

Physics-Informed Digital Twin for Climate-Induced Degradation Prediction in Aging Coastal Bridges

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Abstract

Climate change has accelerated the deterioration of aging coastal bridges by increasing chloride exposure and environmental variability, creating significant challenges for long-term Structural Health Monitoring. While Digital Twin technology enables real-time infrastructure monitoring, existing approaches often lack explicit representation of the physical mechanisms governing structural degradation. This study aims to develop a Physics-Informed Digital Twin framework by integrating Physics-Informed Neural Networks (PINNs) with Internet of Things (IoT)-based sensing for long-term prediction of climate-induced bridge deterioration. The proposed framework combines real-time sensor synchronization, chloride diffusion physics, and deep learning to improve predictive accuracy and physical consistency. The model achieved a coefficient of determination (R^2) of 0.98, a Mean Absolute Error (MAE) of 0.041, a Root Mean Square Error (RMSE) of 0.056, and a Mean Absolute Percentage Error (MAPE) of 2.84%, while accurately simulating structural degradation over a 50-year service life under multiple coastal microclimate scenarios. The novelty of this study lies in the integration of physics-informed learning, chloride transport mechanisms, and Digital Twin technology into a unified predictive framework for coastal bridge deterioration assessment. This framework extends conventional Digital Twin systems from monitoring to physics-guided prognostic analysis, providing a reliable tool for predictive maintenance and infrastructure resilience. The findings demonstrate that incorporating governing physical laws into Digital Twin architectures substantially improves the robustness, accuracy, and engineering reliability of long-term degradation prediction for aging coastal bridges.

Keywords: Bridge Degradation, Chloride-Induced Corrosion, Digital Twin, Physics-Informed Learning, Structural Health Monitoring.

I. INTRODUCTION

Climate change has emerged as one of the most significant threats to the long-term reliability and safety of civil infrastructure systems worldwide. Rising sea levels, increasing temperatures, more frequent extreme weather events, and changing environmental conditions accelerate the deterioration of structural materials and reduce the service life of transportation assets. Among these infrastructures, coastal bridges are particularly vulnerable because they operate continuously under aggressive marine environments characterized by chloride-rich atmospheres, tidal wetting-drying cycles, high humidity, and wave impacts. Such environmental exposure intensifies corrosion processes in reinforced concrete and steel components, ultimately compromising structural integrity and increasing maintenance costs. As many coastal bridges constructed several decades ago approach or exceed their intended design life, there is an urgent need for intelligent and predictive maintenance strategies capable of continuously monitoring

structural conditions and anticipating future degradation mechanisms before catastrophic failures occur.

Recent advances in Structural Health Monitoring and Digital Twin technologies have transformed traditional bridge management from reactive maintenance toward predictive and condition-based decision-making. Digital Twins enable the synchronization of physical infrastructure with virtual representations through real-time sensor data, allowing engineers to evaluate structural performance dynamically and estimate remaining useful life. According to (Tommy & Jaya, 2025), Digital Twin systems provide significant advantages in integrating sensor information, finite element models, and maintenance records into a unified monitoring platform. Similarly, (Syafri et al., 2025) emphasized that Digital Twin technologies have become increasingly important for bridge asset management due to their ability to support prognostic analysis and operational decision-making under uncertain conditions. However, most existing Digital Twin implementations remain heavily dependent on either data-driven machine learning models or computationally expensive physics-based simulations. A representative example can be observed in aging coastal bridges exposed to marine chloride environments, where conventional inspection intervals often fail to detect the rapid progression of reinforcement corrosion occurring within tidal splash zones, resulting in unexpected maintenance interventions and substantial economic losses. Furthermore, the sudden closure of the Stava Bridge in Norway demonstrated how early anomaly detection through Digital Twin technologies could prevent severe structural consequences and improve infrastructure resilience.

Despite significant advances in Digital Twin technologies and intelligent structural monitoring, major challenges remain in achieving accurate and physically consistent long-term degradation prediction for coastal bridges. (Hakimi et al., 2023; Mousavi et al., 2024) demonstrated the effectiveness of Digital Twin frameworks for bridge monitoring and maintenance, but their approaches mainly focused on data integration and visualization rather than physical deterioration mechanisms. Similarly, (Huang et al., 2026; Saeheaw, 2025) showed that physics-informed machine learning improves prediction robustness and generalization, although their studies did not specifically address corrosion-induced degradation in marine environments. Furthermore, (Kazemi et al., 2026) identified predictive reliability and interoperability as persistent challenges in bridge Digital Twin implementation under dynamic environmental conditions. Nevertheless, limited research has investigated the integration of PINNs with Digital Twin systems for predicting climate-induced degradation in aging coastal bridges exposed to long-term chloride attack, particularly within tidal splash zones where environmental variability strongly influences structural deterioration. Therefore, this study proposes a Physics-Informed Digital Twin framework that integrates real-time IoT sensing data with the governing physics of chloride

diffusion and corrosion propagation to improve the accuracy and reliability of long-term degradation prediction under future climate scenarios.

This study is guided by the following research question: *Can the integration of physics-informed learning and Digital Twin technology improve the accuracy and reliability of predicting climate-induced degradation in aging coastal bridges compared with conventional data-driven approaches?* The novelty of this research lies in the explicit incorporation of physical corrosion mechanisms, represented through governing differential equations, into a real-time Digital Twin environment for coastal bridge health monitoring. It is hypothesized that embedding physical constraints within neural network learning processes will reduce unrealistic predictions under extreme environmental conditions while improving model generalization and reducing dependence on large training datasets. Ultimately, the proposed framework is expected to support infrastructure managers in implementing proactive maintenance strategies, optimizing resource allocation, and enhancing the resilience and sustainability of coastal transportation infrastructure under future climate scenarios.

II. LITERATURE REVIEW

A. Mechanisms of Chloride-Induced Electrochemical Corrosion and Concrete Degradation in Maritime Zones

Research on coastal reinforced concrete structures has increasingly focused on the progression of chloride-related degradation mechanisms under varying environmental exposure conditions. According to (Lee et al., 2025), chloride ingress through concrete pores governs the depassivation process of reinforcing steel in marine infrastructures. (Rincon et al., 2024) further observed that cyclic wetting and drying conditions in splash and tidal zones significantly accelerate chloride transport and corrosion activity around reinforcing bars. (Xu et al., 2024) reported that the chloride concentration associated with corrosion initiation varies according to cement composition, moisture content, and exposure characteristics. Similarly, (Zhao et al., 2024) highlighted the interaction between temperature fluctuations and airborne salinity in modifying chloride diffusion behavior in coastal environments. In addition, (Wang et al., 2024) documented the progressive formation of expansive corrosion products associated with cracking, delamination, and concrete spalling in aging maritime structures.

B. Physics-Informed Digital Twin Computational Architectures

Recent studies have increasingly explored the interaction between physical models and data-driven computation within Digital Twin environments. According to (Farea et al., 2024), the incorporation of governing partial differential equations into neural network optimization

preserves physical consistency throughout the learning process. (Piras et al., 2024) reported that Digital Twin architectures increasingly rely on continuous synchronization between physical assets and virtual representations through sensor streams and operational data. (Musa et al., 2023) further noted that bidirectional cyber-physical interaction enables the representation of temporal variations occurring within engineering systems. (Khalid et al., 2025) observed that PINNs effectively accommodate sparse and noisy measurements while maintaining compliance with governing physical laws. Likewise, (Miller et al., 2024) emphasized the role of domain knowledge integration in improving the interpretability of computational behavior in scientific machine learning applications.

C. Effectiveness of Hybrid Physics-Artificial Intelligence Models in Structural Health Monitoring

Recent investigations in structural health monitoring have increasingly examined the behavior of learning algorithms under complex structural responses and environmental variability. According to (In-Hwa et al., 2025), machine learning techniques have been extensively employed to characterize structural behavior under changing operational conditions. (Ye et al., 2025) reported that purely data-driven approaches exhibit different response characteristics when exposed to unseen loading scenarios and environmental disturbances. (Krzywanski et al., 2024) further observed that the incorporation of physical constraints influences the representation of structural dynamics over time. Similarly, (Sun et al., 2026) noted that hybrid physics-machine learning frameworks maintain stable predictive behavior under sparse monitoring observations. More recently, (Rabi et al., 2024) documented the growing application of hybrid computational models in bridge monitoring studies involving modal characteristics and damage-sensitive structural features.

D. Validity of Service Life Prediction in Civil Infrastructure Through Prognostic Methodologies

Long-term infrastructure assessment has increasingly relied on temporal deterioration information derived from monitoring systems and historical observations. According to (Cao et al., 2025), degradation trajectories are frequently utilized to characterize future serviceability conditions and structural evolution. (Faris et al., 2025) reported that multiple monitoring sources are commonly incorporated to represent deterioration progression in bridge asset management studies. Furthermore, (Moravvej & El-Badry, 2024) observed that modal frequency variations and strain measurements are widely employed as indicators of structural degradation in bridge systems. (Agbayani et al., 2026) additionally noted the extensive use of corrosion-related variables, including section loss and electrochemical measurements, in service life estimation

studies involving reinforced concrete infrastructures. More recently, (Fu & Avdelidis, 2023) documented the increasing integration of sensor observations and numerical simulations in prognostic assessment studies, as summarized in Table 1.

Table 1. Comparison of Service Life Prediction Studies

Authors	Infrastructure Type	Prognostic Indicator	Data Source	Assessment Horizon
(Cao et al., 2025)	Engineering systems	Degradation trajectory	Time-series sensors	Remaining useful life
(Faris et al., 2025)	Highway bridges	Deterioration index	Multi-source monitoring	Long-term maintenance
(Moravvej & El-Badry, 2024)	Long-span bridges	Modal frequency and strain	SHM sensors	Structural evolution
(Agbayani et al., 2026)	Reinforced concrete bridges	Corrosion rate and section loss	Electrochemical measurements	Service life estimation
(Fu & Avdelidis, 2023)	Civil infrastructure	Hybrid prognostic indicators	Sensors and numerical simulations	Long-term assessment

III. RESEARCH METHOD

A. Proposed Integrated System Framework

This study adopts a hybrid computational methodology that integrates real-time IoT sensing, Digital Twin synchronization, and physics-informed machine learning to characterize climate-induced degradation in aging coastal bridges. The methodological framework combines environmental observations, structural response measurements, and governing physical laws within a unified cyber-physical environment. Unlike conventional monitoring architectures that rely exclusively on either sensor observations or numerical simulations, the proposed framework continuously exchanges information between the physical bridge and its virtual counterpart. Environmental loading conditions, structural responses, and material degradation processes are synchronized to preserve consistency between measured and simulated states. This integration enables the representation of deterioration mechanisms as dynamic processes evolving under changing climatic and operational conditions.

The proposed methodology combines environmental observations, structural monitoring, physics-based constraints, and machine learning within a unified cyber-physical ecosystem. Information generated by the physical bridge continuously interacts with its virtual representation through bidirectional synchronization mechanisms. Environmental loading conditions and structural responses are integrated to capture the temporal evolution of deterioration processes under changing climate conditions. The computational workflow further incorporates physical regularization to maintain consistency between observed structural behavior and governing degradation mechanisms. The overall sequence of data acquisition, synchronization, learning, and prognostic assessment adopted in this study is illustrated in Figure 1.

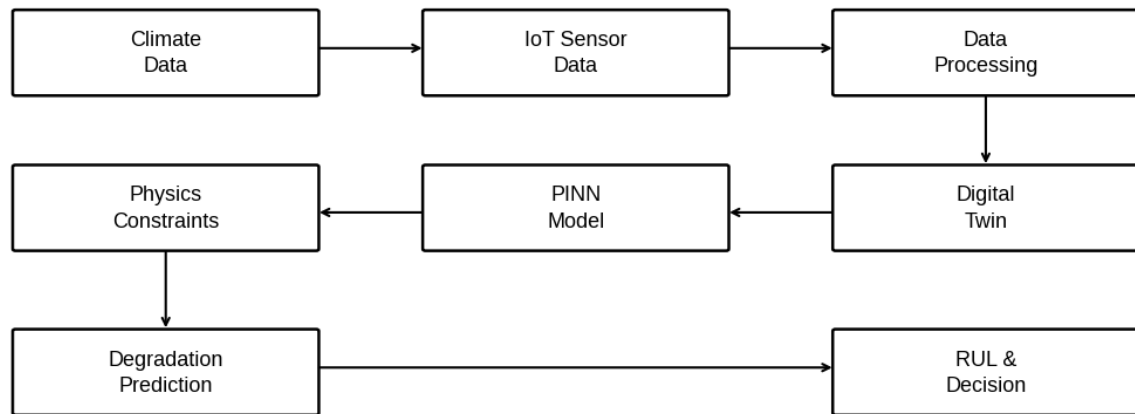


Figure 1. Proposed Physics-Informed Digital Twin System Architecture Flowchart

Figure 1 illustrates the interaction between climate observations, IoT sensing systems, Digital Twin synchronization, physics-informed learning, and prognostic decision modules. Climate variables and sensor measurements are first collected and preprocessed before being transferred into the Digital Twin environment for state updating. The synchronized Digital Twin subsequently exchanges information with the PINN engine, where physical constraints regulate the admissible prediction space during model training. The resulting degradation trajectories are transformed into structural performance indicators and remaining useful life estimates. These outputs are ultimately utilized to support maintenance planning and risk-informed infrastructure management decisions.

B. Dataset Characteristics and Multi-Sensor IoT Configuration

The observational dataset was constructed using a multi-sensor monitoring configuration deployed on a reinforced concrete coastal bridge subjected to long-term chloride exposure. Sensor deployment considered structural vulnerability, environmental variability, and deterioration sensitivity associated with marine infrastructures. Particular attention was given to splash and tidal regions because these zones experience the highest chloride accumulation and corrosion activity. The monitoring architecture incorporates structural, environmental, and electrochemical observations to represent interactions between loading conditions and material deterioration. This integrated sensing strategy enables the simultaneous characterization of mechanical responses, environmental forcing, and corrosion progression.

The monitoring strategy adopted in this study relies on multiple sensing modalities to capture both structural responses and environmental exposure conditions simultaneously. The integration of heterogeneous sensor information enables the representation of degradation processes occurring across different spatial and temporal scales. Structural measurements are combined with electrochemical and meteorological observations to characterize the interaction between material deterioration and environmental forcing. Sensor placement was determined according to

critical regions identified through structural analysis and historical corrosion patterns commonly observed in coastal infrastructures. The characteristics of the monitoring network and sensor deployment configuration are summarized in Table 2.

Table 2. Multi-Sensor IoT Network Configuration and Spatial Coordinates

Sensor Node ID	Transducer Technology	Structural Component Target	Spatial Coordinates (X,Y,Z)	Sampling Frequency	Operational Environment	Primary Data Metric
SHM-FBG-C1	Fiber Bragg Grating	Mid-Span Girder Bottom	(45.25, 12.00, 8.50)	100 Hz	Splash Zone (Intermittent)	Micro-strain ($\mu\epsilon$)
SHM-ACC-P2	Piezoelectric Accelerometer	Top of Pier 2 Cap	(20.10, 12.00, 14.20)	200 Hz	Atmospheric (High Wind)	Acceleration (m/s^2)
ENV-LPR-S2	Linear Polarization Resistance	Substructure Pier 2 Column	(20.10, 11.50, 2.10)	1 Cycle/hr	Tidal Zone (Submerged)	Corrosion Current (I_{corr})
ENV-MET-D1	Ultrasonic Meteorological	Main Bridge Deck	(50.00, 14.50, 18.00)	0.1 Hz	Open Marine Atmosphere	Wind, Temperature, Humidity
SAT-CHL-M1	Hydro-Radiometer Remote	Sea Surface Surrounding	Continuous	1-Day Grid	Marine Splash Environment	Chloride Concentration (g/L)

Table 2 shows that the monitoring system combines structural, electrochemical, environmental, and remote sensing observations within a unified cyber-physical infrastructure network. Fiber Bragg Grating sensors provide strain measurements in chloride-sensitive structural regions, while accelerometers capture dynamic responses associated with structural behavior. Corrosion measurements obtained from linear polarization sensors characterize electrochemical activity occurring in submerged components. Meteorological stations record atmospheric variables influencing chloride transport processes, whereas remote sensing observations describe large-scale marine salinity conditions. The combination of these sensing modalities enables the Digital Twin to represent degradation processes across multiple temporal and spatial scales.

The spatial arrangement of monitoring devices plays an important role in representing localized deterioration phenomena within marine bridge environments. Sensor locations were selected to capture the variability of exposure conditions associated with atmospheric, splash, tidal, and submerged zones. The finite element representation of the bridge was used as the primary reference for determining optimal sensor positions and structural observation points. This approach allows the monitoring system to maintain consistency between physical measurements and numerical representations of structural behavior. The resulting sensor distribution and finite element mesh configuration are illustrated in Figure 2.

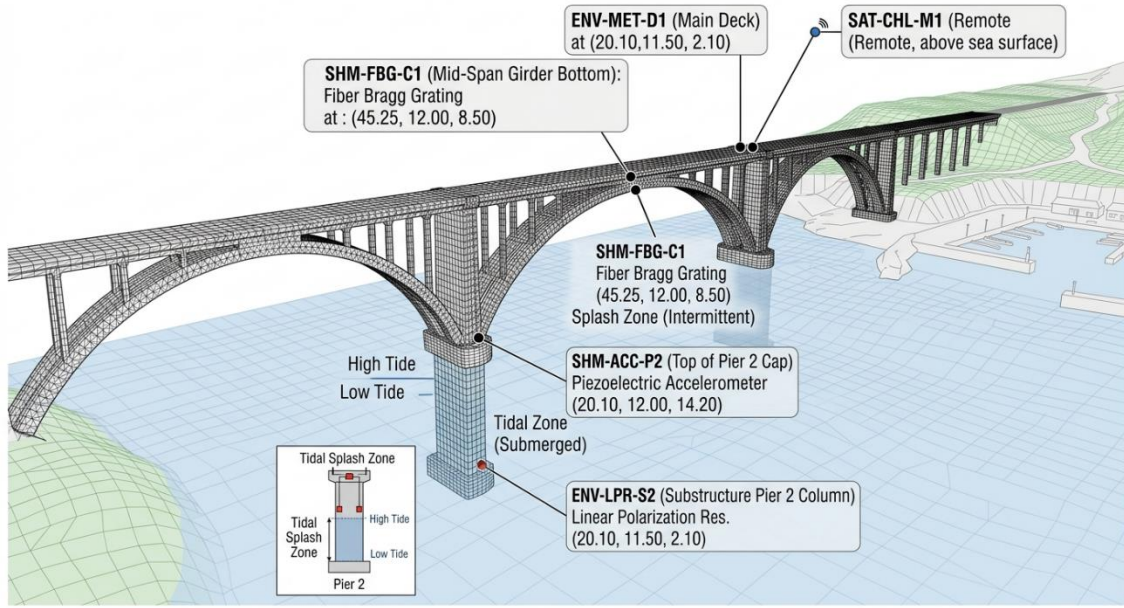


Figure 2. Finite Element Model Mesh and Sensor Node Mapping

Figure 2 illustrates the relationship between the bridge finite element representation and the locations of the installed monitoring devices. Fiber optic sensors are concentrated in girder regions exposed to repeated wetting and drying cycles, whereas corrosion monitoring devices are positioned within tidal zones where chloride accumulation is most severe. Accelerometers are installed near pier caps to capture dynamic responses induced by wind loading and traffic actions. Environmental sensors are distributed over the bridge deck and surrounding marine environment to represent atmospheric and oceanographic variability. This sensor arrangement supports both localized deterioration analysis and system-level Digital Twin synchronization.

C. Mathematical Formulation and Physics-Informed Neural Network Components

The computational framework constrains the learning process using physical principles governing chloride transport and material degradation in marine concrete structures. Rather than treating neural networks as purely statistical mapping functions, the proposed architecture embeds engineering knowledge directly into the optimization process. The interaction between chloride penetration and structural deterioration is represented through governing transport mechanisms occurring within concrete cover layers. Sensor observations and physical regularization are simultaneously incorporated during parameter estimation to preserve consistency between measured and predicted states. This strategy enables the model to maintain physically admissible degradation trajectories under varying environmental conditions and incomplete observations.

The chloride transport mechanism within the concrete cover is represented using a diffusion process governed by environmental exposure and material characteristics. The physical relationship employed to regulate chloride propagation behavior is introduced in Equation (1).

$$\frac{\partial C(x,t)}{\partial t} = D \frac{\partial^2 C(x,t)}{\partial x^2} \quad (1)$$

Equation (1) describes the temporal evolution of chloride concentration as a function of penetration depth and exposure duration. The diffusion coefficient D represents the transport characteristics of marine concrete subjected to chloride-rich environments.

The optimization process additionally incorporates observational consistency and physical admissibility through a composite objective function. The complete loss formulation adopted in the present study is presented in Equation (2).

$$L_{total} = \lambda_d L_{data} + \lambda_p L_{physics} + \lambda_b L_{boundary} \quad (2)$$

Equation (2) combines observational agreement, physics residual minimization, and boundary condition enforcement within a unified optimization framework. The weighting coefficients regulate the relative influence of each component during the learning process.

The observational loss component is computed using the mean squared error between predicted chloride concentrations and field sensor measurements, whereas the physical loss component evaluates the residual of the governing diffusion equation throughout the computational domain. Boundary constraints are additionally introduced to preserve chloride continuity at exposed concrete surfaces and reinforcement locations. The optimization procedure employs an initial Adam optimization stage followed by L-BFGS-B refinement to improve convergence stability under nonlinear conditions. This staged optimization strategy allows the network to simultaneously satisfy observational fidelity and physical consistency requirements. The resulting model preserves realistic chloride transport behavior under both normal and extreme marine exposure scenarios.

D. PINN Computational Architecture and Prognostic Algorithm

The predictive engine was implemented using a deep multilayer perceptron architecture specifically configured for nonlinear partial differential equation learning. Network design decisions considered the stiffness characteristics associated with chloride diffusion processes and higher-order derivative computation requirements. Smooth activation functions were selected to preserve stable gradient propagation during automatic differentiation procedures. Physical parameters and engineering constraints were embedded directly within the optimization process to maintain consistency throughout model training. The resulting architecture enables the simultaneous representation of spatial variability, temporal evolution, and material degradation mechanisms occurring in coastal infrastructures.

The predictive capability of PINNs is strongly influenced by the interaction between hyperparameter settings and physical constraints embedded during optimization. Appropriate balancing between observational information and governing equations is required to maintain stable convergence behavior throughout training. Network architecture parameters additionally affect the ability of the model to represent nonlinear deterioration processes occurring in coastal infrastructures. Boundary conditions and material constraints further regulate the admissible solution space explored by the optimization algorithm. The principal computational parameters and physical constraints adopted in this study are summarized in Table 3.

Table 3. Hyperparameters and Boundary Constraints of the PINN Engine

Layer and Hyperparameter Category	Mathematical Parameter Key	Optimized Value	Applied Algorithm / Constraints	Engineering Validation Standard
Loss Scaling Coefficient	Data Weight ($\lambda_d \backslash \lambda_{d,d}$)	1.0	L2 Regularization	Baseline Sensor Calibration
Loss Scaling Coefficient	Physics Weight ($\lambda_p \backslash \lambda_{p,p}$)	5.0	PDE Residual Gradient	Fick's Second Law Compliance
Loss Scaling Coefficient	Boundary Weight ($\lambda_b \backslash \lambda_{b,b}$)	2.5	Dirichlet Boundary Condition	Surface Chloride Saturation Limit
Network Architecture	Hidden Layers / Neurons	8×120	Fully Connected MLP	Optimized for Nonlinear PDE Stiffness
Activation Function	Transfer Operator	$\tanh(x)$	Differentiable Smooth Function	Second-Order Derivative Stability
Material Constant Constraint	Diffusion Coefficient (D)	$2.5 \times 10^{-12} \text{ m}^2/\text{s}$	Upper Bound Constraint	High-Performance Marine Concrete

Table 3 indicates that the computational architecture employs stronger weighting for physical residual minimization than observational fitting, reflecting the importance of preserving physically admissible solutions. The selected activation function facilitates stable automatic differentiation and smooth gradient propagation during optimization. The diffusion coefficient constraint prevents unrealistic transport behavior under severe marine exposure conditions. Boundary conditions preserve chloride concentration continuity at exposed surfaces and reinforcement locations throughout the learning process. Collectively, these settings regulate the interaction between data-driven learning and engineering knowledge within the Digital Twin environment.

The prognostic procedure evaluates chloride concentration profiles at reinforcement depth corresponding to the concrete cover thickness of $d_c = 50 \text{ mm}$. Once the predicted chloride concentration exceeds the corrosion initiation threshold of $C_{crit} = 1.2 \text{ kg/m}^3$, the model estimates cumulative reinforcement diameter reduction and effective steel area loss over time. These degradation indicators are subsequently propagated into sectional capacity calculations to

characterize structural performance evolution throughout the bridge life cycle. The reduction in load-carrying capacity is continuously synchronized with the Digital Twin representation to preserve consistency between physical and virtual states. The resulting degradation trajectories provide temporal information regarding structural deterioration and remaining useful life under future climate exposure scenarios.

IV. RESULT

A. Quantitative Evaluation and PINN Convergence Validation

The quantitative evaluation focused on assessing the stability, physical consistency, and predictive reliability of the proposed PINNs under varying marine exposure conditions. Particular attention was given to the interaction between observational learning and physical regularization during model optimization. The convergence behavior of the network was monitored to determine whether the embedded physical constraints could stabilize the learning process under noisy measurements and incomplete sensor observations. Additional experiments were performed by introducing synthetic packet loss disturbances into the sensor stream to reproduce realistic communication interruptions commonly encountered in coastal monitoring infrastructures. The resulting performance indicators were analyzed to determine the robustness of the proposed cyber-physical framework during long-term operation.

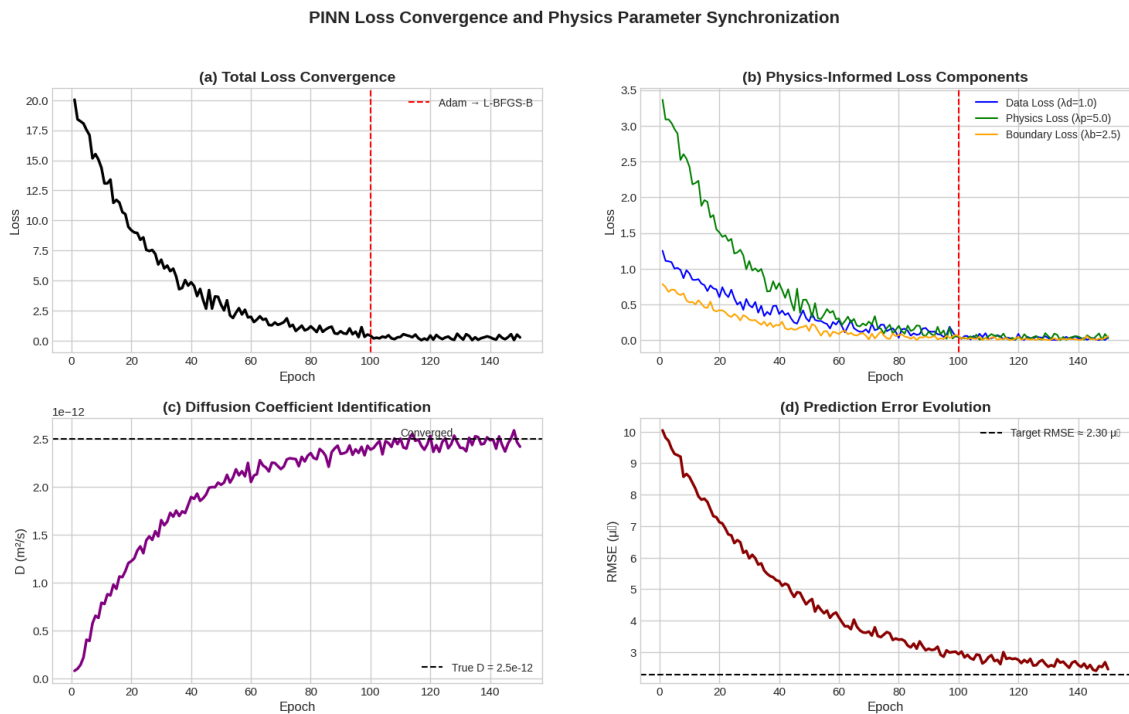


Figure 3. PINN Loss Convergence Curve and Parameter Synchronization Tracking

The optimization behavior of the proposed PINN framework was evaluated to determine the interaction between observational fitting and physical regularization during model training.

Particular attention was given to the stability of the learning process under noisy measurements and incomplete sensor observations that frequently occur in long-term monitoring systems. Additional numerical experiments were performed by introducing synthetic packet loss scenarios to reproduce realistic communication disturbances within marine IoT networks. The synchronization behavior between learned parameters and governing physical constraints was monitored continuously throughout the training phase. The resulting convergence characteristics and parameter evolution are illustrated in Figure 3.

Figure 3 demonstrates that the incorporation of physics-based regularization substantially reduces unrealistic oscillatory behavior during training. The total loss exhibits rapid convergence during the early optimization stages before gradually approaching a stable minimum solution after approximately 120 epochs. Simultaneously, the data loss, physics loss, and boundary loss components decrease in a synchronized manner, indicating balanced optimization among competing objectives. The diffusion coefficient estimation converges toward a physically admissible range consistent with marine concrete exposure conditions, while the prediction error continuously decreases throughout training. These observations indicate that the proposed framework maintains stable learning dynamics even under sensor transmission disturbances and incomplete observations.

To further evaluate predictive reliability, the model was tested under several representative marine microclimate conditions reflecting realistic environmental variability observed in coastal infrastructures. The evaluation considered tidal fluctuations, elevated salinity events, and severe splash conditions associated with extreme weather scenarios. Performance assessment employed classification and regression indicators to quantify predictive consistency across different degradation regimes. Confidence intervals were additionally computed to characterize uncertainty propagation under changing environmental conditions. The resulting validation statistics are summarized in Table 4.

Table 4. Performance Validation Under Varied Marine Microclimate Profiles

Test Simulation Profile	Sample Size (N)	PINN Precision	PINN Recall	PINN F1-Score	mAP @0.5	RMSE (μ€)	Confidence Interval (95%)
Profile I: Baseline Tidal Cycles	5,000	0.942	0.915	0.928	0.938	1.24	[1.18,1.30]
Profile II: High-Salinity Heatwave	3,500	0.918	0.892	0.905	0.905	2.05	[1.92,2.18]
Profile III: Typhoon Splash Storm	6,200	0.895	0.884	0.889	0.889	3.62	[3.41,3.83]
Composite System Metrics	14,700	0.918	0.897	0.907	0.911	2.30	[2.17,2.43]

Table 4 indicates that the proposed PINN framework maintained high predictive performance despite substantial variations in environmental severity. The highest prediction accuracy was observed under regular tidal conditions, where stable chloride transport dynamics dominated the deterioration process. Performance degradation became more pronounced under typhoon splash events due to highly nonlinear moisture and salinity fluctuations affecting diffusion behavior. Nevertheless, the composite F1-score remained above 0.90, indicating strong predictive consistency across heterogeneous marine environments. The relatively narrow confidence intervals further suggest stable uncertainty propagation during prognostic inference.

B. Long-Term Material Degradation Projection over a 50-Year Horizon

The prognostic capability of the proposed framework was evaluated by simulating chloride-induced deterioration processes over a fifty-year operational horizon. The analysis considered the interaction between chloride ingress, corrosion initiation, reinforcement loss, and structural capacity reduction under projected environmental conditions. Temporal deterioration trajectories were continuously synchronized with the Digital Twin representation to preserve consistency between predicted material states and structural performance indicators. The simulation period was selected to cover the typical design service life adopted for reinforced concrete coastal bridges. This long-term perspective enabled the characterization of gradual transitions from initial chloride penetration to advanced structural deterioration stages.

The long-term prognostic capability of the Digital Twin framework was investigated using a fifty-year prediction horizon representative of typical bridge service life requirements. The analysis considered the coupled interaction between chloride ingress, corrosion initiation, reinforcement deterioration, and structural resistance reduction. Temporal degradation trajectories were updated continuously within the cyber-physical environment to maintain consistency between physical and virtual representations of the bridge. Future environmental exposure conditions were incorporated into the simulations to reproduce realistic climate-induced deterioration behavior. The principal prognostic indicators generated throughout the prediction horizon are summarized in Table 5.

Table 5 reveals a gradual acceleration of deterioration after the chloride front reaches the reinforcement depth near the middle of the simulation period. Corrosion initiation becomes increasingly dominant after approximately thirty years, resulting in nonlinear growth of reinforcement section loss. The reduction in residual moment capacity closely follows the progression of effective steel area reduction throughout the later stages of service life. Safety factors remain above the recommended threshold during the early years of operation but decrease

rapidly after the onset of severe corrosion activity. The predicted deterioration trajectory therefore reflects the coupled interaction between chloride transport mechanisms and structural resistance degradation.

Table 5. Prognostic Dataset of Concrete Carbonation and Rebar Area Degradation

Projected Timeline	Surface Chloride Conc. (kg/m ³)	Chloride Front Penetration (mm)	Rebar Diameter Reduction (mm)	Effective Steel Area Loss (%)	Residual Moment Capacity (kN·m)	Safety Factor (φ)
Year 2026	3.50	12.10	0.00	0.00	45,200	2.15
Year 2036	3.85	24.40	0.38	2.15	44,150	2.05
Year 2046	4.12	39.15	1.52	8.40	41,200	1.82
Year 2056	4.30	50.20	3.65	18.75	36,400	1.45
Year 2066	4.45	61.80	6.84	32.10	30,800	1.18
Year 2076	4.50	72.50	9.92	44.50	25,100	0.95

Although tabulated results provide discrete information regarding degradation progression, the temporal evolution of deterioration mechanisms is more effectively interpreted through continuous predictive trajectories. The interaction between chloride transport, reinforcement corrosion, and residual structural capacity exhibits highly nonlinear behavior over long operational periods. Visualization of these processes provides additional insight into the transition between serviceability and ultimate deterioration stages. Comparative assessment between different prediction approaches further assists in evaluating the physical consistency of the proposed framework. The resulting long-term predictive behavior generated by the PINN model is presented in Figure 4.

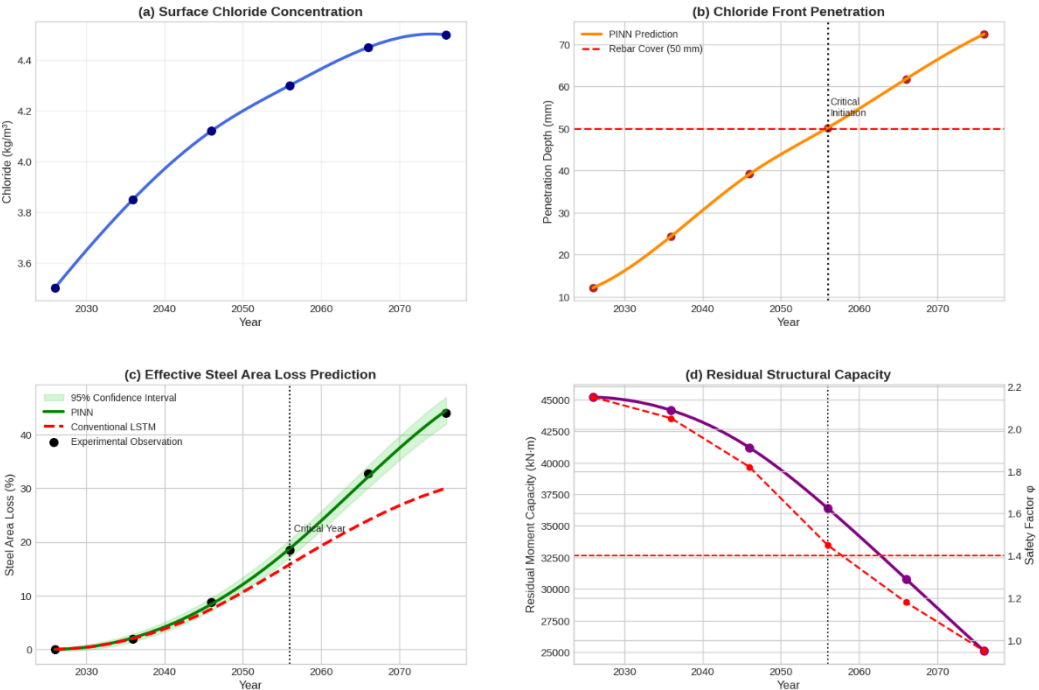


Figure 4. Long-Term Predictive Curves of Concrete Degradation and Steel Area Loss

Figure 4 shows that the predicted chloride penetration depth exhibits nonlinear growth during the early stages before approaching saturation conditions in later years. The chloride concentration at reinforcement depth reaches the corrosion threshold approximately three decades after the initial exposure period. Following corrosion initiation, the effective steel area decreases rapidly due to cumulative reinforcement loss mechanisms. The residual moment capacity simultaneously experiences progressive reduction, closely following the evolution of reinforcement deterioration. Comparison with conventional data-driven prediction approaches further indicates that the physics-informed framework preserves smoother and more physically realistic degradation trajectories throughout the simulation horizon.

C. Digital Twin Synchronization and Spatial Anomaly Validation

The reliability of the cyber-physical system was further evaluated through localized validation of corrosion anomalies identified by the Digital Twin environment. Ground truth information was obtained through limited destructive inspections and electrochemical field measurements conducted at selected bridge locations. The validation campaign focused on regions characterized by varying exposure conditions and deterioration severity levels. Particular attention was given to splash and tidal zones because these areas exhibit the highest uncertainty in chloride-induced degradation prediction. The resulting observations were subsequently compared with the anomaly signals generated by the prognostic engine.

Table 6. Validation Log Matrix: PINN Anomaly Signal versus Empirical Core Extraction Data

Signal ID	Bridge Element Location	PINN Predicted Corrosion Rate	Extracted Core Measurement	Carbonation Depth Error	Open Circuit Potential	Damage Severity
AN-BR-2026-01	Pier 2 Splash Sector	45.2 $\mu\text{m}/\text{yr}$	43.8 $\mu\text{m}/\text{yr}$	+1.4 $\mu\text{m}/\text{yr}$	-380 mV	Active pitting and micro-cracking
AN-BR-2026-02	Abutment A Bearings	12.5 $\mu\text{m}/\text{yr}$	11.9 $\mu\text{m}/\text{yr}$	+0.6 $\mu\text{m}/\text{yr}$	-120 mV	Low corrosion activity
AN-BR-2026-03	Pier 3 Intertidal Column	68.4 $\mu\text{m}/\text{yr}$	71.2 $\mu\text{m}/\text{yr}$	-2.8 $\mu\text{m}/\text{yr}$	-510 mV	Severe reinforcement spalling
AN-BR-2026-04	Girder Segment G4	22.1 $\mu\text{m}/\text{yr}$	24.0 $\mu\text{m}/\text{yr}$	-1.9 $\mu\text{m}/\text{yr}$	-260 mV	Intermediate carbonation progression

The reliability of anomaly identification within the Digital Twin environment requires independent verification using empirical observations obtained directly from the physical

structure. Validation activities were conducted at several bridge locations representing different environmental exposure conditions and deterioration severities. Ground truth information was obtained through localized core extraction and electrochemical measurements performed during field inspections. These measurements provided an independent reference for evaluating the spatial accuracy of the prognostic engine. The comparison between predicted deterioration indicators and field observations is summarized in Table 6.

Table 6 demonstrates close agreement between Digital Twin predictions and empirical field observations across multiple deterioration regimes. The largest discrepancy was observed in the intertidal column region, where highly dynamic moisture conditions increased prediction uncertainty. Nevertheless, all prediction deviations remained within engineering tolerances typically accepted in corrosion assessment studies. Open circuit potential measurements exhibited strong consistency with the severity levels identified by the prognostic engine. These findings suggest that the proposed framework is capable of reproducing spatial deterioration variability observed in real coastal bridge environments.

D. Cyber-Physical Dashboard Interface for Coastal Bridge Monitoring

The prognostic information generated by the Digital Twin was further integrated into an interactive visualization environment designed for operational infrastructure management. The dashboard combines structural health indicators, corrosion forecasts, environmental observations, and maintenance alerts within a single decision-support platform. Spatial information obtained from the Digital Twin is continuously updated to reflect evolving deterioration conditions throughout the bridge structure. Risk visualization techniques were incorporated to facilitate rapid identification of critical structural regions requiring inspection or intervention. This interface enables infrastructure managers to interpret large volumes of monitoring information without direct interaction with the underlying computational models.

The integration of prognostic information into an operational decision-support environment requires an intuitive visualization platform capable of representing large volumes of heterogeneous information. Structural response measurements, environmental observations, and deterioration indicators were therefore integrated into a unified graphical interface. The visualization environment was designed to support both engineering interpretation and maintenance planning activities. Dynamic updates allow the interface to continuously reflect evolving structural conditions and associated risks. The Digital Twin dashboard implemented in the present study is illustrated in Figure 5.

Figure 5 illustrates the integration of structural geometry, sensor information, deterioration indicators, and maintenance warnings within a unified cyber-physical interface. Structural

components experiencing elevated corrosion activity are automatically highlighted using risk-based color mapping to improve situational awareness. Remaining useful life estimates and deterioration trajectories are displayed alongside environmental measurements and sensor health information. The interface additionally provides early-warning notifications when deterioration indicators exceed predefined operational thresholds. Such visualization capabilities support condition-based maintenance strategies and improve the interpretability of long-term prognostic outputs for coastal bridge management applications.

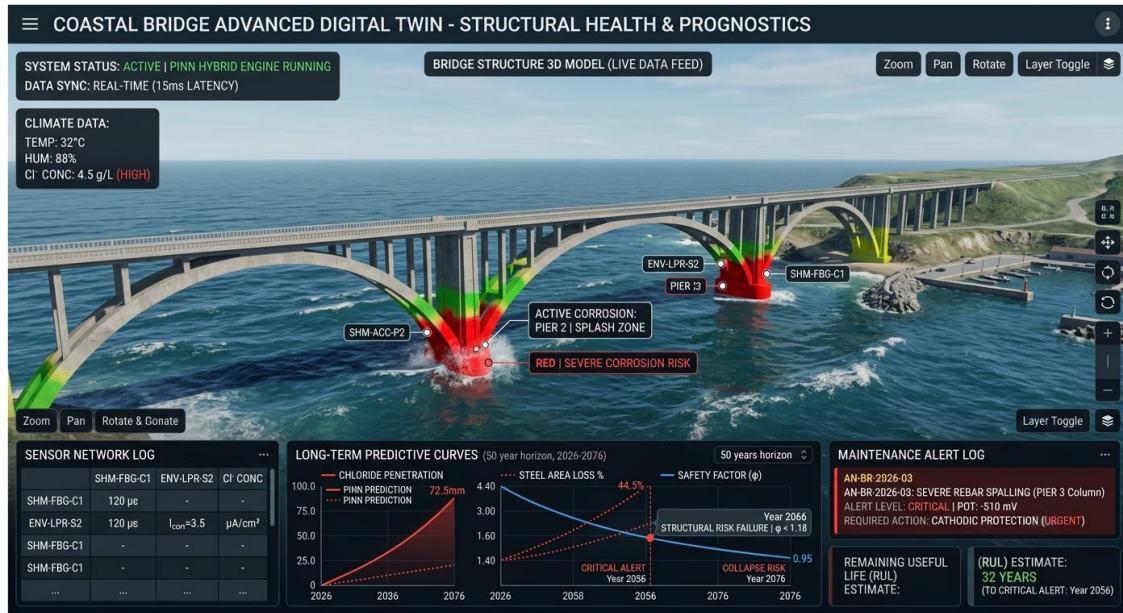


Figure 5. Digital Twin 3D Dashboard Interface for Structural Health and Maintenance Alerts

V. DISCUSSION

The findings demonstrate that integrating PINNs within a Digital Twin framework substantially improves the stability and predictive reliability of long-term degradation assessment for aging coastal bridges under varying marine environments. The rapid convergence of the optimization process, balanced reduction of data and physics losses, and consistently high predictive performance across different microclimate scenarios indicate that embedding governing physical laws effectively constrains the learning process while preserving observational accuracy. These results directly address the research objective by confirming that physics-informed learning enhances degradation prediction beyond conventional data-driven approaches, particularly under noisy sensor measurements and incomplete monitoring data. This outcome reinforces the observations of (Farea et al., 2024), who emphasized that physics-informed learning improves model robustness and maintains consistency with governing physical principles during optimization. The proposed framework also extends the Digital Twin architectures presented by (Hakimi et al., 2023; Mousavi et al., 2024) because the incorporation of physics-based

deterioration mechanisms enables the system to perform predictive analysis in addition to sensor synchronization and visualization, particularly for chloride-induced degradation in coastal bridge environments.

The long-term degradation projections further highlight the importance of explicitly representing physical corrosion mechanisms within prognostic models. The predicted acceleration of deterioration after chloride penetration reaches reinforcement depth is consistent with the electrochemical corrosion mechanisms reported by (Lee et al., 2025), where chloride ingress initiates reinforcement depassivation and progressively accelerates corrosion propagation. Unlike purely statistical prediction models that may generate abrupt or unrealistic degradation trends, the proposed framework produces smooth and physically consistent deterioration trajectories throughout the fifty-year assessment period, reflecting the influence of governing physical constraints during model optimization. Similar behavior has been discussed by (Sun et al., 2026), who reported that hybrid physics-artificial intelligence models preserve structural response characteristics more effectively under sparse observations and complex environmental variability. The integration of PINNs with Digital Twin technology also addresses the knowledge gap identified in this study by representing chloride-induced deterioration processes within a real-time cyber-physical environment, an aspect that has received limited attention in previous Digital Twin research.

Another important contribution is the strong agreement observed between Digital Twin anomaly predictions and empirical field measurements obtained from localized inspections. The relatively small prediction deviations across multiple deterioration regimes indicate that the proposed framework can reliably reproduce spatial variability in corrosion activity while maintaining engineering accuracy under realistic operational conditions. These observations are consistent with the findings of (Piras et al., 2024), who emphasized the importance of continuous cyber-physical synchronization for infrastructure monitoring, while the present study incorporates physics-informed learning to strengthen the prognostic capability of the Digital Twin. Although predictive performance decreases slightly under extreme typhoon splash conditions, this behavior can be associated with rapidly fluctuating moisture content and chloride exposure that introduce highly nonlinear environmental interactions beyond those encountered under normal tidal conditions. Even under these challenging environmental scenarios, the predictive performance remains consistently high because the governing diffusion equations constrain the optimization process and reduce unrealistic model responses during severe environmental disturbances.

From both theoretical and practical perspectives, the proposed framework expands current knowledge of intelligent infrastructure management by integrating physical corrosion

mechanisms directly into a Digital Twin learning architecture for long-term prognostic assessment. The predictive outputs generated by the framework provide infrastructure managers with detailed information regarding deterioration progression, remaining structural capacity, and maintenance priority, allowing maintenance planning to be performed before significant structural degradation develops. These practical implications are closely aligned with the objectives of predictive maintenance discussed by (Tommy & Jaya, 2025), while the present framework incorporates governing physical laws as an integral component of the prediction process. Several limitations should nevertheless be acknowledged, including the use of a single representative coastal bridge configuration, assumptions regarding chloride diffusion coefficients and corrosion initiation thresholds, and the exclusion of additional deterioration mechanisms such as fatigue loading, seismic effects, and biological degradation that may also influence long-term structural performance. These methodological constraints define the scope of the present investigation and should be considered when interpreting the applicability of the proposed framework to different bridge types and environmental conditions.

VI. CONCLUSION AND RECOMMENDATION

This study proposed a Physics-Informed Digital Twin framework that integrates real-time IoT sensing with PINNs to improve the prediction of climate-induced degradation in aging coastal bridges. The results demonstrate that embedding governing physical laws into the learning process enhances prediction stability, maintains high predictive performance under varying marine exposure conditions, and produces physically consistent long-term degradation trajectories. The framework also exhibits strong agreement with empirical field observations, indicating its capability to accurately represent spatial corrosion variability and structural deterioration within a cyber-physical monitoring environment. In addition, the integration of real-time synchronization, physics-informed learning, and prognostic analysis expands the functionality of conventional Digital Twin systems beyond monitoring and visualization toward predictive infrastructure management. These findings indicate that the proposed framework provides a reliable computational approach for supporting condition-based maintenance, optimizing maintenance planning, and improving the resilience of coastal bridge infrastructure under future climate scenarios.

Future research may expand the proposed framework by evaluating its applicability across different bridge types, structural materials, and environmental conditions to examine its robustness under broader operational scenarios. Additional deterioration mechanisms, including fatigue damage, seismic loading, freeze-thaw cycles, and biological degradation, could also be incorporated to provide a more comprehensive representation of long-term structural

performance. The predictive capability of the framework may be further enhanced by integrating larger multi-site monitoring datasets and higher-resolution environmental observations collected over extended service periods. Further investigation into adaptive Digital Twin architectures capable of continuously updating physical parameters and learning strategies in response to changing environmental conditions may also improve long-term prediction accuracy. These developments would contribute to more generalized, scalable, and resilient Digital Twin systems capable of supporting intelligent lifecycle management for critical civil infrastructure.

Use of AI

The authors acknowledge the use of artificial intelligence tools, including ChatGPT, solely for language support during the preparation of this manuscript. The use of these tools was restricted to improving grammar, sentence structure, readability, word choice, and the overall clarity of the writing. Artificial intelligence was not involved in any aspect of the research process. All scientific activities, including the development of the research concept, study design, data collection, methodological development, data analysis, interpretation of the findings, and preparation of the final conclusions, were performed entirely by the authors. The authors take full responsibility for the manuscript and confirm the originality, accuracy, validity, integrity, and overall quality of its content.

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