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Engineering Assurance for AI-Enabled Self-Healing Infrastructure: From Damage Signals to Verified Recovery

A Review of Sensing, Diagnosis, Repair Mechanisms and Post-Intervention Validation

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Abstract: Artificial intelligence, embedded sensing, digital twins and responsive materials are increasingly being explored as ways to create infrastructure that can detect and respond to damage. A warning message or a crack that closes doesn't prove that the structure has regained its required performance. This review looks at self-healing infrastructure from an engineering-assurance perspective: what needs to be measured what can be inferred, which actions are permissible what needs to be fixed and what needs to be tested before a system can be called fixed. Using the review source and its references the paper separates sensing confidence, diagnosis confidence repair feasibility and recovery evidence as separate considerations. It looks at embedded -electromechanical sensors, fiber-optic and piezoelectric sensing, edge analytics, digital-twin state estimation, AI-based prediction and material-level healing methods. A workflow is suggested that connects a detected problem to an action and then to checks done after the repair. The study finds challenges including outside interference sensors changing over time models not working well in different places repairs not reaching far enough actions that can't be undone and the difference between a material fixing itself and the whole system working again. The paper ends by saying that safe self-healing should be seen as a claim that needs proof, clear rules and accountable human oversight, in charge—not as something automated.

Keywords: *Self-Healing Infrastructure; Structural Health Monitoring; Embedded Sensors; Digital Twins; AI Assurance; Repair Verification; Infrastructure Resilience.*

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I. INTRODUCTION

Infrastructure monitoring has moved from visual inspections to continuous sensing and data-supported evaluation. Tiny embedded sensors, wireless networks, digital twins and machine-learning techniques can help engineers identify changes that may be difficult to detect during planned inspections [1], [2], [8]. Research also shows that responsive materials and automated control could allow infrastructure to not only report damage but also initiate a response; it could start a response [3], [6].

The term "self-healing" can hide different claims. A system might find a crack but not find the root cause; it might measure deterioration without knowing if fixing it is safe; a material might seal a crack without restoring stiffness, durability or the ability to carry load. These differences are important because civil infrastructure is safety-critical and normally faces changing loads, weather, ageing and unclear maintenance records. If we treat every detection or material action as evidence of recovery, we may overstate what the system can do.

So, this review asks a focused engineering question: what evidence is required to move from noticing an anomaly to making a defensible claim that an infrastructure component has regained a particular function? Of arranging the discussion around a broad autonomous-infrastructure model or a lifecycle data thread the paper concentrates on assurance, at the intersection of sensing, diagnosis, physical action and acceptance testing.

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The contribution is a synthesis of four assurance questions: is the signal reliable? Is the diagnosis reasonable? Is the planned response safe and doable? Has recovery actually been shown? The resulting workflow is a review, not a field-validated control system. Its stages and acceptance criteria must be tested on each asset before it can be used in practice.

II. REVIEW APPROACH AND ANALYTICAL LENS

The source document was used as the technical foundation. It covered topics like micro-sensors twin syncing, data assimilation, AI-based fault diagnosis, programmable materials, autonomous response, healing verification and deployment limits. The references listed in that document helped ground the discussion in real-world work on sensor-based monitoring, IoT diagnostics, edge intelligence predicting remaining useful life and smart materials [8]–[21].

The two other papers were used for comparison only. This was to avoid repeating their ideas. One focused on a lifecycle digital-thread approach and the other on a transportation-centered closed-loop readiness model.

This paper adopts a narrative review approach. No database search was conducted, no screening count, no meta-analysis and no experiments done for this paper. Instead, the findings are synthesized. Numerical results and performance metrics from individual studies not combined because the test setups, sensors, conditions, labels and evaluation methods varied too much to be compared directly.

The analysis uses a set of five comparison points: how well we can measure how reliable the diagnosis is, whether the fix can be reversed if needed how strong the verification is and how much work the whole process requires.

To make things clearer four levels of evidence are defined. Signal evidence asks: Is the measurement real and meaningful? Diagnostic evidence asks: Does the fault we found actually explain the data change? Intervention evidence asks: Can the action we pick fix the fault without breaking safety rules? Recovery evidence asks: After the fix does the system still meet its performance goals?

These four levels should not be lumped together into one confidence score. Each one matters on its own.

III. SENSING AND DIAGNOSIS: ESTABLISHING A CREDIBLE DAMAGE CLAIM

➢ *Complementary Sensing Modalities (CEM)*

Micro-electromechanical-system (MEMS) accelerometers provide low-power vibration measurements. MEMS accelerometers can be used where space and cost are limited and many MEMS accelerometers can be placed together to monitor a structure [8], [9]. However, MEMS accelerometers depend on mounting conditions, temperature, and background noise and on the frequency range that is being examined. Fiber-optic sensors can measure strain with fine detail and are useful in places where electric noise is high or sensors are spread out. Fiber-optic sensors need installation, connection protection and special interrogation hardware which can make the whole system more complicated [10]. Piezoelectric devices can record changes and can also be used to excite a structure intentionally but interpreting piezoelectric devices depends on how the device is coupled, how consistently it is excited and on the health of the piezoelectric device itself.

No single sensor type provides a complete picture of how a structure is doing. A change in vibration can mean damage. It can also mean a car passing by a change in temperature a change in the way the structure is held or that the sensor has moved. A strain reading can give local information but it might miss a crack that lies outside the area where the sensor is installed. Therefore, a solid claim, about damage should link each measurement to the way it can detect a problem and should say which kinds of problems it cannot see well.

➢ *Sensor Fusion and Environmental Compensation*

Multi-sensor fusion can help improve interpretation by bringing together measurements that react in different ways to the same physical situation. For instance, data about vibration can be looked at together with temperature, humidity, strain, sound or pictures taken during an inspection. The objective is not simply to increase the number of data sources. The goal is to check possible explanations. If a change in stiffness is noticed when the temperature changes and then goes away after the environment is adjusted that suggests there is less proof of real damage than if the change stays even when conditions are similar.

Combining data also brings its challenges. Sensors can have different sampling rates they might not be perfectly in sync they could have different calibration histories they might miss some data in certain places and they might not cover the same area. A system that combines data can give a wrong answer if one part of the input data is unreliable or if the model has never seen that kind of situation before. Systems should keep track of the sensor its calibration details, the time it was recorded any flags, about quality and the changes made before the data is used in a model that checks for problems [11], [12].

➢ *Edge Intelligence and Diagnosis Quality*

Edge processing can filter signals extract relevant features and detect anomalies near the asset. This cuts down on communication load. It enables faster local responses. Lightweight models and knowledge-distillation methods have been studied for anomaly classification on monitoring nodes [13], and low-cost edge systems show how appealing local processing can be [14]. Edge deployment does not take away the need for validation: a model must fit the available memory, energy and compute budgets yet still keep adequate sensitivity to safety-relevant faults.

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A useful diagnostic output should contain more than a class label. A useful diagnostic output should show which fault family is likely the evidence behind that idea, the confidence or uncertainty warnings about data quality and the dangers of a negative or false-positive. False alarms can obligate closures or repairs; missed faults can put users in unacceptable risk. The threshold, for action must therefore depend on consequence and reversibility not on the overall model accuracy.

- *Digital Twins and Prognosis as Engineering Context*

A digital twin brings together the assets shape, material properties how it operates under load real-time sensor readings and past performance into a living computer model [5], [12]. In self-healing systems the valuable part of the digital twin is its ability to provide context. It checks if a new sensor reading matches what the system should be doing helps guess how much damage might be present and allows testing of repair actions before they are actually tried. Just having a model stored somewhere does not make it a real twin. The model must keep changing with data and it must be clear about the uncertainty involved.

Data assimilation helps bring real-world measurements in line with the physics-based model. Techniques like Kalman filtering adjust the model's internal estimates as new data come in. Physics-informed learning adds known rules into data-driven models. Both methods rely on the quality of the underlying model the original model's how accurate the data are and whether the system's internal state can actually be observed. If several different types of damage could produce the sensor results the digital twin should not pick one answer as the only truth. It must keep the uncertainty visible. Avoid giving a diagnosis that isn't supported.

Prognostic models predict damage or how long a structure may remain serviceable based on its current state and how it has been used [15], [17]–[21]. These models provide predictions rather than definitive answers meaning they depend on the assumptions made. Real infrastructure data often contain few actual failure events. A model built for one bridge may not work well for another bridge even if it looks similar because the shape, materials, where sensors are placed or how it's supported may differ. To evaluate these models testing should use data from times and different structures when possible. Results should include uncertainty estimates and how well the model was calibrated, not how close the predictions were to actual outcomes.

When planning repairs or interventions the digital twin should help compare options against real engineering limits. These include how much deformation is allowed how much strength remains, whether the system can keep working during the repair, access issues, weather conditions and what happens if the repair doesn't work. The model can support the decision-making process. A simulated improvement in the model is not the same, as actual physical recovery. Post-intervention observations and tests remain essential.

IV. REPAIR MECHANISMS AND THE LIMITS OF THE WORD SELF-HEALING

- *Material-Level Mechanisms*

Self-healing concrete can rely on processes such as ongoing hydration and mineral precipitation or on engineered mechanisms such as bacteria-based mineral formation, microcapsules, vascular delivery systems, crystalline admixtures and polymer-based agents [6]. Shape-memory alloys and responsive polymers might give crack-closing or shape-recovery abilities in some cases. The suitability of each mechanism depends on crack width, moisture, temperature, chemical surroundings, material compatibility, healing-agent availability and whether the damage can be reached by the mechanism.

Therefore, closing a crack does not mean the structure is fully fixed. A crack that looks closed can still let fluids seep in have bond or stiffness or keep reinforcement corrosion and hidden damage. Some healing mechanisms are single-use only: after a capsule burst or the agent runs out the same location may not be able to heal again. To judge the repair, we must look at closure, transport-property recovery, mechanical-property recovery and durability under subsequent exposure.

- *Component and System Level Response*

At the component level repair can involve actuation, controlled prestressing, sealing, patching or replacement of a damaged module. At the network level self-healing can instead mean fault isolation, load redistribution, rerouting or service restoration while a damaged component stays unrepaired. These responses should be described separately. A power network that isolates a segment may restore service without healing the conductor; a water network that reroutes flow may preserve supply while the leak remains.

The distinction affects checking. Material healing requires tests of the healed zone and its important properties. Component repair requires inspection of the repaired element and its connections. Network restoration requires confirmation that service has been restored without transferring loads or risks to adjacent elements. The strongest defensible claim that can be made is limited by the level actually tested.

V. VERIFICATION-ORIENTED WORKFLOW FOR SELF-HEALING

The review suggests a five-stage assurance workflow. It is a proposed synthesis of the reviewed technical themes, not a validated universal standard.

- Qualify the observation. *Check the sensor health the calibration, the synchronization, any missing data, the environmental context and whether the data's consistent with measurements from nearby sources. If the data quality is not good enough the system should ask for sensing or a human check instead of doing something that can't be undone.*

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- Establish a fault hypothesis. *Compare the problem with how things work, with the physical rules with past checks and with possible reasons that are not about damage. Say where the problem is likely to be and how it happened. Also list possible reasons how sure you are and what could happen if the diagnosis is wrong.*
- Select a response. *List the available actions and what risks they have. Choose actions that can be undone or have effects when you are not sure. Set limits on how much force, how hot chemical use, how much load, how long to stop service and spatial extent of the intervention.*
- Execute with safeguards. *Record the command, who approved it which version of the model was used the data that was input the state of the actuator and any conditions that would stop the action. Require human approval for actions that warrant oversight and have a safe backup plan. If communication is lost. The feedback doesn't match, stop the action before it makes things worse.*
- Verify recovery independently. *Do the measurements again under the same conditions and check them against set rules. Use a check or test when the risk is high. If you can't tell for sure record the outcome as unverified limit its use if needed and send it to an engineer to look at.*

The workflow keeps the control loop from the assurance loop. The control loop checks, guesses and acts. The assurance loop makes sure the evidence is good enough to move and that the action actually worked. This split lowers the chance that a model checks its guess using the same ideas that made the guess in the first place.

➢ *Acceptance Criteria and Measurable Evidence*

Acceptance criteria need to be decided before any action is taken and must connect to what the intended function of the asset. Depending on how the asset's used these criteria might involve things like the permissible crack width after repair how much water can leak through how stiff the asset is or how it vibrates, how strain is spread out load-carrying capacity it, if electricity can flow through it if pressure stays steady resistance to shaking, or if it can be used as needed. Each criterion has to say how to measure it what range of conditions it applies to how much variation is allowed and how long the result needs to last.

VI. IMPLEMENTATION CHALLENGES AND RESEARCH PRIORITIES

➢ *Long-Term Sensing Reliablilty*

Embedded systems need to handle moisture changes in temperature, rust, shaking, power cuts and disturbances associated with maintenance activities. A sensor that slowly changes its readings might look like the system's getting worse. A sensor that stops working might make the problem seem like it’s not there. Studies need to share information about how the system stays working how often it needs to be fixed how many false warnings it gives and how it works when there is no connection—not just how accurate it is, in a short-term test. Getting power from the surroundings can make the system last longer. The power you get depends on where it is and you can't think it will always be the same.

➢ *Model Generalisation and Uncertainty*

A diagnostic model can work well when data similar to its training data. It might not work well when the loading is different or when the construction is not the same or when the sensors are placed in different sensor placements or when the weather is different. Testing should include assets that were not seen before and situations that were not used during training. Estimating uncertainty finding data that differ from the training distribution and allowing the model to say it is not sure are very important when an incorrect decision could have irreversible consequences. Research should also check if the models’ suggestions match what real engineers think and what happens in tests.

➢ *Cybersecurity, Interoperability, and Accountability*

Self-healing systems link sensors, communication networks, computational models and actuators. If a sensor measurement is compromised or a command is unauthorized a harmful physical action could be triggered. Authentication, encrypted communication, signed software and model updates, access control, audit logs and safe behavior during incidents should all be built into the engineering design. Interoperability also needs asset identifiers, units, metadata and interfaces so that evidence can be understood by all vendors and maintenance teams. Responsibility must stay clear. Engineers and asset owners need to know which decisions are automated, which require approval, who can override an action and who accepts any remaining uncertainty. Regulation and standards should separate a technology demonstration, from a safety function. Human oversight should match the risk level not just be nominal. An operator must have time, information and authority to intervene.

➢ *Prioritized Research Agenda*

Four research priorities emerge. First, we must create datasets that link raw sensing, environmental context confirmed damage, intervention records and post-repair tests. Second, we need to develop verification protocols that measure recovery instead of just visual closure or detection accuracy. Third, we should conduct long-duration field trials that include failed interventions, sensor outages and maintenance costs. Fourth, we should quantify the trade-off between autonomy and reversibility across asset classes. Establish clear criteria for when the system must abstain and request human assessment.

VII. CONCLUSION

AI-enabled self-healing infrastructure should be evaluated as an engineering claim supported by a chain of evidence not as a label applied to a sensor network or responsive material. Embedded sensors provide observations. AI systems generate fault hypotheses. Digital twins add context. Repair mechanisms may change the asset. help preserve its service. None of these functions establishes recovery.

The central recommendation of this review is to separate validity, diagnosis, intervention safety and post-repair verification. The assurance workflow proposed here makes

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uncertainty visible. It bounds actuation. It requires acceptance criteria tied to the function that matters. It also recognizes that material-level healing, component repair and network-level service restoration are outcomes. Each requires tests.

A credible path to deployment therefore depends on long-term sensing reliability. It depends on asset-specific validation. It depends on actuation. It depends on responsibility. It depends on field evidence that a repaired asset remains safe under renewed operating conditions. Until these conditions are demonstrated autonomous action should remain constrained by the consequence of failure. It should be supported by a human-governed fallback.

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REFERENCES

[1]. B. Mohammed, "The sentient infrastructure paradigm: a review of novel sensors, digital twins, and AI for civil structural health monitoring," Sensor Review, Jan. 2026, doi: 10.1108/sr-10-2025-0822.

[2]. A. Sivasuriyan, D. S. Vijayan, A. Piętocha, W. Górski, Ł. Wodzyński, and E. Koda, "Advanced sensing and digital monitoring technologies for structural health assessment of civil infrastructure," Buildings, vol. 16, no. 3, 2026, doi: 10.3390/buildings16030656.

[3]. M. B. Mane, N. Vijayakuma, P. Sruthi, R. Arulmozhi, and D. Suresh, "Autonomous and resilient smart infrastructure: an AI-driven cyber physical systems framework with deep reinforcement learning and blockchain security," CompSci & AI Advances, Mar. 2025, doi: 10.69626/cai.2025.0084.

[4]. U. Mutlu and S. Kaewunruen, "Digitalised predictive maintenance in railways: a systematic review of AI, BIM, and digital twins," Infrastructures, Mar. 2026, doi: 10.3390/infrastructures11030087.

[5]. V. Dattani, "Digital twin applications for real-time monitoring of urban infrastructure," Vidhyayana, Feb. 2026, doi: 10.58213/dg3wfy95.

[6]. M. K. Pasupuleti, "Self-healing smart infrastructure: programmable materials for autonomous repair and sensing," International Journal of Academic and Industrial Research Innovations, Feb. 2026, doi: 10.62311/nesx/rp-f32026.

[7]. U. Author, "Develop an AI-driven fault detection model to autonomously troubleshoot electrical power grids in high-risk offshore oil platforms," British Journal of Earth Sciences Research, Apr. 2025, doi: 10.37745/bjesr.2013/vol13n21941.

[8]. F. D. Nuzzo, D. Brunelli, T. Polonelli, and L. Benini, "Structural health monitoring system with narrowband IoT and MEMS sensors," IEEE Sensors Journal, Mar. 2021, doi: 10.1109/JSEN.2021.3075093.

[9]. G. Occhipinti et al., "Shake table tests on scaled masonry building: comparison of performance of various micro-electromechanical system accelerometers (MEMS) for structural health monitoring," Sensors, vol. 25, no. 4, 2025, doi: 10.3390/s25041010.

[10]. N. Golovastikov, N. Kazanskiy, and S. Khonina, "Optical fiber-based structural health monitoring: advancements, applications, and integration with artificial intelligence for civil and urban infrastructure," Photonics, vol. 12, no. 6, 2025, doi: 10.3390/photonics12060615.

[11]. T. J. Saravanan, M. Mishra, A. D. Aherwar, and P. Lourenço, "Internet of things (IoT)-based structural health monitoring of laboratory-scale civil engineering structures," Innovative Infrastructure Solutions, Mar. 2024, doi: 10.1007/s41062-024-01413-9.

[12]. J. Huang, A. Broekman, G. Markou, and H. Chen, "Framework for a practical and cost-effective IoT-enhanced structural health monitoring and damage diagnostics system with digital twinning," Journal of Civil Structural Health Monitoring, Mar. 2025, doi: 10.1007/s13349-025-00927-9.

[13]. X. Yu, Y. Zhao, S. Cui, X. He, Y. Fu, and Q. Yang, "Efficient edge intelligence for onboard data anomaly classification in wireless structural health monitoring using knowledge distillation on low-cost IoT nodes," Structural Health Monitoring, Jul. 2025, doi: 10.1177/14759217251349533.

[14]. E. H. Fort, P. Blanco-Carmona, F. M. Chavero, A. Torralba, and R. Castro-Triguero, "Low-cost, low-power edge computing system for structural health monitoring in an IoT framework," Sensors, vol. 24, no. 15, 2024, doi: 10.3390/s24155078.

[15]. S. Almheiri, Z. Mohamed, M. Ragab, A. Alseiari, and N. Almesafri, "Real-time sensor data streaming for deployment in Edge AI for health index construction and remaining useful life prediction," PHM Society Asia-Pacific Conference, 2026, doi: 10.36001/phmap.2025.v5i1.4646.

[16]. M. M. A. Rony, "AI-enabled predictive analytics and fault detection frameworks for industrial equipment reliability and resilience," ASRC Procedia: Global Perspectives in Science and Scholarship, Jan. 2025, doi: 10.63125/2dw11645.

[17]. Z. Yan et al., "Proactive infrastructure asset health management with a hybrid condition-aware probabilistic approach," 25th Conference of the Electric Power Supply Industry (CEPSI), Oct. 2025, doi: 10.1109/CEPSI66359.2025.11403733.

[18]. J. Qi, Z. Chen, Y. Song, J. Xia, and W. Li, "Remaining useful life prediction combining advanced anomaly detection and graph isomorphic network," IEEE Sensors Journal, Nov. 2024, doi: 10.1109/JSEN.2024.3470231.

[19]. T. Berghout, E. Bechhoefer, F. Djeffal, and W. H. Lim, "Integrating learning-driven model behavior and data representation for enhanced remaining useful life

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prediction in rotating machinery," Machines, vol. 12, no. 10, 2024, doi: 10.3390/machines12100729.

[20]. X. Li, L. Zhang, T. Tan, X. Wang, X. Zhao, and Y. Xu, "Multi-sensor data fusion and vibro-acoustic feature engineering for health monitoring and remaining useful life prediction of hydraulic valves," Sensors, vol. 25, no. 20, 2025, doi: 10.3390/s25206294.

[21]. X. Huang, W. Chen, D. Qu, S. Qu, and G. Wen, "Remaining useful life prediction method based on multisensor fusion under time-varying operating conditions," IEEE Transactions on Instrumentation and Measurement, 2024, doi: 10.1109/TIM.2024.3378308.