Temporal Deep Learning-Based Prediction of Safety Failure Trends in Industrial Equipment

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ABSTRACT Industrial equipment usually works in complex operating environments, where mechanical wear, temperature changes, load disturbances, and external environmental factors may jointly accelerate performance deterioration and induce safety risks. Therefore, forecasting the future degradation tendency of equipment is important for enhancing operational reliability and supporting condition-based maintenance. In this study, a time-series deep learning framework is developed for safety-oriented failure trend forecasting of industrial equipment. Multi-source monitoring data are first processed through missing-value treatment, abnormal-value correction, normalization, and sliding-window sampling. Then, a health indicator is established to describe the continuous deterioration process of equipment. On this basis, a TCN-Transformer network is constructed to extract both local abnormal variations and long-range temporal correlations from multivariate monitoring sequences. The forecasted health indicator is further integrated with a warning strategy to divide equipment conditions into four categories: normal operation, early degradation, moderate risk, and severe failure risk. Experimental results demonstrate that the developed model achieves better forecasting accuracy and warning effectiveness than LSTM, GRU, TCN, and Transformer benchmark models. The proposed framework offers a practical data-driven solution for degradation trend recognition, early risk warning, and maintenance decision support in industrial systems.

INDEX TERMS Temporal deep learning, Industrial equipment, Safety failure trend prediction, Predictive maintenance

I. INTRODUCTION

With the continuous progress of intelligent manufacturing, industrial Internet of Things, and predictive maintenance, condition monitoring for equipment safety has attracted increasing attention in modern industrial systems. Large-scale rotating machinery, power equipment, manufacturing devices, and continuously operating industrial facilities are often exposed to high loads, strong system coupling, and complex operating conditions. Their operating states may be affected by mechanical wear, material fatigue, temperature fluctuations, load variations, and environmental disturbances. Once safety failure occurs, it may lead not only to production interruption and economic losses but also to severe safety accidents. Therefore, accurately identifying the degradation patterns of equipment health states and predicting future safety failure trends based on multi-source sensor data are of great significance for improving equipment reliability, reducing maintenance costs, and ensuring the safe operation of industrial systems [1-3].

Recent studies have achieved notable advances in equipment fault identification and condition-based maintenance. Traditional approaches mainly rely on expert experience, statistical analysis, threshold-based rules, and conventional machine learning models, which have shown effectiveness in current-state identification and fault type classification. However, safety failure in industrial equipment is usually not an instantaneous event, but a progressive degradation process driven by the long-term evolution of multivariate time-series signals. Traditional models still have limitations in capturing nonlinear characteristics, long-term temporal dependencies, and variations under complex operating conditions. With the advancement of deep learning, temporal modeling methods such as LSTM, GRU, CNN, TCN, and Transformer have been increasingly applied to equipment health monitoring, remaining useful life prediction, and anomaly detection [4-8]. Nevertheless, existing studies still focus mainly on improving prediction accuracy, while insufficient attention has been paid to continuous failure trend representation, safety risk level classification, and the practical use of prediction results in maintenance decision-making.

To overcome the above limitations, this work develops a time-series deep learning framework for safety-oriented failure trend forecasting in industrial equipment. First, multi-source sensor data collected during equipment operation are processed through data cleaning, normalization, and sliding-window segmentation, so that sequential samples reflecting dynamic variations in equipment states can be obtained. Second, a health indicator is established to characterize equipment degradation, and a temporal deep learning model is introduced to capture the evolution pattern of health conditions and estimate future failure risks. In addition, the forecasting outputs are combined with a safety warning mechanism to divide equipment operating conditions into different risk categories, thereby supporting maintenance scheduling and safety decision-making. Rather than focusing only on forecasting accuracy, this work further emphasizes degradation trend recognition and engineering-oriented warning generation, offering a practical technical approach for intelligent operation management and condition-based maintenance.

II. RELATED WORK

A. SAFETY-ORIENTED EQUIPMENT PROGNOSTICS AND MAINTENANCE DECISION-MAKING

Safety-oriented equipment prognostics and maintenance decision-making have attracted increasing attention in industrial safety management and intelligent operation systems. Traditional maintenance modes generally include post-failure repair and periodic servicing. Post-failure repair is usually passive and may cause unexpected shutdowns or safety hazards, while periodic servicing can lower the occurrence of faults to a certain degree but may also bring about under-maintenance or unnecessary maintenance. With the rapid development of industrial Internet of Things and sensing technologies, massive monitoring data collected during equipment operation have provided strong support for condition-based maintenance strategies. The main purpose of predictive maintenance is to mine operating information, detect potential abnormalities and deterioration tendencies, and arrange maintenance actions before serious faults occur, so as to improve system reliability and reduce maintenance expenditure.

In equipment prognostics, remaining useful life estimation, fault identification, and health condition evaluation are three highly related research tasks. Remaining useful life estimation focuses on predicting the available operating time or cycles before the equipment reaches a failure state. Fault identification aims to determine the current abnormal mode or fault category, whereas health condition evaluation describes the continuous evolution from stable operation to performance deterioration and eventually to failure. Earlier studies mainly relied on statistical methods, physical degradation models, and traditional machine learning algorithms. Although these approaches can achieve acceptable results under specific working conditions, they often require manually designed features and domain expertise, which limits their adaptability to nonlinear degradation behaviors and changing operating environments.

B. DEEP LEARNING FOR TIME-SERIES EQUIPMENT MONITORING

With the development of deep learning, temporal modeling methods for equipment condition monitoring have received increasing attention. Industrial equipment operation data are typically represented as multivariate time series, in which different sensor variables are coupled with each other and equipment states evolve continuously over time. LSTM and GRU, as representative recurrent network variants, are commonly employed to characterize degradation patterns in equipment monitoring data. Through its gating mechanism, LSTM alleviates the gradient vanishing problem of standard recurrent neural networks in long-sequence training and can effectively capture temporal dependencies in equipment operating states. GRU has a simpler structure and reduces model complexity while maintaining competitive prediction capability.

Convolutional neural networks and temporal convolutional networks provide another effective approach for equipment monitoring. CNN can extract local temporal features and is suitable for equipment signals with clear local patterns, such as vibration, current, and acoustic signals. TCN further expands the receptive field through causal convolution and dilated convolution, allowing it to capture longer-range temporal dependencies while preserving parallel computation. Recently, hybrid models that combine TCN with LSTM, attention mechanisms, or Transformer have been increasingly applied to time-series fault prediction and remaining useful life prediction. Such models can learn both local degradation features and long-term trend information, making them suitable for describing the dynamic transition of equipment from normal states to risk states [9-12].

C. SAFETY FAILURE TREND WARNING

Compared with general fault classification, safety failure trend warning places greater emphasis on the continuity of equipment state evolution and the progression of risk over time. In real industrial systems, safety failure usually does not occur suddenly. Instead, it often develops through a gradual process involving slight anomalies, performance degradation, risk accumulation, and eventual failure. If a model only determines whether the equipment is currently faulty, it may not meet the practical requirements of early warning and maintenance decision-making. Therefore, equipment failure trend prediction should further focus on the future direction of health state changes, the rate of risk increase, and the time at which the equipment may enter a high-risk stage [12-15].

In existing studies, anomaly detection methods are commonly used to identify early abnormal points or abnormal segments during equipment operation. Deep learning-based anomaly detection models based on reconstruction error, prediction error, or attention discrepancy can detect operating states that deviate from normal patterns even when complete failure labels are unavailable [15]. However, anomaly detection alone usually indicates only that an abnormal deviation has occurred, rather than fully describing the degradation trajectory and failure risk level of the equipment. Therefore, in safety failure trend prediction, it is necessary to integrate anomaly detection, health indicator prediction, and risk level classification, so that model outputs can be transformed from simple numerical predictions into engineering-oriented warning information.

III. METHODOLOGY

A. OVERALL RESEARCH FRAMEWORK

This work constructs a time-series deep learning approach for early prediction of safety failure tendencies in industrial equipment. The core idea is to learn the degradation patterns of equipment health states over time from continuously collected multi-source sensor data and further transform the prediction results into safety warning information. Unlike traditional fault diagnosis methods that mainly focus on whether a fault occurs at the current moment, this study emphasizes the continuous evolution of equipment safety states, namely the dynamic transition from normal operation to slight degradation, medium risk, and high failure risk.

The workflow illustrated in Figure 1 covers the main procedures of the proposed method, including raw monitoring data acquisition, preprocessing, sequential sample generation, health indicator modeling, TCN-Transformer prediction, and warning-level determination. In this way, the task of safety failure trend assessment is converted into a forecasting problem based on multivariate equipment time-series data. The model not only evaluates the present operating condition but also provides an estimation of future health-state evolution.

B. DATA DESCRIPTION AND PREPROCESSING

Industrial equipment operating data are usually collected continuously by multiple sensors and are characterized by multivariate structures, high noise levels, non-stationarity, and obvious operating condition fluctuations. Suppose that T time steps are collected during continuous equipment operation, and each time step contains m monitoring variables. The raw data matrix can be expressed as Equation (1).

$$X = [x_1, x_2, \ldots, x_T]^T \in \mathbb{R}^{T\times m} \tag{1}$$

where $x_t = [x_{t1}, x_{t2}, \ldots, x_{tm}]$ refers to the sensor measurement vector at time step t, with m indicating the number of monitored variables. To describe equipment operating behavior and safety-related degradation characteristics, this study takes mechanical signals, thermal signals, electrical signals, and working-condition signals as the main input features. Table 1 provides the corresponding engineering meanings of different variable types.

In the data preprocessing stage, missing values and outliers are first processed. For a small amount of randomly missing data, linear interpolation or the average of adjacent time points can be used for imputation. For long-term missing segments or obviously abnormal data, equipment operation logs are combined for removal or correction. Second, moving average or low-pass filtering methods can be applied to smooth noisy signals. Finally, since different sensor variables have different units and numerical ranges, Z-score normalization is used to standardize the input variables, as shown in Equation (2).

$$\hat{x}_t^j = \frac{x_t^j - \mu_j}{\sigma_j} \tag{2}$$

A sliding-window sampling scheme is employed to organize the monitoring data into sequential inputs, allowing the model to learn the changing patterns of equipment operating states. For a given window length w and prediction horizon h, the i-th sample and its target output are described by Equations (3) and (4).

$$S_i = [x_i, x_{i+1}, \ldots, x_{i+w-1}] \tag{3}$$

$$y_i = HI_{i+w+h-1} \tag{4}$$

C. HEALTH INDICATOR CONSTRUCTION

For safety-related failure trend forecasting, it is necessary to define a health indicator capable of tracking the continuous deterioration of equipment over time. Compared with binary fault labels, a health indicator can describe the gradual transition of equipment from normal operation to accumulated failure risk in a more detailed manner. Therefore, the equipment health state is represented as a continuous variable HI_t, ranging from 0 to 1. In general, the closer HI_t is to 1, the healthier the equipment is; the closer HI_t is to 0, the more severe the degradation and the higher the failure risk.

When the equipment has a clear failure time, a degradation-type health indicator can be constructed according to operating time, as shown in Equation (5).

$$HI_t = 1 - \frac{t - t_0}{t_f - t_0} \tag{5}$$

where t_0 denotes the time when the equipment begins to enter the degradation stage, and t_f denotes the failure time. If the actual data lack explicit failure time information, the health indicator can also be constructed based on the abnormal degree of sensor signals. Let D_t denote the comprehensive degradation degree at time t. The health indicator can be expressed as Equation (6).

$$HI_t = 1 - \frac{D_t - D_{\min}}{D_{\max} - D_{\min}} \tag{6}$$

The purpose of health indicator construction is not to replace the original sensor data, but to provide a clearer target variable for failure trend prediction. The model input still retains multi-source sensor time-series information, while the model output is the future health indicator or failure risk value. This strategy fully utilizes the dynamic information contained in raw data and makes the prediction results more meaningful for safety management.

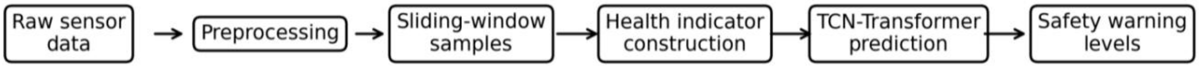

FIGURE 1. Overall workflow of the proposed safety failure trend prediction framework.

TABLE 1. Monitoring variables for equipment safety failure trend prediction

Variable category	Representative variables	Physical meaning
Mechanical signals	Vibration, acceleration	Reflect mechanical wear, imbalance, looseness and bearing degradation
Thermal signals	Temperature	Indicate overheating, friction increase and thermal degradation
Electrical signals	Current, voltage	Reflect load fluctuation and electrical abnormality
Operating condition signals	Speed, pressure, load	Describe working condition and external stress level
Target variable	Health indicator / failure risk	Represent equipment degradation state and safety risk

D. TEMPORAL DEEP LEARNING MODEL

Considering the coexistence of transient fluctuations and persistent degradation patterns in equipment monitoring data, this study builds a TCN-Transformer temporal forecasting model. The network architecture includes five main parts: the input layer, temporal convolutional feature extractor, Transformer encoder, fully connected prediction layer, and output layer. The temporal convolutional component first processes the operating sequence to extract local degradation-related representations. Unlike traditional recurrent neural networks, TCN adopts causal convolution to ensure that future information is not used during prediction, and uses dilated convolution to expand the temporal receptive field. For the input sequence S_i, the TCN feature mapping is shown in Equation (7).

$$H_{\text{TCN}} = F_{\text{TCN}}(S_i) \tag{7}$$

Second, a Transformer encoder is employed to characterize global temporal dependencies and long-term changes in equipment operating conditions. Since equipment degradation often results from the accumulated evolution of multiple monitoring variables rather than a single sudden anomaly, it is necessary to model relationships across a wider time span. The attention-based structure enables the model to evaluate the relevance between different moments in the sequence and assign greater importance to periods that contain critical degradation information. The self-attention operation is formulated in Equation (8).

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{8}$$

After temporal feature extraction, the output representations are mapped by a fully connected layer to obtain the predicted health indicator, which is expressed in Equation (9). For parameter optimization, the model is trained by minimizing the mean squared error loss, as described in Equation (10).

$$\widehat{HI}_{t+h} = F_{\text{out}}(H_{\text{Transformer}}) \tag{9}$$

$$\text{Loss} = \frac{1}{N}\sum_{i=1}^{N}(HI_i - \widehat{HI}_i)^2 \tag{10}$$

TABLE 2. Safety warning levels based on predicted health indicator

Predicted health indicator	Equipment state	Warning level	Maintenance suggestion
$HI \geq 0.80$	Normal	Level 0	Routine monitoring
$0.60 \leq HI < 0.80$	Slight degradation	Level 1	Increase inspection frequency
$0.40 \leq HI < 0.60$	Medium risk	Level 2	Arrange preventive maintenance
$HI < 0.40$	High failure risk	Level 3	Stop operation or conduct immediate maintenance

Compared with a single LSTM or Transformer model, the TCN-Transformer structure can jointly consider local feature extraction and long-term dependency modeling. TCN mainly strengthens the representation of local temporal disturbances and early degradation characteristics, while Transformer enhances the modeling of long-span dependencies and important time intervals in the monitoring sequence. Their joint use enables the framework to produce more accurate and stable predictions of equipment safety failure trends.

E. SAFETY FAILURE TREND PREDICTION AND WARNING STRATEGY

To make the prediction results applicable to practical equipment safety management, this study further constructs a safety failure trend warning strategy. The health indicator or failure risk value predicted by the model is not only used to evaluate the future state of equipment but also converted into different levels of safety warning information. According to the predicted health indicator HI, equipment operating states can be divided into four levels: normal, slight degradation, medium risk, and high failure risk, as shown in Table 2.

During failure trend prediction, if the predicted health indicator continues to decrease, it indicates that the equipment is undergoing degradation. If the decline rate of the health indicator increases significantly, the equipment may be entering a stage of rapid risk accumulation. To further characterize the variation in failure trends, the rate of change

TABLE 3. Experimental settings for equipment safety failure trend prediction

Item	Setting
Input variables	Vibration, temperature, current, pressure, speed, load
Target variable	Health indicator
Window length	50 time steps
Prediction horizon	1 time step
Data split	70% training, 15% validation, 15% testing
Optimizer	Adam
Batch size	64
Learning rate	0.001
Evaluation metrics	MAE, RMSE, R2, warning accuracy

in the health indicator is introduced in Equation (11).

$$R_t = HI_t - HI_{t-1} \tag{11}$$

When $R_t < 0$ and its absolute value continues to increase, the equipment health state is declining at an accelerated rate. In this case, the warning level should be increased or the maintenance interval should be shortened. By considering both the level and the changing rate of the health indicator, the proposed strategy can reduce the warning delay caused by relying only on fixed thresholds.

IV. EXPERIMENTAL ANALYSIS

A. EXPERIMENT DESIGN

To validate the applicability of the developed temporal deep learning framework, a series of experiments were performed on multivariate equipment monitoring datasets. The dataset contains continuous operating signals collected from industrial equipment during normal operation, degradation, and near-failure stages. The input variables include vibration, temperature, current, pressure, rotational speed, and load, which are commonly used to characterize mechanical, thermal, electrical, and operational changes in equipment health conditions. The health indicator constructed in Section 3 was used as the target variable for failure trend prediction, as shown in Table 3.

Before model training, the raw sensor data were processed using missing value imputation, outlier correction, smoothing, and Z-score normalization. A sliding-window strategy was adopted to convert the continuous time-series data into supervised learning samples. For performance evaluation, four widely used sequence modeling methods, namely LSTM, GRU, TCN, and Transformer, were selected as benchmarks. The developed TCN-Transformer framework was assessed in comparison with these benchmark models in terms of health indicator forecasting accuracy and safety warning effectiveness.

B. PREDICTION PERFORMANCE COMPARISON

Table 4 summarizes the forecasting accuracy of different time-series models. Traditional recurrent models such as LSTM and GRU achieved acceptable results, indicating that recurrent structures can capture temporal dependencies in equipment degradation data. However, their prediction errors were relatively high, especially during the rapid degradation stage, where the health indicator changed more sharply. This may be because recurrent models process sequential information step by step, making it difficult to fully capture long-term degradation patterns and abrupt state changes when the sequence becomes complex. Compared with LSTM and GRU, the TCN model achieved lower MAE and RMSE values, which demonstrates the effectiveness of causal convolution and dilated convolution in extracting local degradation patterns. By expanding the receptive field through dilated convolution, TCN can better describe short-term fluctuation characteristics and local trend changes in equipment health indicators.

The Transformer model further enhances forecasting accuracy, as its self-attention structure enables the model to establish associations across distant time steps and focus on critical segments related to equipment deterioration. Different from recurrent networks, Transformer processes temporal information in parallel and dynamically assigns attention weights to important degradation periods. This characteristic makes it more effective in recognizing nonlinear and non-stationary patterns in equipment operation data. Overall, the comparison results indicate that the proposed Transformer-based model provides stronger capability in trend estimation and maintains better stability when handling complex health-state variations and rapid deterioration processes.

Figure 2 compares the prediction errors of different models. It can be observed that the TCN-Transformer achieves the best overall performance, with lower error values than the other baseline methods. This finding indicates that the integration of temporal convolution and self-attention is more effective than relying on a single time-series modeling structure. The TCN module focuses on short-term abnormal

TABLE 4. Model comparison in terms of prediction accuracy

Model	MAE	RMSE	R2	Warning accuracy
LSTM	0.082	0.113	0.874	86.2%
GRU	0.079	0.108	0.889	87.5%
TCN	0.071	0.096	0.912	89.3%
Transformer	0.068	0.091	0.925	90.1%
Proposed TCN-Transformer	0.054	0.076	0.948	93.6%

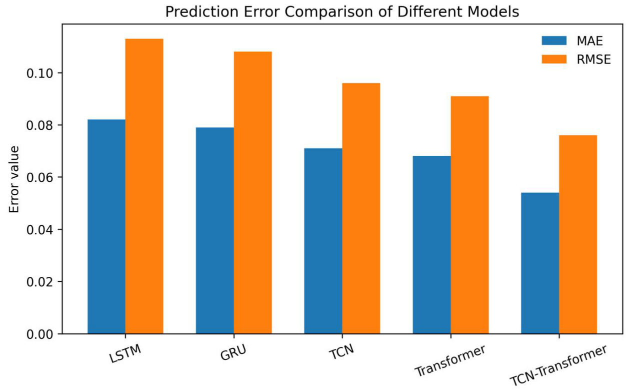

FIGURE 2. Prediction error comparison of different models.

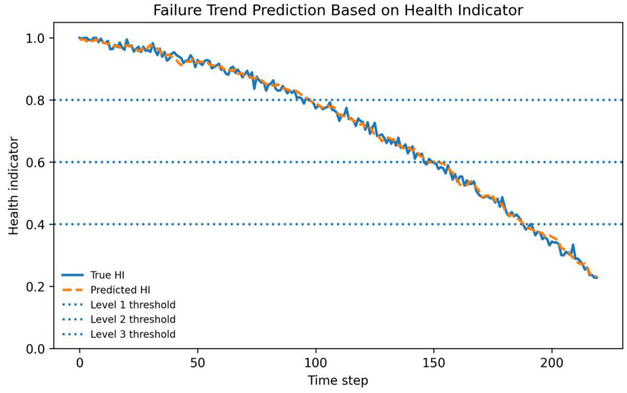

FIGURE 3. Failure trend prediction based on health indicator.

fluctuations, while the Transformer module learns the global degradation pattern. Their combination improves both local sensitivity and long-term prediction stability.

C. FAILURE TREND PREDICTION RESULTS

To further analyze the ability of the proposed model to predict safety failure trends, the predicted health indicator was compared with the predefined safety warning thresholds. Based on the calculated health indicator values, the equipment condition is divided into four stages: normal operation, slight degradation, medium risk, and high failure risk. In the early operating stage, the health indicator remains above 0.80, indicating that the equipment is in a relatively stable and healthy condition. During this period, only routine monitoring is required. As the operating time increases, the health indicator gradually decreases and enters the slight degradation stage, suggesting that minor performance deterioration begins to appear. Although the equipment can still operate normally at this stage, closer monitoring is necessary to track the evolution of potential faults. When the health indicator continues to decline and reaches the medium-risk range, the degradation trend becomes more obvious, and preventive maintenance should be considered to avoid further deterioration. Once the health indicator falls into the high-risk range, the equipment may be close to an unsafe operating condition, indicating that timely inspection, maintenance, or shutdown decisions are required. This stage-based warning analysis demonstrates that the proposed model can not only predict the continuous degradation trend of equipment health but also provide practical support for hierarchical safety warning and maintenance decision-making.

Figure 3 presents the health indicator forecasting performance of the proposed model. The actual health indicator shows a continuous downward tendency during the transition from normal operation to degradation and high-risk conditions. The predicted curve closely follows the real degradation trajectory, especially in the middle and late degradation stages. Although slight deviations appear at several local fluctuation points, the overall tendency remains consistent with the actual health indicator, which is important for early warning and maintenance planning. As operating time increases, the health indicator gradually decreases and crosses the first warning threshold. This suggests that the equipment begins to show slight degradation. When the predicted health indicator drops below 0.60, the equipment enters the medium-risk stage and preventive maintenance should be arranged in advance. In the late stage, the predicted health indicator falls below 0.40, indicating that the equipment has entered the high failure risk stage. The model successfully identifies this transition before the health indicator reaches the lowest level, which demonstrates its early warning capability.

TABLE 5. Ablation study of the proposed model

Model variant	Description	RMSE	Warning accuracy
Without TCN	Removes local convolutional feature extraction	0.089	90.4%
Without Transformer	Removes global attention-based dependency modeling	0.094	89.8%
Without change-rate warning	Uses only fixed HI thresholds	0.082	91.5%
Full model	TCN + Transformer + trend-based warning strategy	0.076	93.6%

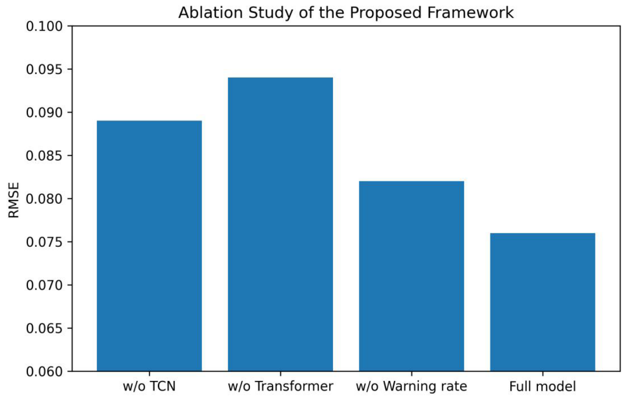

FIGURE 4. Ablation study of the proposed framework.

D. ABLATION ANALYSIS

To further evaluate the effectiveness of each key component, an ablation study was carried out. Specifically, three reduced configurations were established by excluding the TCN module, the Transformer module, and the change-rate-based warning strategy, respectively. Their results were compared with those of the full TCN-Transformer model to clarify the role of each component in prediction and warning performance.

As shown in Table 5 and Figure 4, removing either the TCN or Transformer module leads to a clear decline in prediction performance. When the TCN module is removed, the model becomes less sensitive to local abnormal fluctuations in vibration, temperature, and current signals. The

TABLE 6. Safety warning performance of the proposed model

Warning level	Equipment state	Precision	Recall	Suggested action
Level 0	Normal	95.1%	96.4%	Routine monitoring
Level 1	Slight degradation	92.8%	91.6%	Increase inspection frequency
Level 2	Medium risk	91.3%	90.7%	Arrange preventive maintenance
Level 3	High failure risk	94.2%	92.9%	Immediate maintenance or shutdown

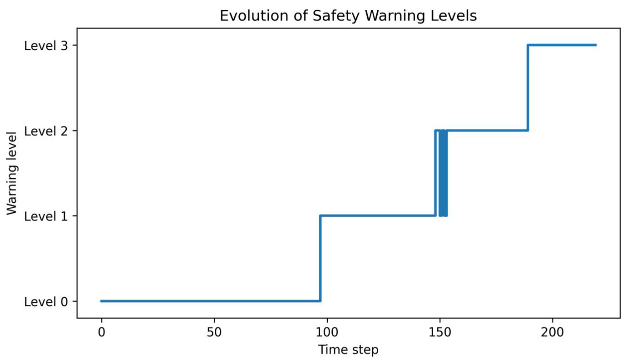

FIGURE 5. Evolution of safety warning levels.

absence of the Transformer module limits the model's ability to extract long-span temporal information, making it less accurate in characterizing the overall evolution of equipment degradation. The model without the health indicator change-rate warning strategy still maintains relatively good numerical prediction accuracy, but its warning accuracy decreases. This indicates that fixed thresholds alone may not be sufficient for safety warning, especially when the health indicator is declining rapidly but has not yet crossed a predefined threshold.

E. SAFETY WARNING ANALYSIS

To verify the practical usefulness of the proposed approach in equipment safety management, the predicted health indicator was transformed into four safety alarm categories. These categories range from Level 0 to Level 3, representing healthy operation, early degradation, moderate risk, and severe failure tendency. Level 0 describes a stable working condition in which no immediate maintenance is needed. When the alarm rises to Level 1, weak degradation characteristics begin to appear, although the equipment can still operate normally under routine monitoring. Level 2 indicates that the deterioration process has become more evident, so preventive maintenance should be considered. Level 3 corresponds to a critical condition, suggesting that the equipment may approach an unsafe state and requires timely inspection or intervention. By discretizing continuous health prediction results into clear alarm categories, the method provides more intuitive support for condition assessment, maintenance planning, and safety risk control.

As reported in Table 6, the proposed method presents reliable classification results for different alarm categories, confirming that the predicted health indicator can be effectively translated into practical risk warning information. The recognition results are especially favorable for Level 0 and Level 3, indicating that the model is capable of distinguishing stable operating conditions from severe risk states. This capability is valuable for equipment safety management, because Level 0 reflects a normal condition with low maintenance priority, whereas Level 3 indicates a high-risk situation that requires timely intervention.

Meanwhile, the relatively stable results for the intermediate alarm categories suggest that the model can recognize gradual degradation evolution, rather than focusing only on normal and extreme fault states. Figure 5 shows that the warning level gradually increases from Level 0 to Level 3 as the predicted health indicator decreases. This stepwise warning evolution is consistent with the degradation trajectory shown in Figure 3, indicating that the warning results can reflect the continuous deterioration process of equipment health. In the early stage, the equipment remains in a normal or slightly degraded state, while in the later stage, the warning level rises progressively as degradation becomes more severe. From the perspective of engineering application, such a warning mechanism is more suitable for predictive maintenance because it provides progressive warning information rather than a sudden fault alarm. Therefore, maintenance personnel can arrange inspection, component replacement, or operational adjustment in advance according to different warning levels, which helps reduce unexpected failures and improve the reliability of equipment operation.

V. CONCLUSIONS

This study develops a temporal deep learning framework for forecasting safety-related degradation trends in industrial machinery. By combining heterogeneous sensor information, health indicator construction, TCN-Transformer modeling, and risk-level mapping, the framework offers an integrated solution for characterizing the progressive deterioration process before severe faults occur. Different from traditional fault diagnosis approaches that mainly emphasize the recognition of existing abnormal states, this work focuses more on the continuous variation of system health and converts predicted trends into actionable warning information for maintenance planning.

The experimental findings demonstrate that the TCN-Transformer model obtains superior forecasting results compared with LSTM, GRU, TCN, and standard Transformer models. It can accurately follow the temporal evolution of health indicators and recognize the stage-wise change from stable operation to early degradation, moderate risk, and critical risk conditions. The ablation analysis further confirms that temporal convolutional feature extraction, attention-based global dependency modeling, and trendoriented warning rules all play positive roles in enhancing forecasting accuracy and alarm robustness. These results suggest that the proposed framework can capture both short-term abnormal disturbances and persistent degradation characteristics from multidimensional monitoring sequences.

In summary, this work provides a practical data-driven strategy for early risk prediction and predictive maintenance of industrial systems. The framework can assist maintenance engineers in identifying potential hazards in advance, optimizing maintenance schedules, and reducing unexpected shutdowns and safety incidents. Future studies may further strengthen the model by integrating physical degradation knowledge, digital twin techniques, domain adaptation, and continual learning strategies. Moreover, improving interpretability and validating the framework in more complex industrial environments will be essential for promoting its broader engineering application.

DECLARATION OF CONFLICTING INTERESTS

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

DATA SHARING AGREEMENT

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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