iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: VI Month of publication: June 2026

DOI: https://doi.org/10.22214/ijraset.2026.83989

Hybrid Deflection-Damage Index (HDDI): A Physics-Informed Framework for Interpretable Structural Health Monitoring

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Abstract: This paper introduces the Hybrid Deflection-Damage Index (HDDI), a practical physics-informed framework for interpretable structural health monitoring of civil infrastructure. The approach combines four key measurable indicators deflection utilization, crack severity, stiffness degradation, and load utilization into a single unified Failure Risk Index that tracks the progressive deterioration of structures. By normalizing these indicators and blending them using a transparent weighting scheme, the framework maintains clear engineering meaning while delivering a continuous measure of structural condition. A simple threshold-based system then classifies the structure into three practical states: SAFE, WARNING, and CRITICAL. This helps engineers and asset managers make informed decisions about inspections and maintenance. Designed as a grey-box model, the HDDI bridges the gap between traditional mechanics-based methods and modern data-driven techniques. Its primary contribution is a straightforward, interpretable, and easily extensible damage indexing approach that can be applied to reinforced concrete structures and other infrastructure systems. The framework aims to support more reliable and explainable structural health monitoring in safety-critical applications.

Keywords: Reinforced Concrete Beams, Structural Health Monitoring, Machine Learning, Grey-Box Modelling, Failure Risk Index, Damage Indicators, Failure Prediction, Structural Condition Assessment.

I. INTRODUCTION

Structural health monitoring (SHM) has become a vital part of modern infrastructure management. It enables early damage detection, performance evaluation, and smarter maintenance planning. As civil structures continue to age and face repeated loading, environmental conditions, and material degradation, the demand for accurate and practical condition assessment tools is growing rapidly [2].Traditional inspection methods still play an important role, but they are often time-consuming, labour-intensive, and highly dependent on the man power [12], [13], [18]. Moreover, they frequently fail to detect internal damage before it becomes visible or critical. These limitations have driven the development of quantitative monitoring systems that turn sensor data into clear, actionable engineering insights.

Even with major advances in sensing technologies, damage detection algorithms, and data analytics, structural health monitoring still faces a key challenge: many existing methods are either easy to understand but somewhat rigid, or highly advanced but difficult for engineers to interpret. In practice, engineers and decision-makers need tools that not only detect damage but also explain why a structure is considered healthy, deteriorated, or at risk. This level of interpretability is especially critical in infrastructure projects, where decisions directly impact public safety, costs, and service life.[2], [11].

In reinforced concrete structures, for instance, damage usually appears through a combination of increasing deflections, widening cracks, loss of stiffness, and higher demand on the remaining capacity. A truly useful monitoring framework should therefore integrate multiple observable indicators rather than relying on one parameter. Single-indicator approaches often miss the bigger picture, while complex black-box models tend to hide the physical meaning behind their results [1], [2], [7], [16]. To address these limitations, this study proposes the Hybrid Deflection-Damage Index (HDDI) a practical, physics-informed framework for interpretable structural health monitoring. The HDDI brings together normalized indicators of deflection utilization, crack severity, stiffness degradation, and load utilization into a single composite Failure Risk Index. This design keeps the assessment firmly grounded in structural mechanics while producing a clear, risk-oriented output that engineers can understand and trust. The main objective of this paper is to present a transparent and flexible damage indexing framework that supports meaningful structural condition evaluation.

The specific contributions are as follows:

- It introduces a hybrid index that integrates deformation, cracking, stiffness loss, and loading demand into one unified formulation.
- It defines a set of normalized indicators that make comparisons consistent across different structures and loading stages.
- It develops a continuous Failure Risk Index that reflects progressive deterioration.
- It establishes simple threshold-based logic to classify conditions as SAFE, WARNING, or CRITICAL.
- It explores how the framework can support practical, interpretable decision-making in reinforced concrete and other civil infrastructure systems.

A. Background of the Study

Reinforced concrete (RC) structures remain one of the most widely used construction systems in civil engineering due to their strength, durability, versatility, and cost-effectiveness. They form the backbone of buildings, bridges, industrial facilities, marine structures, and transportation networks [9], [10]. Within these systems, reinforced concrete beams play a particularly important role in resisting flexural loads and safely transferring forces to supporting elements. The integrity of these beams therefore has a major influence on the overall safety and serviceability of a structure [4], [11].

Throughout their service life, RC beams are exposed to environmental effects, repeated loading, material aging, accidental overloads, and other deterioration processes. These factors lead to progressive damage in the form of cracking, increased deflection, stiffness degradation, reinforcement yielding, and in extreme cases structural failure. If this deterioration goes undetected, it can result in expensive repairs or even catastrophic collapse. Structural Health Monitoring (SHM) has emerged as a valuable tool for assessing the condition of civil infrastructure and guiding maintenance decisions. Conventional SHM systems typically track individual parameters such as deflection, strain, crack width, vibration characteristics, or load response. While these measurements provide useful information, evaluating them in isolation often fails to give a complete picture of the structure’s health. For example, large deflections do not always mean the structure is about to fail, and cracks can appear well before collapse occurs. Recent advances in machine learning have created promising new opportunities for structural condition assessment. These algorithms can uncover complex relationships between sensor data and damage progression [2], [11], [12]. However, many machine learning models function as black boxes, delivering predictions without sufficient explanation. This lack of transparency can reduce confidence among practicing engineers and slow down adoption in safety-critical applications. To overcome these shortcomings, there is increasing interest in hybrid (grey-box) approaches that combine domain knowledge from structural engineering with the power of machine learning. This study proposes the Hybrid Deflection-Damage Index (HDDI) framework, which integrates physics-based damage indicators with flexible classification techniques. The goal is to create a transparent and practical methodology for identifying structural deterioration and supporting informed maintenance planning [1], [2], [12].

B. Problem Statement

Assessing the condition of reinforced concrete beams continues to be a significant challenge in structural health monitoring. Most conventional methods rely on single parameters such as maximum deflection, crack width, or load-carrying capacity[2], [12], [13]. Although these indicators are useful, they often provide only a partial view of the actual deterioration state and can lead to uncertain or conflicting conclusions about structural safety. In recent years, machine learning techniques have shown strong potential for damage detection and condition classification. Nevertheless, many of these models remain black-box systems that offer limited insight into the physical mechanisms driving their predictions [1], [2], [3], [7].

As a result, engineers often struggle to interpret the outputs or verify whether the results align with established structural behaviour. Furthermore, there is still no widely accepted framework that effectively combines multiple mechanics-based damage indicators with interpretable machine learning for reinforced concrete beam assessment. Most existing studies tend to focus either on individual parameters or on purely data-driven models that do not explicitly incorporate engineering knowledge [1], [7], [16]. This research gap highlights the need for a transparent, engineering-oriented framework that integrates real structural response data with machine learning in a way that remains interpretable. The proposed Hybrid Deflection-Damage Index (HDDI) addresses this need by combining physics-based indicators with machine learning classification to assess damage progression and overall structural condition in reinforced concrete beams.

II. RELATED WORK

Structural health monitoring has come a long way from traditional visual inspections and simple sensor measurements. It has gradually evolved into more integrated systems that combine sensing technologies, structural modelling, and advanced data analysis. Early methods mainly relied on observable quantities such as deflection, strain, vibration characteristics, and crack width to assess structural condition. These approaches are still attractive because they are directly connected to real engineering behaviour. However, they often depend on basic thresholds or isolated parameters, which frequently fail to capture the full complexity and gradual progression of structural damage. In most cases, a single measurement simply cannot provide a robust picture of a structure's health. To overcome this limitation, researchers developed damage indices that summarize complex structural behaviour into easy-to-use single values. Many of these indices are based on stiffness loss, energy dissipation, changes in modal properties, or deformation demand. While useful for ranking damage severity and monitoring performance over time, their accuracy often depends heavily on the specific loading conditions, structure type, and calibration process[1], [2], [3], [7]. An index that works well for one system may not perform reliably on another, particularly when different failure mechanisms are involved. This shortcoming has driven the search for more general and physically meaningful damage assessment methods. Meanwhile, machine learning has brought exciting new possibilities to structural assessment. [1], [2], [12], [16] Data-driven models can detect complex, nonlinear patterns in sensor data and often achieve strong performance in damage classification and response prediction when sufficient training data is available. Techniques such as support vector machines, random forests, and neural networks have been widely explored for these tasks. However, a major drawback of many of these models is that they act as black boxes they deliver results without clearly explaining the reasoning behind them. In safety-critical civil engineering applications, this lack of transparency can erode trust and slow down real-world adoption by practicing engineers.

Approach	Physical Indicators Used	Machine Learning	Interpretability	Limitations	Relation to HDDI
Conventional visual inspection	Crack width, spalling, surface distress	No	High	Subjective, labor-intensive, and dependent on inspector experience	HDDI formalizes damage indicators into a computational framework.
Deflection-based assessment	Deflection	No	High	Relies on a single response variable and may overlook other damage mechanisms	HDDI combines deformation with additional deterioration indicators.
Vibration-based SHM	Natural frequency, mode shapes, damping	Optional	Moderate	Sensitive to environmental variability and boundary conditions	HDDI complements global dynamic measures with mechanics-based indicators.
Data-driven machine learning	Raw sensor measurements	Yes	Low	Often produces black-box predictions with limited engineering meaning	HDDI introduces physics-informed features before inference.

Approach	Physical Indicators Used	Machine Learning	Interpretability	Limitations	Relation to HDDI
Physics-based numerical models	Stress, strain, stiffness, load response	No	High	Can be computationally expensive and may have limited adaptability	HDDI balances physical insight with practical interpretability.
Proposed HDDI framework	Deformation, damage manifestation, capacity degradation, demand-capacity utilization	Flexible	High	Requires future experimental validation	Integrates physical understanding and inference within a unified grey-box architecture.

Table 1 Review Of Existing Structural Health Monitoring Frameworks

Explainable artificial intelligence has gained significant attention as a way to address the transparency problem[1], [6], [16]. In structural health monitoring, explainability is especially critical engineers not only need to know what the model predicts, but more importantly, why it reached that conclusion. Grey-box approaches have emerged as particularly promising in this context. They combine established domain knowledge from structural mechanics with the flexibility of computational methods. By preserving physical meaning while still allowing the integration of multiple indicators, grey-box models strike a good balance between accuracy and interpretability. This balance is highly valuable in infrastructure monitoring, where decisions must be both technically sound and defensible to stakeholders, regulators, and the public. Overall, the literature reveals a clear gap: physically meaningful assessment methods often lack flexibility, while advanced computational methods frequently sacrifice transparency. Few approaches successfully combine both strengths in a single framework. The proposed Hybrid Deflection-Damage Index (HDDI) aims to bridge this gap by integrating normalized, physics-based structural indicators into a composite Failure Risk Index. In doing so, it seeks to deliver an interpretable, practical, and scalable tool for structural condition assessment [12], [19].

III. HDDI FRAMEWORK

The Hybrid Deflection-Damage Index (HDDI) framework was developed to provide a structured yet practical approach to evaluating structural condition. At its core, the framework combines several physically meaningful response measurements into a single unified risk index that captures both deformation demand and the progression of damage. Instead of depending on any one measurement, the HDDI integrates multiple complementary indicators that together give a more complete and balanced view of the structure's current state. This multi-indicator strategy results in a more robust assessment that is better suited for real-world engineering decision-making[11], [12], [16].

Design principle	Description
Physical interpretability	Every indicator corresponds to a measurable structural phenomenon, ensuring engineering transparency.
Normalization	All indicators are scaled to a common range from 0 to 1, enabling consistent comparison and fusion.
Modularity	New deterioration indicators can be incorporated without modifying the overall architecture.
Algorithm	The framework supports multiple inference methods, including Random Forest, SVM, XGBoost,

Design principle	Description
independence	and Neural Networks.
Scalability	The method can be applied to reinforced concrete, steel, bridges, and other infrastructure systems.
Explainability	The layered architecture facilitates interpretation of deterioration mechanisms and risk assessment.
Extensibility	The framework can evolve with additional sensing technologies and future SHM methodologies.

TABLE 2 DESIGN PRINCIPLE OF HDDI FRAMEWORK

A. *Framework Architecture*

The HDDI framework is built around four logical layers:

- Physical Observation
- Damage Representation
- Inference
- Risk Interpretation

The physical observation layer collects raw measurable data such as deflection, crack width, applied load, and stiffness changes. The damage representation layer converts these measurements into normalized indicators that reflect structural utilization and deterioration. The inference layer then combines these indicators into a single composite index, while the risk interpretation layer maps the index into practical condition states. This layered architecture ensures that every step remains transparent and physically grounded.

B. *Physical Observation Layer*

The physical observation layer forms the foundation of the framework. It consists of response variables that can be measured directly in both laboratory tests and field conditions. For reinforced concrete members, the most relevant measurements include mid-span deflection, visible crack width, applied load, and the evolution of stiffness. These quantities were selected because they represent different important aspects of structural behavior under both service and ultimate loading conditions. By relying on observable physical responses, the framework stays firmly connected to real structural performance rather than abstract or hidden features.3.3 Damage Representation Layer

In the damage representation layer, raw sensor data is transformed into normalized indicators. Each indicator is chosen to capture a distinct aspect of structural deterioration:

- Deflection utilization measures deformation demands relative to allowable limits.
- Crack severity reflects the development of visible damage.
- Stiffness degradation quantifies the loss of rigidity.
- Load utilization indicates how close the member is to its capacity.
- Using multiple indicators helps avoid over-reliance on any single measurement and provides a more comprehensive view of the structure’s overall health.

C. *Inference Layer*

The inference layer aggregates the normalized indicators into one composite metric, known as the Failure Risk Index. This can be achieved through a simple weighted sum, rule-based logic, or other transparent aggregation methods. In the HDDI framework, the inference process is intentionally kept straightforward. This simplicity allows the contribution of each indicator to be clearly understood and explained an essential feature when presenting results to engineers, inspectors, and asset managers. It also makes the framework easier to calibrate and extend in the future.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

D. Risk Interpretation Layer

The final layer converts the composite index into practical condition states or risk levels. This layer recognizes that structural deterioration is typically a gradual process rather than a sudden binary shift. A continuous risk measure therefore provides richer information than a simple “healthy or failed” classification. By applying suitable thresholds, the framework classifies the structure into three meaningful categories SAFE, WARNING, and CRITICAL which directly support maintenance prioritization and informed decision-making. In essence, this layer turns numerical results into actionable engineering guidance.

3.5.1 Failure Risk Index Interpretation

The Failure Risk Index (FRI) is created by combining the four normalized damage indicators into a single, unified measure. As structural deterioration progresses from the SAFE to the CRITICAL state, the FRI increases steadily. The index successfully tracks the overall trend of damage development and offers a continuous representation of structural condition throughout the loading history. By condensing multiple response parameters into one clear risk value, the FRI serves as a practical and interpretable tool for both structural assessment and maintenance planning

IV. MATHEMATICAL FORMULATION

The mathematical core of the HDDI framework is built around a small set of normalized indicators that represent different aspects of structural deterioration. Each indicator is defined so that larger values correspond to more severe damage or higher utilization. This normalization makes the formulation dimensionless, comparable, and suitable for aggregation into a single risk measure. The resulting structure is simple enough for engineering use while still capturing the main physical processes involved in structural degradation.

A. Deflection Utilization Indicator

Deflection utilization represents the extent to which the observed deformation approaches an allowable limit. It can be expressed as,

$$D_1 = \frac{w}{w_{\text{lim}}},$$

where $w$is the measured deflection and $w_{\text{lim}}$is the reference or allowable deflection limit. When necessary, the value may be bounded within $[0,1]$to prevent excessive influence from outliers:

$$D_1 = \min\left(\max\left(\frac{w}{w_{\text{lim}}},0\right),1\right).$$

This indicator increases as the structure experiences larger deformation demand.

B. Damage Manifestation Indicator

Damage manifestation is represented by crack width, which serves as a direct observable of visible deterioration. The normalized indicator is defined as

$$D_2 = \frac{c_w}{c_{w,\text{lim}}},$$

where $c_w$is the measured crack width and $c_{w,\text{lim}}$is the corresponding allowable or reference threshold. A bounded form may also be used:

$$D_2 = \min\left(\max\left(\frac{c_w}{c_{w,\text{lim}}},0\right),1\right).$$

This quantity captures the progressive appearance and widening of cracks under loading.

C. Capacity Degradation Indicator

Capacity degradation is reflected through stiffness loss, since stiffness reduction is one of the clearest signs of structural softening. If $K_0$is the initial stiffness and $K_s$is the current secant stiffness, the indicator may be written as

$$D_3 = 1 - \frac{K_s}{K_0}.$$

Since secant stiffness is often computed from the ratio of load to deflection,

$$K_s = \frac{P}{w},$$

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ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

where P is the applied load. A bounded version may again be used if required:

$$D_3 = \min\left(\max\left(1, -\frac{K_s}{K_0}0\right), 1\right).$$

Higher values of G_3 correspond to larger loss of rigidity.

D. Load Utilization Indicator

Load utilization measures how close the structure is to its capacity under the applied demand. It is defined as

$$D_4 = \frac{P}{P_u},$$

where P is the applied load and P_u is the ultimate or reference capacity. If needed, this can also be bounded as

$$D_4 = \min\left(\max\left(\frac{P}{P_u}, 0\right), 1\right).$$

This indicator expresses the degree of loading severity relative to the structural resistance.

E. Failure Risk Index Formulation

The Failure Risk Index combines the four indicators into a single scalar measure. A weighted linear aggregation is convenient because it is transparent and easy to interpret:

$$FRI = \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4,$$

subject to,

$$\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1.$$

The weights may be selected based on engineering judgment, calibration data, or structural type. In the proposed framework, the weights emphasize deformation and visible damage while still accounting for stiffness loss and load demand. A possible weighting scheme is

$$FRI = 0.35D_1 + 0.30D_2 + 0.25D_3 + 0.10D_4.$$

This formulation ensures that the final index increases monotonically as the overall structural condition worsens.

Indicator	Symbol	Physical meaning	Mathematical definition	Normalized range
Deformation demand	D_1	Degree of structural deformation relative to the allowable limit	$D_1 = \frac{M_d}{M_{lim}}$	0–1
Damage manifestation	D_2	Observable deterioration such as cracking or spalling	$D_2 = \frac{C_d}{C_{lim}}$	0–1
Capacity degradation	D_3	Reduction in structural stiffness or strength	$D_3 = 1 - \frac{C_t}{C_0}$	0–1
Demand–capacity utilization	D_4	Structural loading relative to ultimate capacity	$D_4 = \frac{L}{L_u}$	0–1
Failure Risk Index	FRI	Overall deterioration level	$FRI = \sum_{i=1}^{n} w_i D_i$	0–1

TABLE 3 HYBRID DEFLECTION-DAMAGE INDEX COMPONENTS

F. Theoretical Properties

The proposed formulation has several useful theoretical properties. First, it is dimensionless, because all indicators are normalized before aggregation. Second, it is monotonic under physically consistent loading, meaning that increasing damage or utilization leads to increasing index values. Third, the structure is interpretable, because the contribution of each component can be examined independently. Fourth, the formulation is modular, so additional indicators can be included if needed for other structural systems.

A threshold-based decision rule can be introduced to convert the continuous index into discrete condition states:.

$$C = \begin{cases} \text{Safe}, & FRI < \tau_1, \\ \text{Warning}, & \tau_1 \le FRI < \tau_2, \\ \text{Critical}, & FRI \ge \tau_2. \end{cases}$$

Here, $\tau_1$and $\tau_2$are decision thresholds selected according to engineering criteria. This mapping makes the output directly usable for structural maintenance and risk communication.

V. INTERPRETABILITY AND DECISION SUPPORT

A key strength of the Hybrid Deflection-Damage Index (HDDI) is that it is designed to be interpretable at every stage. Each indicator has a clear, direct engineering meaning, so the final output can be understood without needing to decipher hidden features or complex transformations. This transparency is particularly valuable in structural health monitoring, where decisions can have serious implications for safety, maintenance costs, and operational continuity. By keeping the entire process grounded in physical principles, the framework aligns closely with the way engineers naturally think and reason.

A. Machine Learning in Structural Health Monitoring

Machine learning has become an increasingly powerful tool in structural engineering. It excels at discovering complex patterns in experimental and monitoring data that might be difficult to identify through traditional methods.

Common applications include:

- Damage detection
- Structural condition classification
- Remaining useful life prediction
- Deflection prediction
- Crack identification

Popular algorithms used in this field include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Machines (GBM). Among these, ensemble methods such as Random Forests and Gradient Boosting often deliver strong predictive performance and good robustness. However, despite their capabilities, many machine learning models function as black boxes, offering limited insight into how or why they make specific predictions[12], [16], [19].

B. Black-Box and Grey-Box Modelling Approaches

Machine learning models in structural engineering are commonly classified into three categories: black-box, white-box, and grey-box models.

5.2.1 Black-Box Models

These models rely purely on data-driven relationships without incorporating prior physical knowledge. Advantages:

- High predictive accuracy
- Strong ability to capture nonlinear behaviour
- Flexible application to complex datasets

Limitations:

- Poor interpretability
- Difficult to validate from an engineering perspective
- Lower confidence from users in safety-critical applications

5.2.2 Grey-Box Models

Grey-box models combine domain-specific physical knowledge with machine learning techniques.

Advantages:

- Significantly better interpretability
- Greater consistency with engineering principles
- Higher user confidence
- Stronger physical relevance

The proposed HDDI framework follows a grey-box philosophy. It integrates well-established mechanics-based damage indicators with flexible machine learning classification, aiming to achieve both reliable performance and clear explainability.

Criterion	Black-Box Models	Grey-Box HDDI Framework
Use of engineering knowledge	Limited	Explicit
Use of physical damage indicators	Limited	Yes
Interpretability	Low	High
Explainable predictions	Limited	High
Feature engineering	Mostly automatic	Physics-informed
Generalization across structures	Moderate	Potentially high
Adaptability	High	High
Maintenance decision support	Moderate	Strong
Suitability for safety-critical applications	Limited	Strong
Engineering transparency	Low	High

TABLE 4 COMPARISON BETWEEN GREY-BOX AND BLACK-BOX MODELS

C. *Engineering Transparency*

The HDDI framework achieves strong engineering transparency by making the contribution of each indicator clearly visible. For instance, a high deflection utilization value immediately signals excessive deformation demand, while an elevated crack severity value points to visible material damage. Similarly, high stiffness degradation indicates loss of rigidity, and high load utilization shows that the member is operating close to its capacity. Because each indicator can be examined and interpreted independently, the overall Failure Risk Index becomes much easier to validate and explain. This level of transparency builds trust in the results and facilitates peer review, expert verification, and clear communication with stakeholders

D. *Decision-Support Mechanisms*

The continuous Failure Risk Index can be readily translated into practical decisions through simple threshold rules and condition classes. Low risk values suggest the structure is operating within acceptable limits, intermediate values indicate the need for closer inspection or monitoring, and high values can trigger detailed evaluation, maintenance planning, or immediate intervention. This dual approach combining a continuous risk score with discrete condition states makes the framework valuable not only for ongoing condition monitoring but also for broader asset management. It offers both analytical depth and operational simplicity for decision-makers.

E. Human-in-the-Loop Use

The HDDI framework is well suited for human-in-the-loop decision-making. Engineers can easily review the individual indicators before accepting the final classification, which helps prevent over-reliance on automated outputs. If a structure is flagged as CRITICAL, the underlying indicators clearly show whether the primary concern stems from excessive deformation, severe cracking, significant stiffness loss, or high load demand. This traceability is especially valuable in real-world infrastructure systems, where decisions often need to be explained and justified to operators, inspectors, regulators, and other stakeholders. Ultimately, the framework is designed to support rather than replace informed engineering judgment[2], [12], [16].

VI. POTENTIAL APPLICATIONS

The HDDI framework can be applied to a wide range of civil infrastructure systems where damage typically develops through deformation, cracking, and stiffness reduction. Its primary strength lies in using common engineering response variables, making it readily adaptable for both laboratory experiments and field monitoring[2], [3], [9], [10], [11]. Due to their normalized and interpretable structure, the framework can be transferred across different structural types with appropriate calibration, making it relevant for both research and practical asset management.

A. Reinforced Concrete Structures

Reinforced concrete structures represent a natural and immediate application area for the HDDI. Cracking, deflection growth, and stiffness loss are central to their behaviour under both service and ultimate loads. The framework is particularly suitable for beams, slabs, columns, and other flexural members where deformation and cracking can be measured effectively. In laboratory settings, it can help compare damage progression across different loading stages. In practice, it supports more informed inspection and maintenance decisions for aging concrete infrastructure.

B. Bridges

Bridges are another important application domain. They are subjected to repeated traffic loading, environmental degradation, and long service lives. The HDDI can be used to monitor bridge girders, decks, and supporting elements particularly where deflection and crack development can be observed or measured. Its risk-oriented output is useful for ranking components according to urgency, thereby supporting inspection prioritization and maintenance planning in bridge management systems [13], [19].

C. Steel Structures

Although the current set of indicators is optimized for reinforced concrete, the framework can be adapted for steel structures by redefining the damage descriptors. For steel members, relevant indicators might include deformation demand, local buckling, residual stiffness, or load utilization ratio. The underlying logic remains the same: select indicators that match the governing failure mechanisms. This adaptability demonstrates that HDDI has potential as a general interpretable framework rather than a material-specific solution.6.4 Smart Infrastructure Systems. In modern smart infrastructure environments, the HDDI can be integrated with sensor networks, data acquisition systems, and decision-support platforms. It's clear and transparent structure makes it well suited for semi-automated monitoring systems where engineers require both numerical results and physical explanations. The framework also aligns naturally with digital twin concepts, where structural condition needs to be continuously updated based on real-time field data. In such systems, HDDI can serve as a reliable and interpretable health indicator[11], [12].

VII. DISCUSSION

The proposed HDDI framework provides a balanced approach to structural condition assessment by combining strong physical interpretability with a unified risk index. Its main advantage is the ability to convert multiple observable responses into a single assessment metric without losing the engineering meaning of the original inputs. This combination is particularly valuable in structural health monitoring, where both detailed information and clear, actionable outputs are often required. As a result, the framework is especially well suited to applications where transparency and trust are essential.

A. Advantages

Key advantages of the HDDI include high interpretability each indicator corresponds to a familiar engineering concept, eliminating the need for specialized decoding. The framework is also flexible and can be recalibrated for different structural types and loading scenarios. The use of normalized indicators makes it easier to compare conditions across structures and over time.

Furthermore, the continuous nature of the index supports gradual condition assessment rather than forcing an artificial binary (healthy/damaged) classification.

B. Limitations

Like any method, the HDDI has limitations that should be acknowledged. Its performance depends on the availability and quality of measured data, particularly deflection, crack width, and capacity-related variables. Selecting appropriate weights and thresholds may require case-specific calibration. Additionally, the current formulation is best suited to flexural and damage-driven behaviour; other failure modes (such as shear, fatigue, or corrosion) may need modified or additional indicators.

C. Future Research Directions

To make HDDI more robust and widely applicable:

1) Experimental validation across a range of concrete structures beams, slabs, columns under different loading and environmental conditions [12], [13], [19]
2) Cyclic loading studies to understand how the four indicators behave under repeated stress, fatigue, and dynamic loading [11]
3) Additional sensing integration: strain gauges, accelerometers, corrosion monitoring, temperature sensors to enrich the information available [2], [13], [18]
4) Explainable AI integration: Combine the HDDI framework with advanced interpretation techniques to make machine learning components (if used) more transparent [1], [6], [16]
5) Digital twin coupling: Integrate with structural finite element models to improve real-time assessment and predictive capability [19]
6) Long-term field deployment on actual infrastructure to validate robustness, catch unexpected failure modes, and refine the approach [13], [19]

Validation stage	Objective	Expected outcome
Numerical simulation	Verify mathematical consistency using finite element models	Evaluate framework under controlled loading scenarios
Laboratory experiments	Compare HDDI predictions with physical structural behaviour	Assess accuracy under realistic conditions
Benchmark dataset validation	Test the framework using publicly available SHM datasets	Demonstrate reproducibility and generalizability
Field deployment	Monitor real infrastructure over extended periods	Evaluate long-term robustness and reliability
Multi-structure evaluation	Apply the framework to RC, steel, and composite structures	Assess adaptability across different structural systems
Explainable AI assessment	Analyse feature importance and decision transparency	Improve engineering confidence in predictions
Uncertainty analysis	Investigate sensitivity to measurement errors and noise	Quantify robustness under practical conditions

TABLE 5 FUTURE VALIDATION STRATEGIES FOR THE HDDI FRAMEWORK

D. Comparison with Existing SHM Concepts

Compared with many conventional SHM approaches, HDDI provides a stronger link between measured response and decision logic. Compared with black-box learning methods, it offers greater transparency and easier engineering interpretation.

Compared with single-parameter damage indices, it captures multiple deterioration mechanisms in one formulation. This combination of physical grounding, simplicity, and interpretability is the main contribution of the framework. It makes HDDI especially attractive for infrastructure applications where decisions must be justified.

VIII. CONCLUSION

This paper proposed the Hybrid Deflection-Damage Index as a physics-informed framework for interpretable structural health monitoring. The method combines normalized indicators of deflection utilization, crack severity, stiffness degradation, and load utilization into a single Failure Risk Index. A threshold-based interpretation scheme then converts the continuous index into practical condition states such as SAFE, WARNING, and CRITICAL. The result is a transparent and engineer-friendly assessment structure that preserves physical meaning while supporting decision-making[12], [13], [19], [16].

The main contribution of the framework is its ability to represent structural deterioration in a way that is both quantitative and interpretable. Unlike black-box data-driven methods, HDDI makes the role of each input variable explicit. Unlike single-response damage indices, it captures multiple aspects of deterioration within one unified formulation. This makes the approach suitable for reinforced concrete structures and potentially adaptable to other infrastructure systems.

The proposed framework is not intended to replace detailed structural analysis or expert judgment. Instead, it is meant to support those processes by providing a clear and interpretable health indicator. Future work should focus on calibration, experimental validation, and extension to more complex loading and failure conditions. With these developments, HDDI has the potential to become a useful tool for practical structural monitoring and maintenance planning.

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Mathematical Notation

Symbol	Definition	Unit
D_i	Normalized deterioration indicator	Dimensionless
D_1	Deformation demand indicator	Dimensionless
D_2	Damage manifestation indicator	Dimensionless
D_3	Capacity degradation indicator	Dimensionless
D_4	Demand–capacity utilization indicator	Dimensionless
M_d	Measured structural deformation	mm
M_{lim}	Allowable deformation limit	mm
C_d	Measured damage quantity	mm
C_{lim}	Allowable damage threshold	mm
C_0	Initial structural capacity	kN or kN/mm
C_t	Current structural capacity	kN or kN/mm
L	Applied structural load	kN
L_u	Ultimate structural load capacity	kN
w_i	Weight assigned to indicator D_i	Dimensionless
FRI	Failure Risk Index	Dimensionless
n	Number of deterioration indicators	—