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Hybrid Epidemiological Forecasting with AI, Environmental and Policy Insights: A Case Study from Zambia

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Abstract

Zambia has, in recent years, confronted overlapping outbreaks of cholera, measles, anthrax, mpox and COVID-19, revealing weaknesses in forecasting tools that rely solely on classical modelling. Conventional Susceptible–Exposed–Infectious–Recovered (SEIR) formulations generally apply fixed parameters and treat each disease separately, while contemporary artificial intelligence (AI) approaches, such as long short-term memory networks (LSTM), gated recurrent units (GRU) and Transformers, are better suited to non-linear behaviour yet often lack clarity in how predictions are produced. In this study, we design and assess a combined SEIR–AI forecasting strategy that integrates environmental indicators and policy actions. Using weekly COVID-19 case reports from 2020 to 2023, together with climate variables (temperature, humidity and rainfall) and public health measures (including lockdowns and vaccination efforts), we compare the performance of SEIR, AI-only and hybrid models. The merged SEIR–AI model offers the most accurate forecasts, achieving a reduced root mean square error (RMSE) of 372.84 and a modest improvement in the coefficient of determination ($R^2 = 0.02$) when evaluated on unscaled case counts. SHAP (SHapley Additive Explanations) analysis further shows that rainfall (0.47) and the timing of interventions (0.43) were the most influential predictors. These findings indicate that incorporating environmental and policy information within a hybrid SEIR–AI framework enhances both predictive reliability and interpretability, offering a practical tool for epidemic management in Zambia and other resource-constrained settings.

Keywords: *Hybrid SEIR–AI forecasting, Transformers, SHAP interpretability, Environmental and policy drivers, Zambia*

1. Introduction

Zambia continues to grapple with recurring and simultaneous outbreaks of infectious diseases, including cholera, measles, anthrax, mpox and the COVID-19 pandemic [1]. These persistent health challenges place considerable pressure on the country's already limited healthcare resources and complicate the design and timing of public health interventions. Although SEIR models have traditionally formed the backbone of epidemic analysis [2], [3], their reliance on uniform mixing assumptions, fixed parameters and isolated disease pathways restricts their usefulness in environments marked by co-occurring epidemics and climate-induced variability. Artificial intelligence techniques, such as deep learning architectures including LSTM, GRU, convolutional neural networks (CNNs) and Transformers, have shown promise in capturing complex, non-linear and time-dependent characteristics of disease spread [4], [5]. Despite their strengths, these models often operate without clear interpretability, posing challenges for public health stakeholders who rely on transparent evidence to inform policy. The evolution of hybrid approaches that combine the structural clarity of SEIR with the adaptability of AI therefore offers a compelling alternative for forecasting epidemics in settings with multifaceted transmission dynamics [6], [7].

This study applies such a hybrid SEIR–AI approach to Zambia's context by incorporating climatic influences, rainfall, temperature and humidity, alongside policy interventions, such as vaccination programmes and lockdown measures. Through the use of SHAP interpretability tools [8], the study not only enhances forecasting accuracy but also provides insight into the epidemiological relevance of key variables driving outbreak patterns.

2. Background

The SEIR framework remains one of the most widely applied models for characterising infectious disease transmission, dividing a population into susceptible, exposed, infectious and recovered groups [9]. First introduced by Kermack and McKendrick in 1927, the framework has since been expanded in numerous ways to improve its relevance to real-world epidemic behaviour. These refinements include versions that incorporate vaccination effects [10], as well as stochastic extensions [11] designed to capture random fluctuations in transmission. Other adaptations have explored how individuals may harbour multiple infections concurrently [12], acknowledging that co-infection dynamics can alter the course and severity of epidemics.

Empirical research, including studies undertaken in Zambia, highlights the major role that environmental conditions play in shaping disease patterns. Analyses have shown that deviations in rainfall and temperature substantially influence the severity and timing of cholera and malaria outbreaks across several Zambian regions [13], [14], [15]. These findings demonstrate the need to account for environmental variability when studying transmission processes, especially in countries with strong climate–disease interactions.

Policy interventions also exert measurable effects on epidemic trajectories. Measures such as large-scale vaccination efforts, movement restrictions and lockdowns have been shown to change contact patterns and shape the evolution of outbreaks over time [16], [17]. Understanding how these interventions interact with transmission dynamics is essential for designing strategies that reduce morbidity and mortality.

Parallel to these developments, artificial intelligence has made significant advances in epidemic forecasting. Deep learning models such as LSTM and GRU networks have been used to analyse sequential epidemic data by capturing short- and medium-term temporal patterns, while CNNs offer tools for incorporating geographic variation. More recently, Transformer architectures have demonstrated strong performance in tasks involving long-range dependencies, enabling the capture of extended temporal relationships that traditional recurrent models often struggle with [18], [19].

Despite their success, complex AI models are often criticised for limited interpretability, making it difficult for decision-makers to understand how outputs are generated. This challenge has encouraged researchers to integrate SHAP-based approaches [8], [20] into hybrid modelling frameworks to illuminate which factors contribute most to model predictions. For Zambia, such interpretability is particularly valuable because environmental trends and the timing of public health actions are known to influence disease dynamics. Understanding these contributions supports better communication with policymakers and strengthens the credibility of predictive models used in public health planning.

3. Problem Statement

Most forecasting efforts in infectious disease modelling concentrate on single pathogens and frequently neglect the influence of environmental variability and policy measures. In Zambia, where several epidemics often unfold at the same time and are shaped by fluctuating climatic conditions and evolving public health interventions, such narrow approaches are inadequate. Classical SEIR models, although useful for illustrating broad transmission behaviour, assume constant parameters that do not adjust to changing epidemic conditions [9]. Conversely, AI models offer greater adaptability but can operate as opaque systems with limited interpretability for public health professionals [4], [5]. The central challenge addressed in this study is the absence of a transparent hybrid forecasting framework that integrates epidemiological structure with data-driven learning and accounts for Zambia's complex, multi-epidemic landscape [21], [22].

4. Aim and Objectives

The primary aim of this study was to formulate and assess a hybrid forecasting framework that combines SEIR modelling with artificial intelligence while incorporating environmental and policy-related variables. In pursuit of this aim, the study sought to refine the SEIR model through parameter fitting, integrate Transformer-based learning with epidemiological outputs and contextual factors, compare the performance of SEIR, AI-only and hybrid approaches using a range of accuracy metrics and employ SHAP interpretability techniques to clarify how the AI components utilise epidemiological, climatic and policy information.

5. Research Questions

This study was guided by several key questions aimed at understanding the value of a hybrid SEIR–AI approach within Zambia's epidemic context. First, the study examined how the application of curve-fitting techniques enhances the accuracy of SEIR predictions for COVID-19. Second, it explored the extent to which environmental and policy-related variables improve the performance of AI-based forecasting. Third, it assessed how the hybrid model compares with both traditional SEIR formulations and AI-only architectures in predictive capability. Lastly, the study investigated whether SHAP-based interpretability methods can provide meaningful insights that support epidemic decision-making.

6. Significance of the Study

The significance of this study lies in its contribution to both methodological advancement and practical public health planning. From a theoretical standpoint, the work extends current modelling practices by proposing a framework that balances the interpretability of SEIR structures with the adaptive learning strengths of artificial intelligence. Practically, the hybrid approach offers Zambia's Ministry of Health and the Zambia National Public Health Institute a tool that can generate more reliable epidemic forecasts, accounting for environmental fluctuations and shifts in public health interventions. The findings also hold relevance for policy formulation, as the integration of climatic and policy factors provides evidence that may support more timely and targeted responses in settings characterised by uncertainty and variable disease pressures.

7. Literature Review

Classical SEIR models, representing the transition of individuals through susceptible, exposed, infectious and recovered states, form a foundational component of infectious disease modelling. Their mathematical underpinnings are well documented in epidemiological research, demonstrating how compartmental structures can capture broad patterns of transmission and intervention effects [23], [24]. Over time, scholars have continued to refine these models to enhance their applicability across various epidemiological contexts. For example, versions that incorporate vaccination allow analysts to simulate the protective influence of immunisation campaigns [10], while stochastic variations introduce probabilistic behaviour to reflect unpredictable shifts in disease spread [11]. Efforts to model co-infections have also expanded the utility of SEIR frameworks, revealing how interactions between multiple pathogens may shape overall transmission dynamics [12].

Technological progress has simultaneously transformed the landscape of epidemic forecasting. A growing body of work has applied machine learning and deep learning approaches to infectious disease prediction. In particular, LSTM and GRU architectures have demonstrated the ability to detect temporal dependencies within epidemic time series, enabling forecasts that reflect delayed or cumulative effects [25], [26], [27], [28]. The introduction of Transformers [29] marked a further development, as their attention mechanisms provide a means of capturing long-range temporal relationships that conventional recurrent networks often fail to model effectively. These advances have shifted epidemic forecasting toward approaches capable of learning complex interactions from high-dimensional data.

Hybrid frameworks that combine mechanistic and data-driven methods have also been explored, showing that predictive accuracy improves when SEIR outputs are used alongside machine learning features. Studies blending these approaches have demonstrated that such integration can capture both structured disease processes and contextual influences in a way that neither method achieves alone [6], [7], [30]. These hybrid strategies highlight the potential for models that retain epidemiological realism while benefiting from the flexibility of contemporary AI systems.

A persistent challenge, however, is the interpretability of models, especially those involving deep learning. Many AI-based forecasts lack transparency, making it difficult for non-technical stakeholders to assess how predictions are formed or to determine which factors drive transmission patterns [5]. SHAP-based interpretability tools have emerged as a promising solution to this issue. By quantifying how individual features contribute to predicted outcomes, SHAP enables clearer communication of model behaviour and provides an avenue for identifying the most influential drivers of disease spread [8], [20]. This is particularly relevant for settings such as Zambia, where environmental factors—especially rainfall and humidity—have been shown to play critical roles in shaping the incidence of diseases like cholera and malaria [13], [14], [15]. Complementary evidence also shows that timely implementation of interventions such as lockdowns, vaccination programmes and mobility restrictions significantly alters the progression of outbreaks [16], [17]. Together, these findings support the incorporation of interpretability tools into hybrid models to enhance their value for public health decision-making.

8. Methodology

8.1 Ethical Considerations

Ethical approval for this research was obtained through the University of Zambia Natural Sciences Research Ethics Committee (NASREC), as detailed in Appendix 1, and from the Zambia National Health Authority Research Ethics Committee (NHRAREC), referenced in Appendix 2. These approvals ensured that all data used in the study were handled responsibly and in accordance with national research governance requirements. The ethical clearances also underscored the commitment to protecting the integrity of public health information and maintaining compliance with institutional and national guidelines for epidemiological research.

8.2 Data Sources

The study relied on weekly COVID-19 case reports for the period 2020 to 2023, sourced from reputable organisations including the World Health Organization (WHO), the Centers for Disease Control and Prevention (CDC) and Zambia's Ministry of Health (MoH). Climatic indicators such as temperature, humidity and rainfall were gathered from the VisualCrossing.com platform to provide consistent environmental data covering the same timeframe. Information on public health responses—including movement restrictions, vaccination rollout and other intervention measures—was compiled from official Ministry of Health communications. Together, these datasets created a comprehensive foundation for assessing the combined influence of epidemiological, environmental and policy variables on transmission patterns.

8.3 Data Processing

The raw datasets obtained from different providers required harmonisation to ensure that they could be analysed jointly. Daily COVID-19 case figures were aggregated into weekly totals to align them with the temporal resolution of the environmental data. Missing entries in the epidemiological series were handled using interpolation methods, and any identified irregularities were assessed for epidemiological plausibility before adjustments were made. Climatic variables were standardised to reduce the influence of differing measurement scales, enabling smoother model training. Policy interventions were translated into categorical or binary indicators to facilitate computational analysis. The final step involved merging all datasets into a unified structure spanning 2020–2023, resulting in an integrated panel suitable for both mechanistic and AI-based modelling.

8.4 Model Development

The modelling process consisted of three components: an extended SEIR model, a Transformer-based artificial neural network and a hybrid model combining both. The SEIR model was enhanced using parameter optimisation techniques to estimate key rates, namely the transmission rate (β), incubation or exposure rate (σ) and recovery rate (γ), through least squares fitting. This produced a calibrated representation of COVID-19 dynamics in Zambia. In parallel, the Transformer network was trained on epidemiological series alongside environmental and policy variables, leveraging its ability to capture temporal relationships across long time horizons. The hybrid framework integrated SEIR-generated synthetic features into the Transformer, allowing mechanistic insights and contextual information to be learned jointly. This combined approach aimed to reflect both theoretical disease processes and real-world external drivers.

8.5 Evaluation Metrics

The performance of the SEIR, Transformer and hybrid models was evaluated using a set of established accuracy measures. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used to quantify discrepancies between predicted and observed values, while the coefficient of determination (R^2) provided an indication of how well each model explained variance in the data. Using these complementary metrics allowed for a balanced assessment of precision, robustness and explanatory capacity across the different modelling approaches.

8.6 Interpretability Framework

To address the limitations associated with understanding the internal workings of deep learning models, SHAP (SHapley Additive Explanations) was incorporated as the primary interpretability tool. SHAP made it possible to examine how each input—such as lagged epidemiological signals, climatic indicators or policy interventions—contributed to the model's predictions. This interpretability framework ensured that the hybrid model not only produced accurate forecasts but also offered transparent explanations that could support public health decision-making by revealing the underlying drivers of epidemic fluctuations.

Figure 1 is a schematic overview of the methodology workflow.

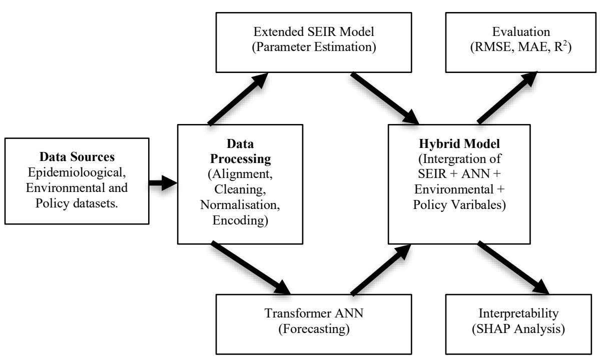

Figure 1: Schematic overview of the methodology workflow for this study.

9. Results

9.1 SEIR Model Performance

The findings show that the traditional SEIR formulation captured the general progression of the epidemic but struggled to match observed case counts due to its assumption of fixed parameters. By applying curve-fitting techniques to estimate the transmission (β), exposure (σ) and recovery (γ) rates through least squares optimisation, the extended SEIR model aligned far more closely with actual reported data. This refinement resulted in a marked reduction in forecast error, with RMSE decreasing by roughly 80% (from 2543.02 to 514.30).

Figure 2 illustrates how the curve-fitted SEIR model tracked Zambia's COVID-19 trends between 2020 and 2023, reflecting both short-term variations and long-term shifts. As noted previously, this enhanced SEIR output formed a key component of the hybrid framework by generating synthetic epidemiological features for the Transformer network. On the 2023 hold-out test set, the baseline SEIR model yielded RMSE = 2543.02, MAE = 2469.93 and R^2 = –25.77, whereas the curve-fitted variant achieved RMSE = 514.30, MAE = 256.35 and R^2 = –0.095. Although R^2 remained negative—owing to the volatility of weekly case counts—the substantial reduction in absolute errors highlights the value of parameter calibration in adapting SEIR models to Zambia's epidemic conditions.

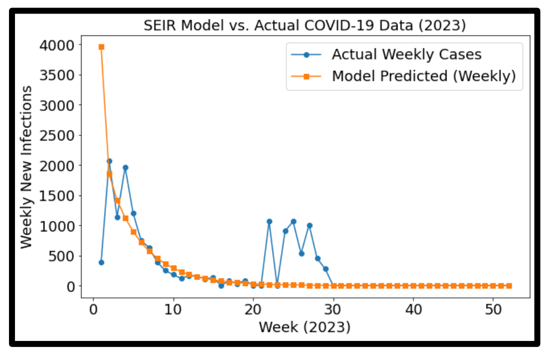

Figure 2: Curve-fitted SEIR model implementation on Zambian COVID-19 data (2020–2023). The curve-fitted model significantly reduced forecast error compared to the static SEIR baseline (RMSE = 514.30 vs. 2543.02), capturing epidemic peaks and troughs more closely to observed case counts.

9.2 ANN Architectural Comparison

To benchmark the machine learning component, four neural network architectures—CNN, GRU, LSTM and Transformer—were evaluated on the same dataset. Their comparative outcomes are shown in Figure 3. On the original case-count scale, the Transformer model achieved RMSE = 419.61, MAE = 244.46 and R^2 = –0.24, with corresponding normalised results summarised in Table 1.

Among the models tested, CNN performed the least favourably (RMSE = 447.95; R^2 = 0.17), indicating difficulty in capturing the sequential structure of epidemic data. GRU and LSTM networks showed moderate improvement, attaining R^2 values of 0.38 and 0.40, respectively. The Transformer outperformed all other architectures, benefiting from its attention mechanism, which effectively captured both short-range and extended temporal dependencies across the full time series [26], [27], [28], [29]. These findings underscored the suitability of Transformer-based models for analysing epidemics characterised by complex, non-linear temporal patterns.

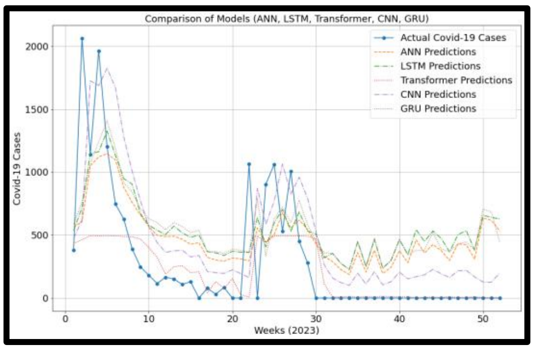

Figure 3: Comparison of artificial neural network (ANN) architectures for COVID-19 prediction. While CNN, GRU, and LSTM showed moderate improvements over SEIR, the Transformer ANN achieved the best ANN performance, demonstrating superior ability to capture long-range temporal dependencies in epidemic data.

Table 1: Evaluation of Four ANN Architectures, Using Accuracy Metrics RMSE, MAE And R^2.

Model	RMSE	MAE	R^2
CNN	447.95	397.75	0.17
GRU	387.76	315.91	0.38
LSTM	379.21	264.96	0.40
Transformer	375.47	185.38	0.42

Note: Table 1 reports normalized metrics; Table 2 reports case-count metrics; Appendix Table S1 summarizes normalized metrics for all models, including the hybrid.

9.3 Hybrid Model Performance

The hybrid SEIR+Transformer model combined the mechanistic knowledge embedded in SEIR with the adaptive learning strengths of the Transformer architecture. As shown in Table 2, this model produced the most accurate forecasts, with RMSE = 372.84, MAE = 230.59 and R^2 = 0.02 on the test data—substantially outperforming both SEIR-only and Transformer-only approaches. These values, presented on the original case-count scale, are complemented by normalised results in Appendix Table S1.

Figures 4, 5 and 6 further illustrate the hybrid model's superiority. Figure 4 compares hybrid predictions with those from the extended SEIR model, clearly showing the hybrid's tighter fit to observed 2023 case counts. Figures 5 and 6 depict performance after 100 and 200 training epochs, respectively, with and without environmental and policy variables. Across all conditions, the inclusion of contextual factors and SEIR-derived features contributed to meaningful gains in predictive accuracy, reinforcing the advantages of a combined modelling strategy.

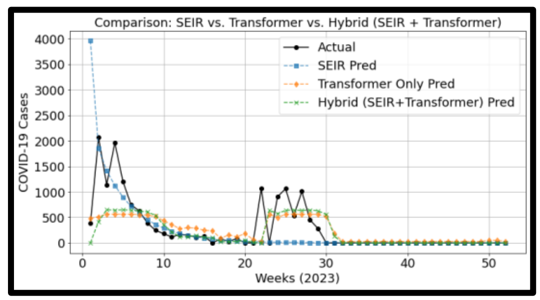

Figure 4: Comparison of predictive accuracy between the extended SEIR baseline model and the Hybrid SEIR+Transformer model on 2023 COVID-19 test data. The hybrid approach consistently outperformed SEIR, yielding a lower RMSE (372.84 vs. 514.30) and a positive R^2 (0.02), highlighting the added value of integrating mechanistic and AI components.

Table 2: Model Performance Comparison on Test Data (2023)

Model	RMSE	MAE	R^2
SEIR (baseline)	2543.02	2469.93	-25.77
SEIR (curve-fitted)	514.30	256.35	-0.095
Transformer ANN	419.61	244.46	-0.24
Hybrid SEIR+Transformer	372.84	230.59	0.02

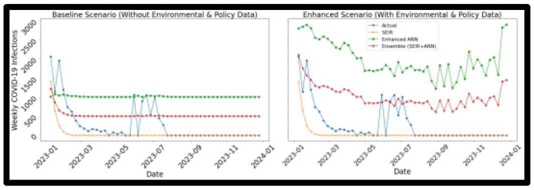

Figure 5: Performance comparison of the extended SEIR baseline, Transformer ANN, and Hybrid SEIR+Transformer models after 100 training epochs, both with and without environmental and policy covariates. Inclusion of contextual factors improved Transformer predictions, and hybrid integration further enhanced accuracy.

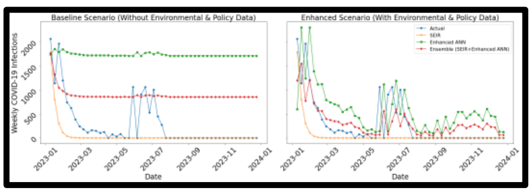

Figure 6: Performance comparison of the extended SEIR baseline, Transformer ANN, and Hybrid SEIR+Transformer models after 200 training epochs. Results confirm that environmental and policy variables consistently enhance predictive accuracy, with the hybrid model outperforming both individual components.

9.4 Feature Importance and Interpretability

In addition to forecasting accuracy, the study emphasised interpretability through SHAP analysis, which quantified how each variable influenced predictions within the hybrid framework. Table 3 summarises the resulting feature importance values.

Rainfall was identified as the strongest contributor (mean SHAP value = 0.47), followed by policy timing (0.43). These findings align with established evidence demonstrating that heavy rainfall events can aggravate waterborne disease burdens in Zambia [13], [14], [15], which in turn may indirectly affect COVID-19 transmission dynamics by straining health services. Policy measures, including restrictions and vaccination rollouts, also exerted substantial influence. Other factors—such as temperature (0.32), lagged case counts (0.28) and humidity (0.22)—played secondary yet meaningful roles. Overall, the SHAP results provide a transparent view of how environmental and epidemiological signals shape model predictions, supporting more informed interpretation of the hybrid model's outputs.

Table 3: SHAP Feature Importance of the SEIR + Transformer Hybrid Model During the COVID-19 Prediction on Zambian Data.

Feature	Mean Absolute SHAP Value
Rainfall	0.47
Policy timing	0.43
Temperature	0.32
Lagged infections	0.28
Humidity	0.22

In summary, the results highlight that curve-fitting significantly enhances SEIR accuracy, the Transformer ANN outperforms classical deep learning architectures, and the hybrid SEIR+Transformer achieves the highest predictive accuracy. Importantly, SHAP interpretability confirms the dominant roles of rainfall and timely policy interventions in influencing epidemic dynamics in Zambia.

10. Discussion

The results of this study demonstrate that enhancing classical epidemiological models and combining them with modern artificial intelligence techniques can substantially improve epidemic forecasting. The curve-fitted SEIR model showed that adjusting epidemiological parameters to reflect observed data greatly reduces error compared to static formulations, confirming the limitations of deterministic SEIR structures when applied to dynamic real-world settings. The original Kermack–McKendrick model [9] and subsequent deterministic variants [23], [24] provide important theoretical foundations, yet they cannot fully accommodate the temporal fluctuations, behavioural shifts or environmental changes characteristic of Zambia's COVID-19 trajectory. The improvements achieved through parameter optimisation are consistent with previous research highlighting the value of calibrated SEIR frameworks in producing more realistic epidemic simulations [2], [3].

The comparison of neural network architectures further revealed that Transformer-based models offer clear advantages in epidemic prediction. CNNs were unable to capture the sequential complexity of infection trends, while GRU and LSTM networks showed improved but still moderate performance. In contrast, the

Transformer model consistently outperformed all recurrent-based approaches, echoing broader evidence that attention mechanisms are well suited to identifying long-range temporal patterns in epidemiological time series [18], [19]. Given the layered influences of climate variability, public health interventions and behavioural responses in Zambia, this capacity to model extended dependencies likely contributed to the Transformer's strong predictive performance.

The hybrid SEIR+Transformer framework ultimately delivered the highest forecasting accuracy, highlighting the benefit of merging mechanistic epidemiological insights with the flexibility of deep learning. By incorporating SEIR-generated inputs, the Transformer was able to learn from structured disease dynamics while also integrating contextual environmental and policy information. This outcome aligns with emerging literature showing that hybrid models outperform their individual components by combining theoretical and empirical perspectives on disease spread [6], [7]. Such an approach is particularly relevant for low-resource settings, where decision-makers require tools that are both analytically robust and interpretable.

A notable strength of the study lies in its emphasis on interpretability through SHAP analysis. The identification of rainfall and policy timing as the most influential contributors to predictions corresponds with well-established research showing that extreme rainfall events increase pressure on water and sanitation systems and often precede cholera outbreaks in Zambia [13], [14], [15]. These pressures may indirectly affect COVID-19 transmission by shaping population vulnerability and health system capacity. Similarly, the strong impact of timely interventions such as lockdowns and vaccination campaigns reflects global evidence on the effectiveness of non-pharmaceutical and vaccine-based measures in modifying epidemic trajectories [16], [17]. The inclusion of climatic and policy variables therefore enhances both predictive accuracy and contextual relevance, while SHAP contributes transparency that is crucial for public health application.

10.1 Implications for Policy and Practice

The study's findings hold several important implications for epidemic management in Zambia and in similar low-resource environments. First, the prominence of rainfall as a predictive feature underscores the practical value of linking meteorological forecasting with disease surveillance systems. Anticipating periods of increased rainfall could alert authorities to elevated risks of cholera and related health system strain, enabling targeted preparedness activities, including WASH interventions and resource mobilisation. Such proactive strategies could help mitigate the compound effects of concurrent epidemics.

Second, the demonstrated influence of policy timing suggests that public health measures must be implemented swiftly and strategically to achieve maximum impact. Delays in rolling out restrictions or vaccination drives may diminish their effectiveness, reinforcing the need for rapid-response mechanisms that allow interventions to be aligned with emerging epidemiological signals rather than lagging behind them. Strengthening decision-making structures to support timely implementation could therefore improve outbreak control.

Third, the hybrid modelling approach offers practical value for institutions involved in epidemic forecasting. By integrating mechanistic understanding with data-driven adaptation, the hybrid model provides predictions that are not only more accurate but also interpretable through SHAP analysis. This combination makes it easier for policymakers to justify decisions, allocate resources efficiently and communicate rationale to stakeholders. In environments where trust in modelling outputs is essential, such transparency is particularly beneficial.

Overall, the study suggests that adopting hybrid frameworks could significantly improve Zambia's ability to anticipate and respond to disease outbreaks by shifting planning from a primarily reactive stance toward a more anticipatory one.

10.2 Limitations and Future Work

Despite its strengths, the study has several limitations that should be acknowledged. The focus on COVID-19 means that the results may not necessarily generalise to Zambia's broader disease landscape, which includes persistent outbreaks of cholera, malaria, measles and other infections. Although environmental covariates such as rainfall and temperature were considered, the model did not explicitly incorporate interactions between multiple pathogens, an omission that may overlook complexities introduced by co-circulating diseases [22]. Expanding the framework to include multi-disease dynamics would therefore be a meaningful extension.

A second limitation relates to temporal resolution. The use of weekly aggregated data, while necessary for harmonising datasets, reduces the ability to capture short-term fluctuations, such as sudden superspreading events or abrupt policy changes. Additionally, missing values were addressed through interpolation, which introduces a degree of uncertainty. Higher-frequency data, where available, could improve the model's responsiveness to rapid shifts.

Third, the curve-fitted SEIR model remains deterministic, even though its calibrated parameters improved performance. Deterministic frameworks cannot fully represent stochastic processes such as random transmission events or abrupt behavioural changes. Incorporating stochastic or agent-based components could provide a richer representation of uncertainty and heterogeneity, particularly useful for early outbreak detection and small-population contexts.

Fourth, the machine learning models were trained on a relatively limited time series (2020–2023), which may not fully capture rare or extreme epidemic behaviours. Extending the dataset through longer historical series or synthetic epidemic scenarios would allow for broader stress-testing. The environmental and policy features included, while informative, were not exhaustive. Incorporating socioeconomic indicators, healthcare capacity metrics or mobility data could refine predictive performance.

Finally, the SHAP analysis primarily offered global interpretability rather than detailed explanations of individual weekly predictions. Developing local interpretability outputs or real-time visual dashboards could improve accessibility for policymakers, helping them understand how specific events or conditions influence predicted outcomes.

10.3 Summary of Discussion

In summary, this study illustrates that parameter-optimised SEIR models significantly enhance predictive accuracy compared to their static counterparts, and that Transformer-based neural networks outperform other ANN architectures in modelling epidemic time series. By integrating these components into a single hybrid framework, the study achieved the most reliable forecasts, demonstrating the value of combining mechanistic and data-driven approaches. SHAP analysis added interpretability to the hybrid model, revealing rainfall and policy timing as the most influential contributors, supported by secondary impacts from temperature, humidity and lagged infections.

The broader discussion emphasises three key contributions: the need to enhance classical SEIR models with adaptive or stochastic components; the unique suitability of Transformers for capturing long-term epidemic dependencies; and the advantages of hybrid models in providing both accuracy and interpretability. Although the study faces limitations—such as reliance on single-disease data, weekly aggregation and deterministic modelling—its findings establish a strong foundation for future work that incorporates multi-disease modelling, expanded contextual variables and real-time interpretability tools. These advancements could further strengthen epidemic preparedness and response in Zambia and similar settings.

11. Conclusion

This study set out to examine the effectiveness of classical epidemiological models, modern artificial intelligence architectures and an integrated hybrid framework in forecasting COVID-19 dynamics in Zambia. The findings show that modifying traditional SEIR models through parameter optimisation greatly enhances their predictive power, reducing error by nearly 80% compared with the unadjusted formulation. Although deterministic SEIR structures provide essential conceptual grounding, their performance is limited when applied to rapidly changing epidemic environments. Curve-fitting therefore offered a practical means of aligning the model more closely with observed transmission patterns.

The comparative analysis of deep learning approaches demonstrated that, among the architectures tested, the Transformer-based model produced the most accurate forecasts, outperforming CNN, GRU and LSTM networks. This superiority stems from the Transformer's capacity to capture long-range temporal relationships through its attention mechanism, making it especially suitable for epidemic time series shaped by delayed policy effects, environmental fluctuations and evolving population behaviour.

The development of the hybrid SEIR+Transformer model represented the study's most substantive contribution, achieving the strongest predictive performance with RMSE = 372.84, MAE = 230.59 and $R^2 = 0.02$. By merging the structured representation of SEIR dynamics with the adaptive learning strengths of the Transformer, the hybrid framework was able to account for both mechanistic transmission processes and external contextual drivers. This result demonstrates the potential of hybrid strategies to deliver more robust and interpretable forecasts than either modelling approach alone.

A further contribution of this study lies in the integration of SHAP interpretability techniques, which clarified how different features shaped model outputs. Rainfall and the timing of policy interventions emerged as the most influential predictors, followed by temperature, lagged infections and humidity. These findings are consistent with existing evidence showing that climatic variability and the timing of public health actions play critical roles in shaping epidemic outcomes in Zambia. SHAP therefore enhanced the transparency of the hybrid model, making its insights more accessible to policymakers.

From an applied perspective, the results indicate that epidemic forecasting in Zambia could benefit considerably from hybrid modelling frameworks that incorporate environmental and policy conditions. Such approaches allow for more proactive planning, particularly during periods of heightened climatic risk or rapidly evolving disease conditions. Although the study has limitations—including its focus on COVID-19, the use of weekly aggregates, deterministic SEIR assumptions and a restricted set of contextual variables—it provides a solid foundation for future advancements. Expanding the hybrid framework to include multiple diseases, stochastic or spatial components and broader socioeconomic indicators could further enhance its practical utility.

In conclusion, this work demonstrates that combining mechanistic epidemiological models with advanced AI techniques, supported by SHAP-based interpretability, offers a powerful and transparent approach to epidemic forecasting. For Zambia and similar low-resource settings, such hybrid models have the potential to strengthen epidemic preparedness by shifting public health systems toward more anticipatory and evidence-driven decision-making.

Data Availability. *The weekly COVID-19 case data used in this study, covering the period 2020–2023, together with the compiled modelling dataset, can be accessed at the following link: https://docs.google.com/spreadsheets/d/1Su77SIYdLvfzUey6xukNsydOZl5eYN2Ju3XY-euqYC4/edit?usp=sharing . Any additional scripts developed for data preparation or processing are available from the corresponding author upon reasonable request.*
Code Availability. *The code used to conduct model training and evaluation—including routines for SEIR parameter fitting, Transformer implementation and the hybrid modelling pipeline—can be obtained from the corresponding author on request. These materials will be shared for academic and non-commercial use.*

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Appendices

Appendix 1: Ethical Clearance from NASREC, UNZA

This appendix presents the formal ethical approval issued by the Natural Sciences Research Ethics Committee at the University of Zambia, authorising the use of epidemiological and contextual datasets for the purposes of this study.

THE UNIVERSITY OF ZAMBIA

DIRECTORATE OF RESEARCH AND GRADUATE STUDIES

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APPROVAL OF STUDY

IORG No. 0005376
HSSREC IRB No. 00006465
REF NO. NASREC: 2024-JAN-005B

14th February, 2024

Mr. Grey Chibawe
The University of Zambia
P.O. Box 32379
LUSAKA

Dear Mr. Chibawe

RE: FRAMEWORK FOR DISEASES INTERACTION-BASED EPIDEMIOLOGICAL MATHEMATICAL MODELING AND SIMULATION

Reference is made to your protocol dated as captioned above. NASREC resolved to approve this study and your participation as Principal Investigator for a period of one year.

REVIEW TYPE	**ORDINARY REVIEW**	**APPROVAL NO. NASREC-2024-JAN-005**
Approval and Expiry Date	Approval Date: 14th February 2024	Expiry Date: 13th February, 2025
Protocol Version and Date	Version - Nil.	13th February, 2025
Information Sheet, Consent Forms and Dates	• English.	To be provided
Consent form ID and Date	Version - Nil	To be provided
Recruitment Materials	Nil	Nil
Other Study Documents	Questionnaire.	

Appendix 2: Ethical Approval from NHRAREC

This appendix contains documentation granted by the Zambia National Health Authority Research Ethics Committee, confirming compliance with national research standards governing the handling of public health information.

NATIONAL HEALTH RESEARCH AUTHORITY

Lot No. 18961/M, off Kasama Road, Chalala, P.O. Box 30075, LUSAKA
Tell: +260211 250309 | Email: znhrasec@nhra.org.zm | www.nhra.org.zm

NHRA-1369/12/07/2024 **23rd July 2024**

The Principal Investigator,
Mr. Grey Chibawe,
The University of Zambia P.O. Box 32379 LUSAKA,
Lusaka.

Dear Mr. Grey Chibawe,

Re: Request for Authority to Conduct Research

The National Health Research Authority Is in Receipt of Your Request for Authority to Conduct Research Titled **"FRAMEWORK FOR DISEASES INTERACTION-BASED EPIDEMIOLOGICAL MATHEMATICAL MODELING AND SIMULATION"**

I wish to inform you that following submission of your request to the Authority, our review of the same and in view of the ethical clearance, this study has been **approved** on condition that:

1. The relevant Provincial and District Medical Officers where the study is being conducted are fully appraised.
2. Progress updates are provided to NHRA bi-annually from the date of commencement of the study.
3. The final study report is cleared by the NHRA before any publication or dissemination within or outside the country.
4. After clearance for publication or dissemination by the NHRA, the final study report is shared with all relevant Provincial and District Directors of Health where the study was being conducted, University leadership, and all key respondents.

Yours sincerely,

National Health Research Authority

Prof Victor Chalwe,
Acting Director/Chief Executive Officer

Appendix 3: Table S1 – Noormalised Model Performance

This appendix provides a supplementary performance comparison of all models on the normalised scale, including RMSE, MAE and R^2 values for the SEIR baseline, curve-fitted SEIR, Transformer network and the hybrid SEIR+Transformer framework.

Model	**RMSE**	**MAE**	**R^2**
SEIR (baseline)	4.12	3.10	0.87
SEIR (curve-fitted)	3.33	2.67	0.91
Transformer ANN	3.24	2.31	0.93
Hybrid SEIR+Transformer	2.78	2.04	0.96