Deep Learning based Predictive Early Warning System for Heat and Ventilation Risks in Naturally Ventilated Hospital Wards

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SUMMARY (Max 150 words)
Hospital wards in tropical climates face persistent challenges in maintaining thermal comfort and indoor air quality, where mechanical ventilation is limited. Using over two years of 15-minute sensor data across 14 naturally-ventilated wards in two Ghanaian hospitals, together with weather data, we develop an early warning system to forecast indoor temperature, relative humidity, and CO_2 over a 24-hour horizon. We compared a multi-output XGBoost baseline with a Temporal Fusion Transformer (TFT). Results reveal a dual risk profile, where overheating and high humidity are widespread and strongly diurnally structured, whereas CO_2 exceedance is more localised and time-dependent. TFT improves temperature and humidity forecasting, while CO_2 prediction remains challenging and better served by XGBoost. Overall, the proposed approach can inform proactive interventions ahead of critical events and demonstrates the feasibility of data-driven ventilation forecasting in tropical hospitals, offering a scalable pathway toward smart, health-oriented indoor climate management in naturally ventilated facilities.

KEYWORDS
Overheating ; Insufficient Ventilation; Early Warning System; Machine Learning; Hospitals

1 INTRODUCTION

Maintaining healthy indoor environments in hospitals is critical to patient recovery, infection control, and staff wellbeing. In tropical regions, this is especially difficult to achieve due to the limited availability of mechanical cooling and ventilation systems. Overheating is associated with thermal discomfort, heat-related illness, and mortality among vulnerable patients (Kenny et al., 2024) while poor ventilation, commonly inferred through elevated indoor CO_2 concentrations, is linked to higher risks of airborne infection transmission (Roberts et al., 2025).

Recent research has increasingly explored using machine learning to predict indoor air quality (IAQ) and thermal comfort. However, most applications to date have been limited to controlled environments such as offices, classrooms, or experimental testbeds (Godasiaei et al., 2025; Tekler et al., 2024; Boutahri et al., 2024), where occupancy patterns and ventilation systems are relatively stable and well-instrumented. In contrast, naturally ventilated hospital wards, particularly in low-resource environments, present a more complex challenge as they often lack real-time environmental monitoring or automated control systems and are characterized by continuous patient presence, mixed-use clinical functions, variable airflow patterns, and heightened vulnerability to environmental stressors (Roberts et al., 2022). As emphasised in WHO guidelines on natural ventilation in healthcare facilities, such environments are especially prone to fluctuating indoor conditions and airborne transmission risks (WHO, 2014). Consequently, fixed ventilation schedules and reactive control strategies are rarely sufficient to ensure occupant safety and comfort. Therefore, there is a pressing need for predictive tools that are both accurate and interpretable, enabling healthcare staff to anticipate risks and implement timely, low-cost mitigation measures (e.g., adjusting window openings, deploying fans, or relocating patients). Such tools could significantly improve operational resilience, particularly in low-resource settings where infrastructure upgrades are not always feasible.

To address this gap, we propose a low-cost, data-driven forecasting framework to support proactive indoor climate management in naturally ventilated healthcare settings. Our approach uses over two years of 15-minute interval sensor data collected from 14 hospital wards in Ghana and weather data to predict indoor temperature, relative humidity, and CO_2 concentrations. We implement the Temporal Fusion Transformer (TFT) architecture, a state-of-the-art transformer model that integrates sequence modeling with variable selection and uncertainty estimation. The resulting multi-output forecasts provide interpretable, real-time early warnings that can inform low-resource operational strategies, offering a scalable and practical pathway toward health-centric building management in tropical hospitals.

2 MATERIALS/METHODS

Study Context and Setting

This study was conducted at two regional healthcare facilities (i.e., Central and Teaching hospitals) in Tamale, Northern Ghana. Tamale experiences a tropical savannah climate, characterized by high daily temperatures, distinct wet and dry seasons, and limited access to mechanical cooling. The hospitals serve a broad patient population and rely predominantly on natural ventilation. Fourteen hospital wards were selected to represent a wide range of clinical functions, including maternity, paediatrics, neonatal care, emergency, and general inpatient areas. All monitored spaces were primarily naturally ventilated, with airflow facilitated through operable architectural features such as louvred windows, sliding panes, and bottom-hung casements. Mechanical systems were limited, where only two neonatal wards had ducted air conditioning (without staff control), and one paediatric space had a ductless wall-mounted AC unit. Standalone ceiling or pedestal fans were used intermittently across wards to provide ventilation.

Data Collection

Environmental data were collected using Eltek MS47B wall-mounted sensors installed in each ward. These devices recorded indoor temperature (°C), relative humidity (%), and carbon dioxide (CO_2, ppm) at 15-minute intervals (Table 1). CO_2 was used as a proxy for occupancy and ventilation effectiveness. Sensors were mounted between 1.6 and 2.2 meters from the floor, positioned to avoid direct sunlight, doors, or heat sources. An additional outdoor sensor was deployed to monitor ambient weather conditions including temperature and humidity.

Table 1. Measured indoor variables and sensor specifications

Sensor	Variable	Frequency	Unit	Range	Resolution	Accuracy
Eltek (MS47B)	Temperature	15	°C	-30 to +65	0.1	±0.4 (+5 to +40) ±1.0 (-20 to +65) ±1.5 (-30 to -20
	Relative Humidity	15	%	0 to 100	0.1	±2 (10 to 90) ±4 (0 to 100)
	Carbon Dioxide	15	ppm	0 to 5000	3	±50

Data were collected over a continuous two-year period from 08 June 2022 to 18 January 2025 covering both wet and dry seasons. Quality control procedures included the removal of implausible outliers (e.g., CO_2 spikes from tampering or placement shifts) and linear interpolation for short missing intervals (<1 hour). Ward-level metadata, including patient type, floor area, ventilation type, ceiling fan count, and sensor height were summarised in Table 2.

Table 2. Tamale hospital ward-level metadata

Ward ID	Hospital	Ward Type	Patient Type	Floor Area	Natural Ventilation	Ceiling Fans	Sensor Height
6584	Central	Outdoor	All	-	-	-	2.4
6597	Central	Labour	Pregnant women	20.5	Adj louvres	-	1.6
6598	Central	Waiting Area	Pregnant women & neonates	133	Fire exit door	4	2.2
6600	Central	Emergency	All	36	Adj louvres	-	1.6
6608	Central	Maternity	Pregnant & postpartum	106	S-hung casement	-	1.6
6609	Central	Male	Adult males	114	Adj&fix louvres	-	1.6
6578	Teaching	Paediatrics (< 6m)	Infants under 6 months	34	Adj&fix louvres	2	1.7
6579	Teaching	Paediatrics (> 6m)	Children over 6 months	18	Adj louvres	-	1.6
6588	Teaching	Neonatal Int. Care	Neonates (Unstable)	33	Sliding panes	0	2.2
6586	Teaching	Kangaroo	Neonates (Stable)	39	Adj louvres	0	1.6
6581	Teaching	Post-natal	Postpartum & neonates	46	Adj&fix louvres	4	1.7
6589	Teaching	Pre-natal	Pregnant women	63	Adj&fix louvres	4	1.7
6585	Teaching	Emergency (Y)	All	105	Sliding panes	6	1.8
6587	Teaching	Outdoor	All	-	-	-	2.4

Mechanical ventilation was present only in the Neonatal Intensive Care Unit and Kangaroo Mother Care ward via ducted air conditioning, which was not staff controlled. The Paediatrics (<6 months) ward contained a ductless wall-mounted AC unit operating in recirculation mode.

Outdoor weather data was obtained from the ERA5 reanalysis dataset, developed by the European Centre for Medium-Range Weather Forecasts (ECMWF, 2024). ERA5 provides hourly estimates of key atmospheric variables including ambient temperature, dew point, surface pressure, and solar radiation at a horizontal resolution of approximately 31 km. For this study, the weather data was spatially interpolated to the hospital locations in Tamale and temporally aligned with the indoor environmental sensor data. The ERA5 data were resampled to 15-minute intervals using forward-filling within each location to ensure synchronization with the indoor monitoring frequency and support consistent forecasting input.

Air Quality Standards

To assess environmental risk in each ward, we compared observed values against internationally recognized IAQ thresholds. According to CIBSE TM40 and WHO guidelines, indoor temperatures in patient care spaces should not exceed 27 °C, particularly in tropical regions. ASHRAE Standard 170 and WHO also recommended keeping CO_2 concentrations below 1000 ppm to ensure adequate ventilation. For humidity, a range of 30%–60% RH is recommended to balance comfort and infection control by minimizing pathogen viability and maintaining mucosal health.

Table 3. Reference indoor air quality thresholds for hospital environments

Variable	**Recommended Range**	**Reference**
Temperature (°C)	≤ 27 °C	WHO (2009); CIBSE TM40 (2020)
CO_2 Concentration (ppm)	≤ 1000 ppm	ASHRAE 170 (2021); WHO (2021)
Relative Humidity (%)	30% – 60%	ASHRAE 170 (2021); WHO (2009)

Model Development

In this study, we employed two distinct approaches to forecast indoor environmental conditions in hospital wards: the Temporal Fusion Transformer (TFT) as a deep learning transformer model and XGBoost as a gradient-boosted tree ensemble baseline. Both models were developed to predict indoor temperature T_t, relative humidity RH_t, and carbon dioxide concentration CO_{2t} for future time steps based on historical measurements and contextual features.
The forecasting problem was formulated as a multivariate, multi-output, multi-step time series regression task. Given a sliding input window of w historical steps and static metadata $\mathbf{Z}$, the models learn a mapping from past observations to the next k steps of all three target variables:

$$f: \left(T_{t-w:\,t}, RH_{t-w:t}, CO_{2\,t-w:t}, W_{t-w:t}, Z\right) \rightarrow [T_{t+1:\,t+k} \,+\, RH_{t+1:\,t+k} \,+\, CO_{2\,t+1:\,t+k}\,] \quad (1)$$

where $Tt - w{:}\,t, RHt - w{:}\,t, CO2\,t - w{:}\,t$ represent the lagged time-varying indoor environmental variables, $Wt - w{:}\,t$ represents the lagged weather variables, and $\mathbf{Z}$ encodes static attributes including ward type, city, and hospital type. We set $w = 288$ (3 days) and $k = 96$, corresponding to a 24-hour forecast horizon at 15-minute resolution. A sliding window with a stride of 4 steps (1 hour) is also introduced to reduce data redundancy while maintaining good temporal coverage. Both models were trained using a per-ward chronological split, where the first 80% of each ward's time series was used for training and the latter 20% for testing, ensuring that the resulting test performance reflects generalization to unseen time periods across different wards. Forecast accuracy was evaluated using mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) across the 24-hour forecast horizon.

Temporal Fusion Transformer (TFT): TFT (Lim et al., 2021) is a sequence-to-sequence architecture designed for multi-horizon forecasting with interpretable outputs. It integrates long short-term memory (LSTM) encoders for short-term sequential patterns and multi-head self-attention mechanism to capture long-range temporal dependencies. TFT performs dynamic variable selection via gated residual networks and fuses static and temporal covariates through learned embeddings. The model was configured with a hidden state size of 64, 4 attention heads, a dropout rate of 0.1, and a hidden continuous size of 32. Static categorical features (city, hospital, ward type) were encoded as learned embeddings, while time-varying variables (hour of day, day of week, month, week of year, outdoor weather forecasts) provided future-known temporal context. The three indoor environmental targets served as time-varying unknown variables, where per-ward group normalization was also applied.
TFT was trained with the Adam optimizer (learning rate 10^{-3}), a batch size of 256, gradient clipping at 0.1, and a maximum of 50 epochs. 10% of the training data was also held out chronologically as a validation set for early stopping. The TFT model was optimised using a quantile loss function to produce probabilistic forecasts. For a predicted quantile $\hat{q}$ and target value y, the pinball loss is defined as:

$$L_q\,(y, \hat{q}) = \max[\, q(y - \,\hat{q}), (q - 1)(y - \hat{q})] \quad (2)$$

with $q \in \{0.02, 0.1, 0.25, 0.5, 0.75, 0.9, 0.98\}$ representing the desired quantile levels. This yields a full predictive distribution for each target variable over the forecast horizon, with the median (50th percentile) used as the point forecast.

XGBoost: As a baseline, we also implemented XGBoost (Chen & Guestrin, 2016), a widely adopted gradient-boosted decision tree algorithm that provides fast training, low computational overhead, and interpretable feature importance. A single multi-output XGBoost model was trained using the native multi-output tree strategy, jointly predicting all three target variables across all 96 horizon steps. The input feature vector was constructed by flattening the 288-step lookback window of dynamic features, comprising of the three indoor target variables, cyclical time encodings (sine/cosine transforms of hour, day of week, month, and week of year), and outdoor weather variables, and finally concatenating one-hot encoded static ward metadata. The model was configured with 100 estimators, a maximum tree depth of 3, a learning rate of 0.15, row subsampling of 0.8, and column subsampling of 0.7 per tree, using the histogram-based tree method and squared error loss. Early stopping was also applied using a 90/10 chronological train/validation split within the training partition.

3 RESULTS

Risk analysis of current environmental conditions in naturally ventilated hospital wards

This section evaluates measured indoor conditions across 14 wards against international IAQ and thermal comfort thresholds (Tab. 3) to identify where and when risks are most prevalent. We focus on three indicators that are practical for naturally ventilated, low-resource hospitals and directly actionable for risk mitigation: temperature (overheating risk), relative humidity (moisture comfort and hygiene risk), and CO_2 (a proxy for ventilation adequacy and rebreathed air). Fig. 1 summarizes both the upper-tail diurnal behaviour of each indoor environmental variable using the 95th percentile by hour and the hourly exceedance rate of international standards for the most affected wards, capturing spatial heterogeneity and time-of-day structure.

Overheating risk. Across wards, overheating is pervasive. The temperature 95th-percentile profiles (Fig. 1a) remain above 27°C throughout the day for most wards and typically peak in the early–mid afternoon, indicating sustained overheating under worst-case daily conditions rather than short-lived events. Consistently, the hourly exceedance curves for the highest-risk wards (Fig. 1b) remain close to 100% across the full day, confirming chronic non-compliance. This suggests that thermal risk is driven by sustained heat loads and limited cooling capacity typical of naturally ventilated buildings in tropical climates. Mitigation is therefore likely to require facility-wide strategies, including improved solar control (e.g., shading), optimisation of airflow management (cross-ventilation pathways), night flushing where safe and feasible, and prioritisation of cooling support in clinically vulnerable spaces.

Moisture comfort and hygiene risk. Relative humidity (RH) non-compliance is also widespread, with many wards operating outside the recommended 30–60% band for substantial portions of time. The RH 95th-percentile profiles (Fig. 1a) frequently sit above the 60% upper bound across the day, while exhibiting a consistent mid-day dip and evening/night recovery, reflecting temperature-driven RH dynamics. The corresponding hourly exceedance patterns (Fig. 1b) show persistently high non-compliance in the most affected wards, with reduced exceedance around mid-day and higher risk overnight/early morning. These findings indicate that effective mitigation will likely require a combination of moisture-source management (where feasible) and timed ventilation actions targeted to higher-risk periods.

Ventilation adequacy and rebreathed air risk. In contrast to temperature and RH, CO_2 risk is more spatially concentrated**.** The CO_2 95th-percentile profiles (Fig. 1a) show markedly elevated concentrations in a small subset of wards, particularly neonatal and paediatric spaces, while other wards remain comparatively low. The hourly exceedance curves (Fig. 1b) demonstrate strong time-of-day dependence, with sustained exceedance in the highest-risk wards and more episodic peaks in others, consistent with ventilation–occupancy mismatches that vary with ward activity. These results indicate that ventilation improvements and operational controls (e.g., reducing crowding at peak times, ensuring consistent airflow pathways, and implementing CO_2-informed ventilation protocols) can be prioritised for a small number of high-risk wards to achieve meaningful reductions in exposure.

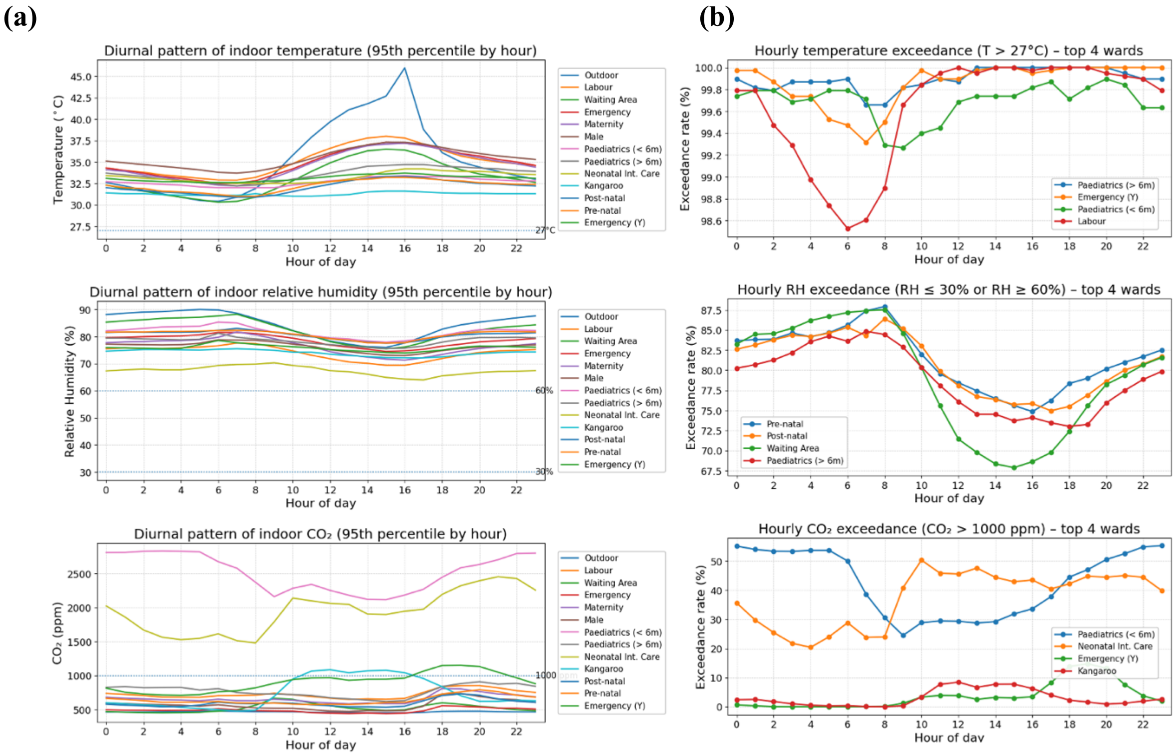

Figure 1. (a) Diurnal pattern of indoor variables compared to international standards (95th percentile by hour) by ward type. (**b)** Hourly exceedance patterns for the top 4 most affected wards, highlighting both spatial differences and diurnal timing.

Forecasting Model Performances

Table 4. Overall forecasting performance between XGBoost and TFT aggregated across wards and 24-hour forecast horizon.

Model	Temperature (°C)			Relative Humidity (%)			CO_2 Concentration (ppm)		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
XGBoost	1.19	1.69	4.09	6.21	7.78	14.3	**103**	**211**	14.8
TFT	**0.812**	**1.15**	**2.75**	**3.67**	**5.05**	**8.34**	117	269	**14.6**

Based on the overall forecasting performance reported in Table 4, the TFT demonstrates consistently stronger performance than XGBoost for variables related to indoor temperature and RH. Specifically, TFT reduces error for indoor temperature by approximately 31.8–32.8% across MAE, RMSE, and MAPE, and improves RH forecasting by approximately 35.1–41.7% across the same metrics. Collectively, these results indicate that TFT provides a substantial gain in predictive performance for variables that exhibit relatively smooth temporal evolution and pronounced diurnal structure. In contrast, CO_2 dynamics appear more difficult to forecast with Table 4 indicating that CO_2 prediction is better served by the XGBoost baseline. This divergence highlights that forecasting performance is variable-dependent and closely linked to the underlying drivers of each indoor environmental variable.

A plausible explanation for TFT's advantage in temperature and RH forecasting is that it is explicitly designed for multi-horizon sequence prediction and incorporates architectural components well matched to the ward forecasting setting. These include learned embeddings for static categorical context (e.g., ward or hospital identity), future-known time features (e.g., hour/day/week/month), gated variable selection, and attention mechanisms for learning longer-range dependencies. These components allow TFT to better (i) represent multi-scale temporal structure, combining short-term autocorrelation with diurnal and seasonal dependencies; (ii) condition predictions on static ward context; and (iii) dynamically select and weight covariates related to time and meteorological drivers. On the other hand, CO_2 frequently exhibits event-like dynamics with abrupt spikes driven by occupancy patterns and ventilation disturbances. This pattern allows tree-based ensemble models like XGBoost to be comparatively more effective for such threshold-like behaviour due to their ability to model sharp nonlinearities without necessarily smoothing them.

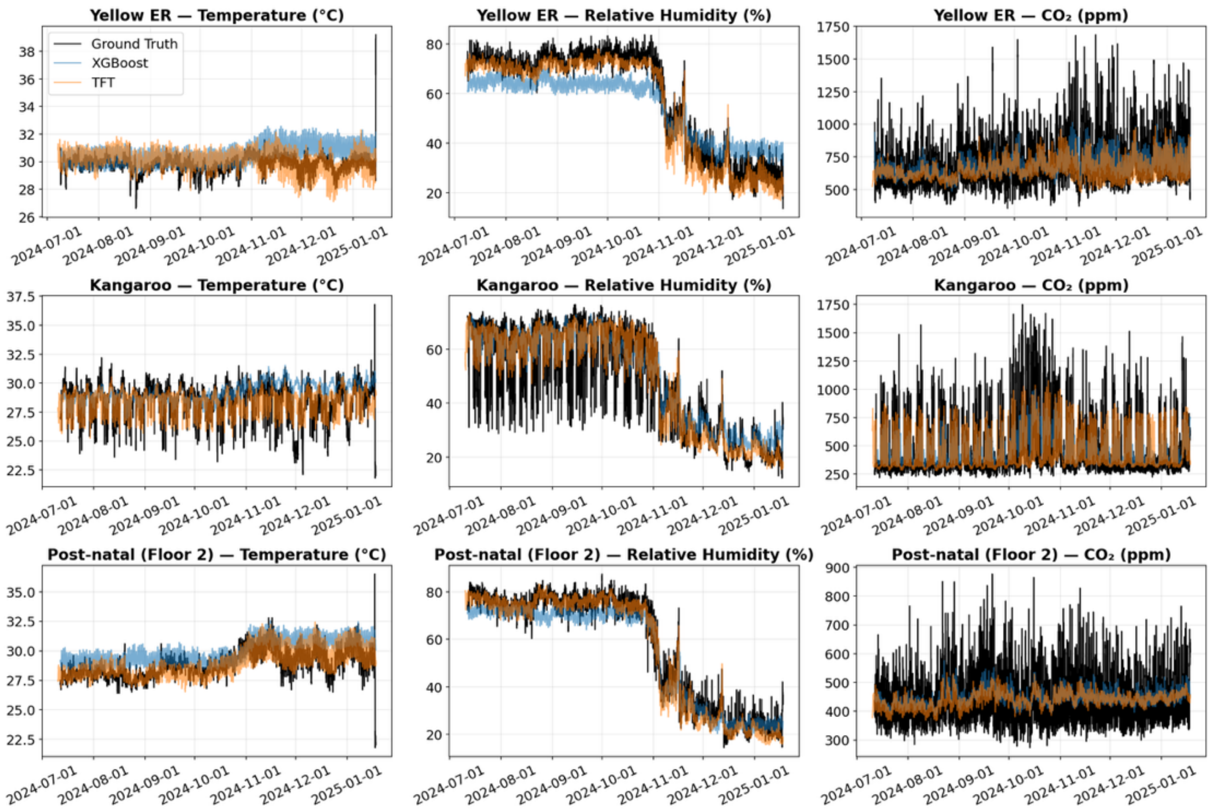

Figure 2. Multi-step forecasts produced by XGBoost and TFT against the ground truth for three representative wards (Yellow ER, Kangaroo, and Post-natal Floor 2) across the three indoor variables: temperature (°C), relative humidity (%), and CO_2 (ppm).

Beyond the overall metrics in Table 4, Figure 2 demonstrates that TFT forecasts for temperature and RH align more closely with the ground truth baseline level and longer-term drift, particularly during periods of gradual change. On the other hand, XGB, more often exhibits bias when the trend shifts. However, for CO_2, both models were able to track the general time-series trend but underrepresent the magnitude and frequency of sharp spikes, indicating that peak-driven dynamics remain insufficiently captured by the current feature set.

4 DISCUSSION

The risk analysis indicates a clear dual profile in naturally ventilated tropical wards: overheating and high humidity are widespread and persistently structured by time of day, whereas CO_2 risk is more localised and strongly time-dependent, implying ventilation–occupancy mismatches concentrated in specific ward types and periods. This distinction is also reflected in model performance. Aggregated over all 14 wards and the 24-hour horizon, TFT substantially improves forecasts for temperature and RH, consistent with these variables exhibiting smoother dynamics that can be captured from lagged indoor conditions, time features, and weather covariates. In contrast, CO_2 remains harder to predict, with XGBoost achieving lower error scores, likely because CO_2 contains sharper event-like excursions driven by episodic occupancy and airflow changes that are less well explained by the available covariates. Figure 2 further supports this interpretation with TFT being better at tracking gradual shifts in temperature and RH, whereas both models under-represent the magnitude/frequency of CO_2 spikes. The findings support facility-wide heat/moisture mitigation (e.g., shading and airflow management) with targeted, CO_2-informed operational protocols in high-risk wards and peak periods, while highlighting the need to better capture ventilation/occupancy dynamics to forecast CO_2 peaks.

5 CONCLUSIONS

Using two years of 15-minute sensor data across 14 wards, this study demonstrates multi-step forecasting to support early warning of indoor environmental risks in naturally ventilated tropical hospitals. Risk profiling indicates chronic overheating and RH non-compliance across wards, while CO_2 exceedance is more concentrated and time-dependent, enabling targeted interventions to high-risk spaces and periods. TFT outperforms XGBoost for temperature and RH, but XGBoost performs better for CO_2 forecasting, with both models under-capturing sharp CO_2 peaks. Future work will incorporate stronger proxies for occupancy and ventilation and peak-/exceedance-aware objectives to better predict CO_2 spike for operational decision support.

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