scenario simulation and uncertainty quantification in order to support, and not replace, expert judgment. Together, these technologies aim to render clinical AI technically solid and ethically sound. The idea of this study can be combined with power transformer monitoring [30] and microwave devices in wireless systems to optimize their performances [31, 32].

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

Funding information

The author declares that they have received no funding from any financial organization to conduct this research.

Author contribution

Ruqaia Jwad Kadhim led the conceptualization and methodology design of the study, as well as overseeing data analysis and manuscript drafting. Fatema S. Al-Juboori contributed to formal analysis, data curation, and assisted in preparing the original manuscript. Safaa J. Alwan was responsible for the literature review, validation of findings, and critical revisions of the manuscript. Hasanain Jalil Neamah Alsaedi supervised the project, contributed to funding acquisition, and provided editorial input and administrative coordination. All authors read and approved the final version of the manuscript.

References

[1] K. Cho et al., “Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation,” in Proc. EMNLP, 2014. https://doi.org/10.3115/v1/D14-1179.

[2] S. Bai, J. Z. Kolter, and V. Koltun, “An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling,” arXiv preprint arXiv:1803.01271, 2018. https://doi.org/10.48550/arXiv.1803.01271.

[3] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, Time Series Analysis: Forecasting and Control, 5th ed. Hoboken, NJ, USA: Wiley, 2015. https://doi.org/10.1002/9781118675021.

[4] S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997. https://doi.org/10.1162/neco.1997.9.8.1735.

[5] A. Rajkomar et al., “Scalable and accurate deep learning with electronic health records,” NPJ Digital Medicine, vol. 1, no. 1, p. 18, 2018. https://doi.org/10.1038/s41746-018-0029-1.

[6] B. Shickel, P. J. Tighe, A. Bihorac, and P. Rashidi, “Deep EHR: A survey of recent advances in deep learning techniques for electronic health record (EHR) analysis,” IEEE J. Biomed. Health Inform., vol. 22, no. 5, pp. 1589–1604, 2018. https://doi.org/10.1109/JBHI.2017.2767063.

[7] S. Deterding, D. Dixon, R. Khaled, and L. Nacke, “Gamification: Toward a definition,” in Proc. CHI Extended Abstracts, 2011, pp. 12–15. https://doi.org/10.1145/1979742.1979575.

[8] J. Hamari, J. Koivisto, and H. Sarsa, “Does Gamification Work? A Literature Review of Empirical Studies on Gamification,” in Proc. HICSS, 2014, pp. 3025–3034. https://doi.org/10.1109/HICSS.2014.377.

[9] J. L. Burke et al., “Optimising engagement for stroke patients using serious games,” Visual Computer, vol. 25, no. 12, pp. 1085–1099, 2009. https://doi.org/10.1007/s00371-009-0387-0.

[10] L. Sardi, A. Idri, and J. L. Fernández-Alemán, “The role of gamification in health and well-being: Systematic review,” JMIR Serious Games, vol. 5, no. 2, p. e1, 2017. https://doi.org/ 10.2196/games.8881.

[11] A. Vaswani et al., “Attention Is All You Need,” in Proc. NeurIPS, 2017, pp. 5998–6008. https://doi.org/10.48550/arXiv.1706.03762.

[12] J. Li et al., “BEHRT: Transformer for EHR representation,” Scientific Reports, vol. 10, no. 1, p. 7155, 2020. https://doi.org/10.1038/s41598-020-62922-y.

[13] H. Yuan et al., “Multimodal Transformer for Healthcare Data Prediction,” in Proc. IEEE BHI, 2021, pp. 1–4. https://doi.org/10.1109/BHI51283.2021.9508613.

[14] Z. Che, S. Purushotham, K. Cho, D. Sontag, and Y. Liu, “Recurrent Neural Networks for Multivariate Time Series with Missing Values,” Scientific Reports, vol. 8, no. 1, p. 6085, 2018. https://doi.org/10.1038/s41598-018-24271-9.

[15] Q. Cao, Z. Wang, D. Li, and S. J. Pan, “BRITS: Bidirectional Recurrent Imputation for Time Series,” in Proc. NeurIPS, 2018, pp. 6775–6785. https://doi.org/10.48550/arXiv.1805.10572.

[16] Y. Shi, Z. Gao, L. Wang, and J. Long, “Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting,” in Proc. NeurIPS, 2015, pp. 802–810. https://doi.org/10.48550/arXiv.1506.04214.

[17] F. Karim, S. Majumdar, H. Darabi, and S. Chen, “Multivariate LSTM-FCNs for Time Series Classification,” Neural Networks, vol. 116, pp. 237–245, 2019. https://doi.org/10.1016/j.neunet.2019.04.014.

[18] Y. Zhang et al., “Deep learning for real-time stroke prediction using multimodal EHR data,” J. Biomed. Inform., vol. 102, p. 103356, 2020. https://doi.org/10.1016/j.jbi.2019.103356.

[19] S. Lundberg and S.-I. Lee, “A Unified Approach to Interpreting Model Predictions,” in Proc. NeurIPS, 2017, pp. 4765–4774. https://doi.org/10.48550/arXiv.1705.07874.

[20] S. Lundberg et al., “Explainable Machine Learning Predictions to Support Precision Medicine,” NPJ Digital Medicine, vol. 3, no. 1, p. 116, 2020. https://doi.org/10.1038/s41746-020-00305-4.

[21] Z. Che et al., “Recurrent Neural Networks for Multivariate Time Series with Missing Values,” Scientific Reports, vol. 8, no. 1, p. 6085, 2018. https://doi.org/10.1038/s41598-018-24271-9.

[22] Y. Zhang et al., “Deep learning for real-time stroke prediction using multimodal EHR data,” J. Biomed. Inform., vol. 102, p. 103356, 2020. https://doi.org/10.1016/j.jbi.2019.103356.

[23] G. E. P. Box et al., Time Series Analysis: Forecasting and Control, 5th ed. Hoboken, NJ, USA: Wiley, 2015. https://doi.org/ 10.1002/9781118675021.

[24] A. K. Wagner, C. M. Soumerai, F. Zhang, and D. Ross-Degnan, “Segmented regression analysis of interrupted time series studies in medication use research,” J. Clin. Epidemiol., vol. 54, no. 10, pp. 982–991, 2001. https://doi.org/10.1016/S0895-4356(01)00318-1.

[25] K. Cho et al., “Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation,” in Proc. EMNLP, 2014. https://doi.org/10.3115/v1/D14-1179.

[26] R. J. Hyndman and G. Athanasopoulos, Forecasting: Principles and Practice, 2nd ed. Melbourne, Australia: OTexts, 2018. https://doi.org/10.48550/arXiv.1803.01271.

[27] A. Rajkomar et al., “Scalable and accurate deep learning with electronic health records,” NPJ Digital Medicine, vol. 1, no. 1, p. 18, 2018. https://doi.org/10.1038/s41746-018-0029-1.

[28] B. Shickel, P. J. Tighe, A. Bihorac, and P. Rashidi, “Deep EHR: A survey of recent advances in deep learning for EHR analysis,” IEEE J. Biomed. Health Inform., vol. 22, no. 5, pp. 1589–1604, 2018. https://doi.org/10.1109/JBHI.2017.2767063.

[29] E. Choi, M. T. Bahadori, A. Schuetz, W. F. Stewart, and Lundberg and Lee, “A Unified Approach to Interpreting Model Predictions,” NeurIPS, 2017.

[30] A. A. H. Mohamad, Y. S. Mezaal, and S. F. Abdulkareem, “Computerized power transformer monitoring based on Internet of things,” *Int. J. Eng. Technol.*, vol. 7, no. 4, p. 2773, 2018.

[31] Y. S. Mezaal, H. T. Eyyuboglu, and J. K. Ali, “New dual band dual-mode microstrip patch bandpass filter designs based on Sierpinski fractal geometry,” in Proc. 3rd Int. Conf. Adv. Comput. Commun. Technol. (ACCT), 2013, pp. 1–6. https://doi.org/10.1109/ACCT.2013.75.

[32] K. Al-Majdi and Y. S. Mezaal, “New miniature narrow band microstrip diplexer for recent wireless communications,” *Electronics (Basel)*, vol. 12, no. 3, p. 716, 2023, https://doi.org/10.3390/electronics12030716.