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REVIEW

Recent Applications of Unsupervised Machine Learning in Structural Health Monitoring

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ABSTRACT: Unsupervised machine learning has recently gained attention in structural health monitoring as engineers seek methods that can interpret large and complex data sets without prior labeling. Traditional diagnostic approaches often rely on predefined models or manual analysis, which limits their adaptability and efficiency when dealing with evolving structural behaviors or unforeseen conditions. Despite the growing interest in this domain, the literature remains fragmented, with limited systematic and bibliometric reviews that consolidate progress, identify prevailing trends, and clarify methodological limitations. This study addresses this gap through a comprehensive systematic and bibliometric review of research on unsupervised machine learning applied to structural health monitoring. The review examines the evolution of techniques, their applications in various structural systems, and the frequency and quality of their adoption in scientific literature. The aim is to present a consolidated understanding of how unsupervised learning contributes to data-driven monitoring, fault detection, and predictive maintenance. This research is important as it provides an evidence-based overview that supports future methodological improvements and guides the selection of suitable algorithms for practical engineering applications, ensuring a stronger link between data science and structural reliability.

KEYWORDS: Unsupervised learning; structural health monitoring; damage detection; machine learning applications; bibliometric analysis

1 Introduction

Structural health monitoring has matured from periodic inspections toward continuous sensing frameworks that record vibration, strain, acoustic and imaging data at high volume, which calls for algorithms that can make sense of changing patterns with minimal manual supervision [1–3]. Many civil and mechanical structures operate under variable temperature, humidity, traffic, and loading, which shapes their measured responses and can mask early signs of condition change if models rely on fixed baselines or labeled events gathered under narrow conditions [4–6]. Data streams from bridges, dams, buildings and pipelines are often incomplete or noisy, which makes label creation expensive and time consuming, while the event of interest may be rare or evolving in form [7–9].

Supervised learning typically assumes that representative labels exist for the conditions of interest and that class definitions remain stable over time. In structural health monitoring, these assumptions are difficult to satisfy in practice because true damage events are rare, labels are expensive to obtain, and imbalance between healthy and damaged states can dominate training and evaluation. Monitoring campaigns may also experience evolving damage manifestations, changing operational regimes, and sensor or network modifications that alter the data distribution over long horizons. These constraints motivate interest in unsupervised learning for novelty detection, clustering, and representation learning, where models can be trained primarily on abundant ambient measurements without relying on curated damage labels [10–12].

Unsupervised approaches can search for departures from healthy behavior, group similar states, and build compressed features that are less sensitive to variability, which suits output-only conditions common in civil infrastructure [13–15]. Recent studies emphasize that operational viability depends on robustness to environmental and operational variability, resilience to missing data, and stability as sensors age or monitoring networks evolve [16–18]. Work across the literature also shows that performance can degrade when feature distributions drift with seasons or operational patterns, so many studies focus on stabilizing decision rules under such drift [19–21].

Representation learning has emerged as a central mechanism for forming compact indicators from high-dimensional response histories, while anomaly scoring and thresholding remain core elements for operational decision making under unlabeled conditions [22,23]. In addition, long-term deployments often face missing segments and nonstationary disturbances, which has encouraged the use of generative and reconstruction-oriented ideas to preserve continuity and improve reliability in downstream assessment [7,24,25]. A parallel direction considers monitoring scenarios where permanent instrumentation is limited, which includes indirect and drive-by monitoring as well as image-based inference of structural response quantities [26–28].

Applications span long-span bridges, arch dams, rail systems, and offshore assets, where temperature variability and operational shifts present recurring hurdles for stable alarms across seasons and sites [29–31]. Population-based monitoring and domain adaptation aim to transfer knowledge across nominally similar structures, which is essential for regional programs that seek consistent decision rules across a fleet of bridges or wind assets [32–34]. Unsupervised learning is also increasingly adopted in guided waves and ultrasonic testing, where thermal cycles and access constraints make extensive calibration difficult [35–37]. Streaming settings further highlight the need for methods that adjust to concept drift while maintaining sensitivity to rare events, which links algorithm design to online updating and computational efficiency [13–15].

Interpretability and performance metrics remain central for practical adoption because operators must distinguish spurious alarms from meaningful condition changes under changing environments [4,38,39]. Advances in indirect monitoring, including drive-by methods and computer vision with learned features, also show that unsupervised learning can function with heterogeneous data sources and sparse labels, which broadens the reach of monitoring to resource-limited operators [40–42].

Despite this momentum, the literature remains dispersed across sensing modalities, structural types, and algorithm families, which makes it difficult to gauge prevailing methods, adoption patterns, and common limitations at a glance [43–45]. Prior reviews have tended to focus on specific sensors or single algorithmic themes, which leaves open questions regarding cross-cutting progress, reporting practices, and evidence strength across field and laboratory studies [12,46,47]. Bibliometric mapping has rarely been combined with a structured technical synthesis for unsupervised learning in structural health monitoring, which limits visibility into prolific venues, influential studies, and collaboration networks needed for coherent advancement. The literature lacks a consolidated account that draws together sensing domains, algorithm classes, evaluation practices, and adoption trends for unsupervised learning in structural health monitoring. The aim of this study is to conduct a systematic and bibliometric review that characterizes recent applications of unsupervised learning across structural systems, methods, and evaluation choices, while mapping trends and identifying recurring limitations.

2 Bibliometric Analysis

This study assembled a Scopus dataset to map research that links unsupervised machine learning with structural health monitoring (SHM). The search required the terms to appear in the title, abstract, or keywords and returned 221 records for 2000–2026. VOSviewer was then used to process the set and extract publication patterns and keyword relations.

Document types show a strong tilt toward journal outlets. Fig. 1 reports 158 articles, 58 conference papers, and 5 book chapters, which together match the 221-record total. The dominance of articles points to a field that favors archival reporting and method validation, while conferences remain a secondary route for early-stage results.

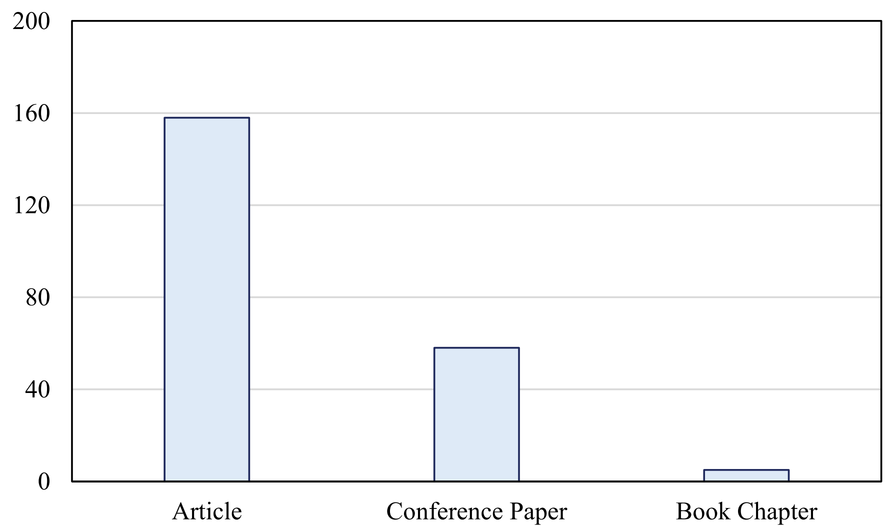

Figure 1: Types of indexed documents in Scopus database.

Publishing activity gathered pace only recently. Early years were quiet, with one paper in 2010 and one in 2011, followed by small steps between 2013 and 2016. A steady climb appears from 2018 onward, reaching 21 items in 2021, then 19 in 2022, and a clear surge in 2023 and 2024 with 41 and 39 items. The peak of the period is 2025 with 46 records. A small bar for 2026, three records, likely reflects partial indexing at the time of retrieval. These counts trace a rapid expansion of interest in unsupervised methods within SHM, as seen in Fig. 2.

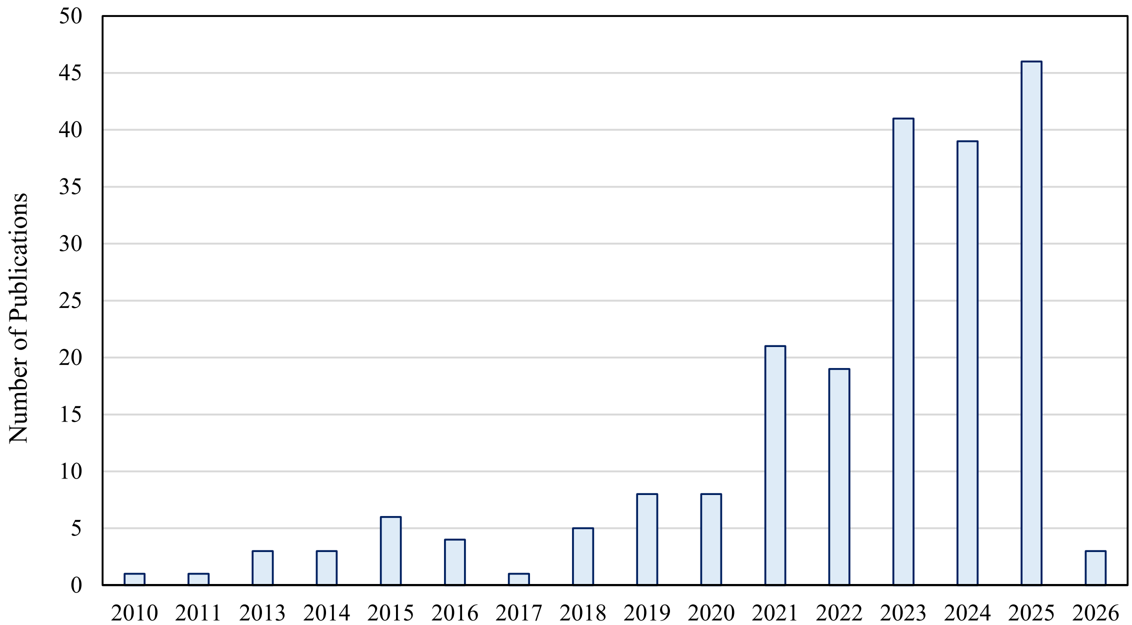

Figure 2: Number of yearly publications in Scopus database.

Keyword co-occurrence brings the focus of the field into view. "Structural health monitoring" appears 193 times and "damage detection" 123 times. Method-oriented terms remain frequent, with "unsupervised learning" 67, "deep learning" 42, "auto encoders" 40, and "anomaly detection" 41. General tags include "machine learning" 34. Classic tools are present through "principal component analysis" 19 and "clustering algorithms" 20. Application terms include "bridges" 19, "environmental conditions" 16, and "guided electromagnetic wave propagation" 15. The phrase "unsupervised machine learning" itself occurs 17 times. These counts place SHM and damage detection at the center, with method clusters around autoencoders, principal components analysis (PCA), clustering, and convolutional approaches, and with application cues related to bridges, guided waves, cables, vibration, and crack detection. The network view in Fig. 3 shows these hubs and their connections.

From an engineering perspective, the rise of terms such as "anomaly detection," "auto encoders," and "deep learning" alongside persistent references to environmental conditions suggests that the field is converging on practical workflows that can sustain reliable alarms under real operational variability rather than relying on short, controlled datasets. The strong presence of unsupervised and deep feature-learning terms is consistent with the increased availability of dense sensing and long-duration monitoring archives, where manual labeling remains costly and often incomplete. In parallel, the appearance of application cues such as bridges and guided waves reflects the operational demand for methods that can function under output-only measurements and temperature-driven drift, which are common deployment constraints. These bibliometric patterns therefore indicate an applied research trajectory that prioritizes field robustness, environmental compensation, and computationally feasible representation learning for continuous monitoring.

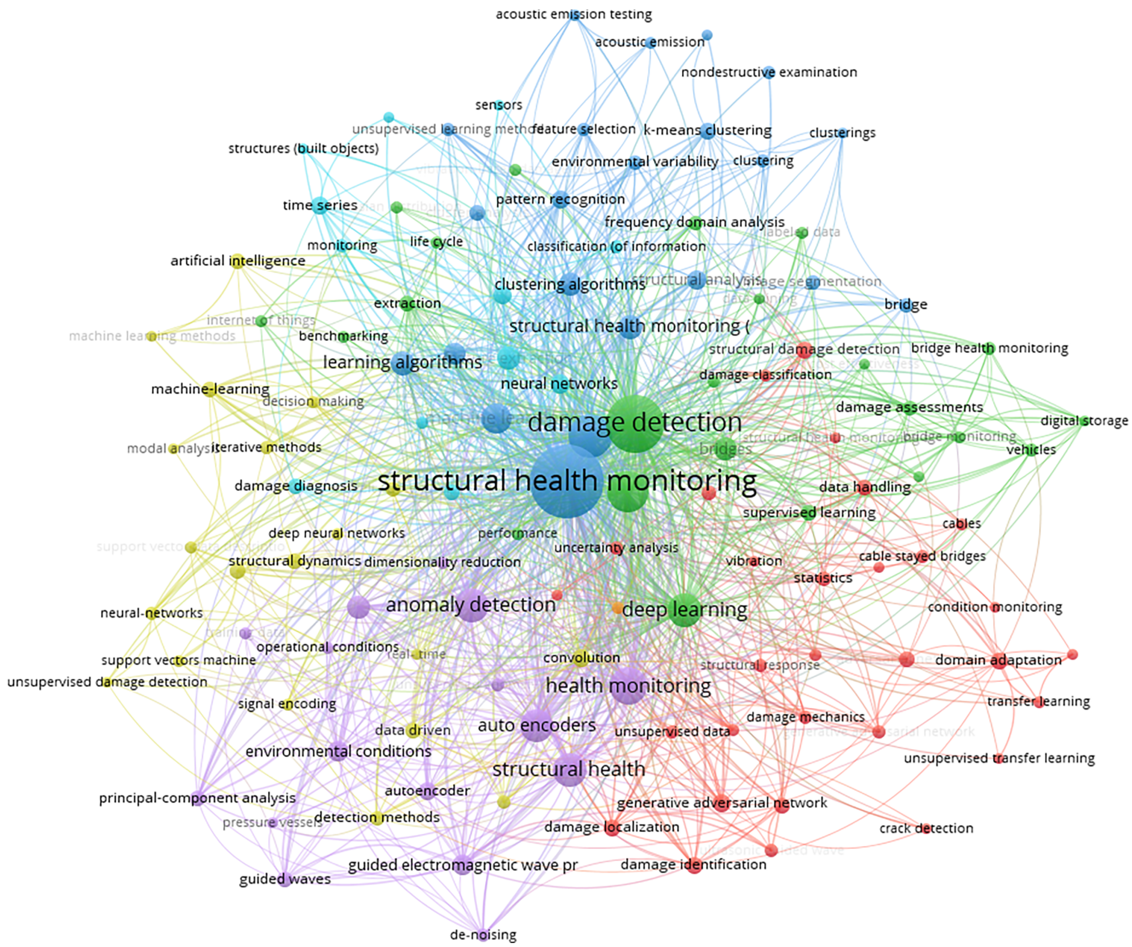

Figure 3: Co-occurrence of keywords in previous studies in Scopus database.

3 Fundamentals of Unsupervised Machine Learning for Structural Health Monitoring

Unsupervised learning in structural health monitoring focuses on extracting condition information from unlabeled measurements gathered during routine operation. Civil infrastructure often runs under changing temperature, load and boundary conditions, so methods that organize responses, reduce dimensionality and indicate departures from normal behavior suit field monitoring where labeled events are scarce [1,13,43,48,49]. Reported studies show three model families at the center of current use. Clustering assigns unlabeled samples to consistent groups while isolating points that differ from the bulk of historical data, and this idea appears across vibration, acoustic emission and imaging datasets for a range of structures [50–53]. Novelty detection learns a boundary that characterizes healthy response, then scores future data against that boundary, which fits cases where only undamaged measurements exist [1,39,54,55]. Representation learning compresses high-dimensional measurements and tracks reconstruction error or latent changes as indicators of condition shift, with applications to bridges and laboratory structures using autoencoders and variational autoencoders [22,23,56].

Feature extraction and dimensionality reduction sit at the core of these systems. Classical approaches such as principal component analysis and frequency-response features remain common, and recent work adopts autoencoders and variational autoencoders to form low-dimensional descriptors that remain stable under seasonal variation [22,57,58]. Hybrid encoders with temporal models have been proposed for state evolution, where latent trends and reconstruction statistics serve as compact indicators across long horizons. Studies on benchmark bridges report that such encoders can compress many channels into a reliable latent space for continuous assessment [23,59].

Clustering remains a central device in practice because it organizes operating states while revealing outliers. Density-based and consensus strategies have grouped vibration and acoustic responses, often after a preliminary reduction step, and have been applied to masonry, bridges and composite components [3,52,60]. Healthy subspace and hypersphere formulations define compact regions of normal response and detect departures in a way that is resilient to moderate environmental drift, an idea extended to populations of similar structures [20,32,61]. Studies have also combined modal analysis with density-based spatial clustering of applications with noise (DBSCAN) for bridge scour assessment and tested immune-inspired recognition for composite and steel members, which shows the breadth of unsupervised grouping tools under field variability [62–64].

Generative modeling and domain adaptation address gaps that arise in long campaigns. Long-term datasets often contain outages, so imputation with generative adversarial networks has been adopted before detection and localization, and recurrent-generative hybrids have been used for damage localization under dynamic excitation [7–9,65]. Domain adaptation transfers features across structures and conditions, which is central in drive-by settings where vehicle characteristics differ between sites, and in high-arch dams with strong state changes after earthquakes [18,33,34,66]. Ultrasonic and guided-wave studies report that attention mechanisms and temperature-aware encoders help stabilize decisions across thermal cycles and operational shifts, and related work treats corrosion in underwater pipes and response shifts in arch dams within the same unsupervised transfer view [29,36,37,65,67].

Environmental and operational variability remains a major concern for vibration-based monitoring. Reported solutions include kernel null-space mappings, local metric learning and feature weighting that separate environmental influence from structural change [19,21,68]. Healthy boundaries that evolve with measurement periods maintain performance over slow shifts in temperature and loading, while hybrid designs link physical response expectations with learned features to stabilize decisions [17,20,32,69]. Bridge and dam case studies document the routine use of such normalization in long-term settings [30,70].

Unsupervised methods span several sensing modalities. Vibration and strain dominate, although guided waves, acoustic emission and imaging are increasingly present. Self-organizing maps and independent component analysis appear in vibration-based work, while acoustic emission studies apply shape-based clustering to sort fatigue activity in composites. Infrared and camera-based observations analyzed with deep clustering or unsupervised segmentation support assessment of reinforced concrete and cable systems [27,41,71–74]. Indirect and drive-by monitoring combine these ideas with vehicle responses, forming bridge indicators where permanent instrumentation is limited [18,34,40].

Streaming operation places attention on online learning and computational efficiency. Real-time novelty indices, moving windows and incremental encoders have been tested on railway bridges and laboratory structures, while fast algorithms address dense networks and long records [5,13–15,47,75,76]. Evaluation practice reflects these constraints. Receiver operating characteristic curves, precision–recall analysis and reconstruction statistics appear frequently, with benchmark datasets such as Z24 supporting comparative tests of autoencoders, one-class models and clustering [4,23,43,59]. Studies highlight that simple distance-based rules coupled with careful normalization often match more complex models in stability and transparency, which continues to drive adoption in the field [10,12,19,30,44,51].

Evaluation practice commonly relies on receiver operating characteristic and precision–recall curves for threshold setting in unlabeled contexts, and several comparisons find that simple algorithms paired with careful normalization achieve stable results [4,10,43,46]. Historical work on unsupervised statistical diagnostics provided early templates for these approaches and remains relevant for modern clustering designs [77–81].

4 Clustering-Based Approaches for Damage Detection and Pattern Recognition

Clustering organizes unlabeled data into groups that mirror consistent structural states, then isolates observations that depart from those groups. Early work introduced this idea for vibration data and event identification, laying the groundwork for later systems that couple clustering with feature learning and environmental normalization [1,3,44,82,83]. Density-based and consensus schemes are common because they do not require a preset number of clusters and can absorb irregular sampling, which suits vibration and acoustic emission contexts where operating patterns change across seasons or usage [52,62,73]. Case studies on bridges and masonry structures report condition changes that remain visible after grouping, even when measurements vary with temperature and traffic [60,84].

Prototype-based clustering, including self-organizing maps and k-means variants, continues to appear in vibration work owing to its computational economy and ease of visualization. Applications include unsupervised vibration-based detection with self-organizing maps and grouping of frequency response and strain features with k-means or genetic search [41,57,85]. Hierarchical clustering and immune-inspired recognition have been tested for composite and steel members, where a layered view of patterns helps relate grouped features to likely degradation paths [50,63,64].

Table 1: Summary of unsupervised damage detection methods in recent studies.

Reference	Aim of the Study	Findings	Remarks
Wan et al. [86]	Introduced a three-stage spatio-temporal sparse integration framework to distinguish normal, mildly anomalous, and significantly anomalous SHM patterns using GMM clustering, sparse reconstruction, and a mask-based ResNet18.	Reported overall accuracies of 98.36% and 95.51% on two real bridges and showed that the staged indicators progressively isolated significant, mild, and local anomalies with limited tuning and no labels.	Established a practical unsupervised workflow that reduced over-generalization and handled diverse anomaly types encountered in operational monitoring.
Hoda et al. [87]	Implemented principal-component-based novelty detection on an FPGA to enable compact, low-power, real-time SHM for a full-scale rural bridge under controlled vehicle loading.	Matched MATLAB SVD outputs for the first principal component and produced a normalized novelty index that correctly separated undamaged and damaged states during field testing.	Confirmed that unsupervised ML could be pushed to edge hardware for on-site classification with stringent latency and power constraints.
Talukder et al. [88]	Designed a regression-based 1D-CNN that learned the undamaged acceleration sequence pattern so that deviations became damage-sensitive features in an unsupervised setting.	Detected bridge damage down to 5% severity using a single sensor in simulation and validated reliable detection on a laboratory bridge irrespective of sensor position by managing high-dimensional features with DTW.	Indicated that sequence-pattern learning captured non-stationary responses effectively without requiring damaged-state labels.

(Continued)

Table 1 (continued)

Reference	Aim of the Study	Findings	Remarks
Gunes & Gunes [89]	Employed autoencoders on transmissibility functions to extract unsupervised features and classified damage with a one-class SVM.	Improved detection robustness in noisy simulations and correctly localized damage on a masonry arch bridge model by leveraging nonlinear encoding rather than PCA alone.	Showed that transmissibility functions provided efficient, locally sensitive features for autoencoder-based SHM.
Deng et al. [90]	Built a fully unsupervised data-cleaning pipeline that transformed signals into wavelet time–frequency images, extracted features with a pre-trained GoogLeNet, and clustered with K-means to generate pseudo-labels.	Reached 98.4% precision for normal data and 97.9% accuracy across all data types on a large cable-stayed bridge, thereby automating low-cost cleaning without manual screening.	Demonstrated that unsupervised cleaning substantially improved downstream anomaly detection reliability in long-term SHM.
Liu et al. [91]	Developed U-GraphFormer, an unsupervised spatiotemporal graph model with sensor-specific temporal attention to flag point-wise anomalies and summarize severity.	Obtained up to 0.99 precision and 0.98 recall for severe damage and produced interpretable segment-wise severity statistics that tracked damage progression across standard benchmarks.	Provided real-time, low-cost inference and adaptive scoring that generalized across frames, bridges, and wind turbine datasets.
Xue et al. [92]	Integrated multi-source sensor fusion with an unsupervised algorithm to identify construction activities that endangered historical relics during protective works.	Delivered timely alerts whenever settlement, tilt, crack width, or acceleration exceeded thresholds and successfully associated detected anomalies with site activities that impacted heritage integrity.	Illustrated that unsupervised monitoring could support conservation decisions where labeled “damage” data were unavailable.
Boratto et al. [93]	Proposed agglomerative clustering with an unsupervised feature selection strategy using box-plot statistics to reduce dimensionality and enhance interpretability.	Improved homogeneity, completeness, V-measure, and adjusted Rand scores across four monitoring campaigns by retaining the most informative temporal, statistical, and spectral features.	Highlighted that principled feature selection strengthened cluster structure and reduced computation for large SHM datasets.
Wei et al. [94]	Introduced an unsupervised graph learning network for early damage recognition in CFRP that extracted dual-order similarity features and clustered states without labels.	Identified early damage samples with 100% accuracy on a public accelerated-life dataset and produced an evaluation curve that clearly separated normal and incipient damage.	Demonstrated a complete unsupervised pipeline from feature learning to state clustering and quantitative assessment for composites.
Wan et al. [95]	Combined a deep convolutional variational autoencoder with support vector data description to capture multisensor correlations and enclose healthy states within a tight hypersphere.	Outperformed autoencoder-SVDD, AR-OC-SVM, and PCA baselines on a computational frame and a laboratory grandstand by reducing false alarms and improving separation of anomalous windows.	Showed that probabilistic latent encoding stabilized unsupervised detection under environmental variability.

(Continued)

Table 1 (continued)

Reference	Aim of the Study	Findings	Remarks
Fang et al. [96]	Coupled a denoising sparse wavelet network with dynamic-inner PCA to extract multiscale features online for health assessment under big-data conditions.	Verified effective synthesis of heterogeneous sensor signals on a 5-DoF model and tracked the integrity of a wind turbine over a year by aligning latent correlations dynamically.	Suggested that multiscale sparse representations improved stability when handling large volumes of high-frequency data.
Li et al. [97]	Proposed a deep convolutional autoencoder with a hybrid loss and wavelet-transmissibility spectra, followed by an OPTICS-based picker for automatic damage discrimination in bridges.	Accurately identified damage on a curved bridge numerically and on a laboratory suspension bridge experimentally without requiring damaged-state samples for training.	Addressed the scarcity of labeled damage data by combining rich spectral features with unsupervised clustering.
Giglioni et al. [23]	Reconstructed short acceleration sequences with autoencoders and used reconstruction-loss indices, optionally ensembled across sensors, to flag anomalies.	Detected local damage on the Z24 Bridge using limited sensors and modest computation by focusing on short macro-sequences rather than full time histories.	Avoided system identification and remained practical for near-real-time bridge assessment.
Boccagna et al. [45]	Built an end-to-end unsupervised deep-learning anomaly detector for building and bridge data from preprocessing through output interpretation.	Flagged damaged scenarios in a railway bridge digital twin and detected anomalous behavior in the Historical Tower of Ravenna more reliably than several state-of-the-art baselines.	Provided a cohesive pipeline that integrated model choice, training, and decision logic for near-real-time monitoring.
Sarmadi & Yuen [19]	Developed a one-class kernel null Foley–Sammon transform novelty detector with probabilistic thresholding based on extreme value theory.	Succeeded in detecting damage under strong environmental variations on the Z24 Bridge and a laboratory wooden bridge by projecting healthy data into a null space and estimating a reliable alarm limit.	Offered a transparent, computationally inexpensive alternative for long-term SHM with stable thresholds.
Shi et al. [98]	Proposed a real-time unsupervised damage detection method that combined neural-network-based statistical modeling with deep support vector domain description and an iterative strategy to select an effective window length.	Verified damage existence and damage levels on simulated IASC-ASCE benchmark data and shake-table experiments while training on healthy data only, and reported low probability of false alarms with real-time execution feasibility.	Provided a deployment-relevant novelty detection example where alarm density and windowing strategy influence practical sensitivity and false-alarm behavior in real-time SHM pipelines.

Environmental and operational variability shapes cluster quality, so many contributions place normalization before or within the clustering stage. Healthy subspace and hypersphere models help separate normal and abnormal behavior across temperature cycles, and related designs apply kernel mappings and local metric adjustment to refine distances under drift [5,17,19–21,32,68,99]. Latent-space clustering has gained traction, where deep encoders first construct compact embeddings from vibration or deflection records and grouping occurs in that reduced space, often with improved separation of states [22,59]. Hybrid pipelines pair encoders with one-class classifiers or deep clustering networks when sensitivity to unseen conditions is required [39,54,100].

Table 1 highlights that clustering-based pipelines often achieve stable separation of operating states when the feature space is explicitly normalized for environmental and operational variability, whereas the same clustering rules can fragment the healthy state when seasonal drift enlarges dispersion or when sensor faults introduce non-structural outliers. Density-based clustering is generally tolerant of noise and irregular cluster shapes, yet it can misinterpret slow environmental drift as a new "cluster" and raise false alarms if thresholds are not drift-aware. Prototype-based methods can remain computationally economical, although their decision boundaries may become brittle when the response distribution is multi-modal or when the number of operating regimes changes over time. Consensus and ensemble designs tend to improve robustness to initialization and noisy channels, but the added computation and tuning overhead can reduce their attractiveness for resource-constrained deployments. These patterns motivate a recurring trade-off in field SHM, where modest increases in model complexity are valuable only when they yield demonstrably lower false-alarm rates under realistic environmental shifts and sensor degradation.

Guided-wave applications make extensive use of clustering with learned features. Temperature-compensated encoders followed by grouping have been reported for defect localization, and attention mechanisms or wavelet features extend this approach to environments with strong thermal variation [36,37,65,101,102]. Acoustic emission and infrared imaging provide further examples, where consensus clustering separates emission signatures over long fatigue tests and unsupervised segmentation partitions thermal images of reinforced concrete [72–74].

Indirect and drive-by monitoring adapt clustering to vehicle-induced responses. Feature spaces obtained from adversarial autoencoders or domain-adapted encoders are grouped to reveal bridge state variation that is less sensitive to vehicle type and speed, and this pattern appears across multiple sites and platforms [18,26,34,40,103]. Feature selection remains important for these pipelines. Principal component analysis, manifold learning and feature weighting remove redundant variability before grouping, while time-series modeling helps craft features that remain responsive under output-only conditions [11,13,57,58,104–106].

Probabilistic perspectives support decision making when data quality varies. Bayesian formulations and reliability-oriented clustering express uncertainty in group assignments, and recent work integrates probabilistic features from neural encoders to strengthen anomaly indication [91,95,107,108]. Full-scale experiments have validated many pipelines that combine encoders and clustering, including studies on operational bridges and streaming algorithms that update clusters in real time [15,38,47,87,109,110]. Work on imputation before clustering addresses missing data and maintains continuity, while recurrent-generative schemes supply embeddings suited for localization [7–9,65]. Data fusion with strain, acceleration and imaging features has also been tested, as have fleet-level applications in offshore wind where shared cluster definitions assist scheduling across assets [31,61,69,111,112].

Evaluation practice commonly relies on receiver operating characteristic and precision–recall curves for threshold setting in unlabeled contexts, and several comparisons find that simple algorithms paired with careful normalization achieve stable results [4,10,43,46]. Historical work on unsupervised statistical diagnostics provided early templates for these approaches and remains relevant for modern clustering designs [77–81].

5 Dimensionality Reduction and Feature Extraction Techniques in SHM

Feature extraction and dimensionality reduction convert large sensor datasets into compact indicators suitable for detection and tracking under unlabeled and variable conditions. Matrix factorization methods were among the first tools in this setting. Singular value decomposition has been used for virtual strain sensing and anomaly indication in operational bridges, and frequency-domain decomposition coupled with clustering has separated modal shifts from environmental effects in bridge monitoring [62,113]. Principal component analysis remains common for low-dimensional vibration features, including population-based projections that support cross-comparison within groups of similar structures [57,61,114]. Probabilistic decompositions such as Bayesian factor analysis have supported one-class assessments for cables, and factor models with genetic clustering have sorted operating conditions from strain measurements [55,115].

Nonlinear reduction has expanded as datasets increased in size and complexity. Kernel null-space learning and manifold-based selection aim to separate normal and abnormal behavior when temperature and boundary conditions vary, and local metric learning with feature weighting helps maintain stable relations across measurement periods [5,16,19,104]. Autoencoders play a central role in current practice. Deep and variational encoders trained on vibration data produce latent spaces and reconstruction errors that track condition change in bridges and laboratory structures, with results reported on the Z24 benchmark and other datasets [22,23,46,59,116]. Hybrid encoders combined with one-class support vector machines or probabilistic layers refine extracted features for unsupervised decisions [39,95].

Time-frequency and wavelet features remain important for guided waves and broadband vibration. Deep convolutional autoencoders have been trained on wavelet transmissibility patterns for bridge assessment, and temperature-compensated guided-wave encoders have run on edge devices for local inspection [36,37,97]. Multi-head attention encoders provide temporal focus on informative segments of vibration signals during variable conditions [117]. Sequential and generative models add further options. Bidirectional long short term memory (LSTM) encoders with distribution modeling support quantitative estimates of change, and generative adversarial network (GAN)-based designs supply reconstruction and localization support for dynamic tests [65,118]. Domain adaptation extends these representations to dams, pipelines and composite structures where operating conditions differ across sites [29,65,119].

Dimensionality reduction also appears as a preparatory step for cleaning and imputation. Generative approaches restore missing segments in bridge datasets, while convolutional cleaning with clustering removes noisy samples before feature extraction, which stabilizes downstream detection [7–9,90,120]. Population-based and transfer designs rely on shared latent spaces to compare structures and reuse information when labeled damage data are unavailable, as shown in bridges and pedestrian crossings under domain shifts [33,99,121]. Edge and embedded computing motivate compact encoders that meet power and bandwidth limits, with field programmable gate array (FPGA) and TinyML studies reporting real-time feasibility [87,122]. Data fusion through unsupervised encoders integrates strain, acceleration and imaging features, and related indirect methods merge visual and vibration cues for bridges where direct instrumentation is limited [26,28,112]. Imaging tasks have used encoders for deflection and tension estimation, and unsupervised transfer learning supports cross-dataset crack segmentation in composite members, while infrared thermography has been grouped through clustering features [27,74,119].

Table 2 shows that imaging and localization tasks often rely on representation learning to convert high-dimensional wavefields or images into compact latent descriptors that can drive probabilistic mapping or pixel-level segmentation without dense manual labels. A recurring contrast is that localization accuracy is strongly tied to whether the representation is stable under temperature and operational drift, which is why several studies embed explicit temperature compensation or baseline reconstruction steps before localization and segmentation decisions. Another visible trend is the movement from handcrafted tomography features toward end-to-end learned reconstructions that reduce artifacts and improve repeatability, although these gains are typically conditional on careful design of the reconstruction target so that damage-sensitive differences remain visible in the residual or latent space. These patterns clarify that the central practical challenge is not only extracting compact features, but also ensuring that the learned compression does not remove the subtle, damage-related variations that localization depends on under field variability.

Table 2: Summary of studies on damage localization/imaging and pixel-level segmentation.

Reference	Aim of the Study	Findings	Remarks
Liao et al. [102]	Proposed a baseline-free localization framework that used a Kolmogorov-Arnold autoencoder to learn guided-wave responses and a modified probabilistic elliptical imaging algorithm to build damage probability maps.	Localized single and multiple damages on wind-turbine blades and composite plates and surpassed baseline-free and classical approaches in localization accuracy.	Demonstrated that end-to-end unsupervised learning could feed high-fidelity probabilistic imaging without handcrafted features.
Song et al. [101]	Developed a temperature-compensated, delay-based probabilistic imaging method that reconstructed baseline signals via a path-fusion autoencoder and then computed scattering for localization.	Achieved 99.9% detection accuracy from 20°C–60°C on the OGW benchmark and localized four damage sites with a mean error of 13.85 mm and a 5.82 mm standard deviation.	Showed strong robustness to environmental drift by reconstructing temperature-matched baselines in an unsupervised manner.
Junges et al. [123]	Compared convolutional autoencoders and conditional GANs for unsupervised Lamb-wave processing and downstream damage probability mapping.	Correctly localized pseudo and real damage on composite panels and on a full-scale composite wing, with comparable accuracy across both deep models.	Validated fully unsupervised pipelines that avoided prior feature extraction and still yielded precise localization.
Lomazzi et al. [124]	Combined convolutional auto-associative neural networks with an in-house tomographic approach to transform predictions into damage probability maps.	Outperformed classical diagnosis algorithms in locating damage on aluminum and composite structures while remaining independent of handcrafted tomography features.	Reduced artifacts typical of tomography by relying on learned reconstructions before imaging.
Han et al. [125]	Introduced InpRailDiffusion, a cold-diffusion, pixel-level, unsupervised segmentation model for rail damage that used inpainting noise and a Mamba-enhanced U-Net.	Surpassed state-of-the-art unsupervised baselines on RSDDs-I/II with MIoU/F1 of 0.864/0.844 and 0.845/0.814, reducing both missed detections and false positives.	Demonstrated that diffusion-style reconstruction differences could drive precise, label-free pixel segmentation in complex textures.

(Continued)

Table 2 (continued)

Reference	Aim of the Study	Findings	Remarks
Zhao et al. [119]	Integrated CycleGAN-based bidirectional feature transfer with an attention-enhanced U-Net to improve crack segmentation under domain shift without labeling target data.	Mitigated over-adaptation and preserved fine crack width and orientation while generalizing across heterogeneous concrete/composite datasets.	Emphasized instance- and feature-level alignment to stabilize unsupervised segmentation across sites.
Tanveer & Cho [126]	Trained a self-supervised Vision Transformer to learn crack patterns from unlabeled images and applied probability thresholding to suppress low-confidence pixels.	Reached mean F1 of 75.02% and mean IoU of 66.14% after thresholding on 1399 test images and handled high-resolution field imagery via sliding windows.	Reduced labeling burden while retaining practical field utility for large crack images.
Chun & Kikuta [127]	Proposed a self-training unsupervised domain adaptation framework for crack segmentation that filtered pseudo-labels by Bayesian uncertainty and injected spatial crack priors.	Increased F1 for Bayesian DeepLabv3+ and Bayesian U-Net after adaptation and further improved performance by few-shot synthetic images from Stable Diffusion.	Enabled high-precision segmentation with as few as 100 target images by combining uncertainty and prior-guided screening.
Meng et al. [128]	Presented a crack-segmentation transfer pipeline with a GAN-based style transfer and a Swin-Transformer-CNN hybrid (Swin-CrackFormer).	Improved segmentation on unlabeled crack datasets via transfer and achieved state-of-the-art results on METU, surpassing existing models.	Demonstrated that style transfer plus hybrid attention-convolution features enhanced cross-domain crack parsing without labels.
Huang et al. [129]	Optimized CycleGAN to transform above-water crack images into underwater styles for training underwater dam crack detectors where data were scarce.	Produced synthetic underwater images that improved classification, detection, and segmentation tasks, thereby strengthening underwater crack models.	Offered a pragmatic route to domain-appropriate training data when *in-situ* imaging was costly or hazardous.

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Table 2 (continued)

Reference	Aim of the Study	Findings	Remarks
Belmokhtar et al. [62]	Applied a revisited FDD and an EVD-MAC subspace method to identify modes and then clustered frequency behavior with unsupervised learners to monitor scour.	Separated modal clusters under varying temperature and water levels and tracked natural-frequency shifts over more than a year on a real bridge.	Showed that unsupervised clustering on subspace trajectories could operationalize scour assessment with ambient data.
Zhang et al. [130]	Proposed a local diagnosis method that isolated a substructure, computed pseudo-free responses, and extracted AR-spectrum features to capture local stiffness loss.	Validated effective localization on a simulated four-story plate–column structure and a three-story testbed (LANL) by mitigating uncertainties in PFR computation with a nearest-neighbor log-spectral rule.	Addressed the common gap where linear stiffness-reduction damage evaded traditional output-only time-series models.
Liu [100]	Combined dynamic graph convolutional networks with Transformers and introduced a "localization score" that fused data-driven and physics-aware cues.	Localized damage on a benchmark steel frame and a cable-stayed bridge using only time-series data, while maintaining generalization across structures.	Bridged high-capacity temporal models with structural dynamics insights for interpretable localization.

Several studies discuss the trade-off between compression and information retention. Results indicate that moderate reduction can preserve sensitivity while improving generalization and interpretability for long-term monitoring, a point that aligns with the steady preference for clear features and simple thresholds in field deployment [58,106,131]. Early statistical diagnostics on response surfaces and delamination detection established this logic and continue to inform current designs that combine deep encoders with careful normalization [78,132].

6 Emerging Unsupervised and Hybrid Frameworks for Structural Condition Assessment

Recent work shows a shift toward unsupervised and hybrid frameworks that process large unlabeled datasets while accommodating variable environments. These emerging frameworks commonly treat environmental normalization, missing-data imputation, and domain adaptation as enabling layers that stabilize clustering, novelty detection, and representation learning when models face drift, outages, and cross-site variability in real deployments. Besides, these frameworks couple reconstruction-based learning with one-class decisions, transfer across sites through domain adaptation and incorporate probabilistic layers for uncertainty handling. Bridges, dams, composite structures and pipelines appear frequently in this stream of studies [45]. Autoencoders with one-class modules provide compact features and alarms that remain stable across environmental shifts, while recurrent-generative designs aim to support localization as well as detection [25,39,65,89].

Population-based monitoring extends these ideas from single structures to fleets. Shared latent spaces and meta-learning enable cross-comparison and adaptation under missing data or irregular sampling, which is relevant for regional programs and long corridors [61,70,99,133,134]. Hybrid designs couple statistical normalization and physical knowledge with learned features. Locally unsupervised adjustments remove environmental effects across measurement periods, and feature weighting or metric tuning treats mitigation as a learning task in its own right [16,17,21,135]. Physics-informed hybrids combine finite element expectations with unsupervised grouping or one-class detection for field bridges, seeking reliable decisions when conditions change widely [136,137].

Domain adaptation and transfer learning have become a regular part of these frameworks. Reported cases include high-arch dams after earthquakes, corrosion in underwater steel pipes and composite crack detection, as well as transfer between pedestrian and highway bridges [33,65,66,119,121]. Generative and sequential architectures supply the internal engines for these transfers. Variational and adversarial encoders learn compact dynamics, and bidirectional LSTM units describe temporal relations that support condition estimation and response forecasting with attention to normal variability and potential damage [25,65,118,123].

Hardware-aware learning brings these models closer to continuous deployment. FPGA studies show real-time autoencoder inference on operational bridges, while TinyML guided-wave implementations handle temperature compensation on low-power devices [37,87,122]. Probabilistic reasoning appears in several designs. Bayesian factor analysis has been used for cables under ambient vibration, and unsupervised deep models that quantify uncertainty in latent features supply more informative alarms for anomaly detection [55,95]. Hypersphere and subspace learning provide clear decision boundaries for robust operation under changing conditions [20,53].

Data reconstruction has moved from a convenience step to a standard layer. Generative imputation networks fill gaps before detection and localization, and convolutional cleaning with clustering eliminates noise and outliers that would otherwise bias encoders [7–9,90,120]. Guided-wave and vibration studies continue to report benefits from hybrids that combine learned features with physics-inspired representations, including multi-head attention LSTM encoders, wavelet transmissibility features and probabilistic imaging for localization under changing temperatures [97,101,117].

Multimodal fusion appears often in this literature. Encoders that merge strain, acceleration and imaging features supply richer condition descriptions for bridges, and computer vision systems based on adversarial encoders estimate quasi-static displacements and image-based indicators in indirect settings [26,28,112]. Infrared and camera data have been segmented in an unsupervised way for reinforced concrete and composite components, which extends SHM beyond purely vibration-based sensing [74,102]. Drive-by monitoring continues to benefit from unsupervised and hybrid adaptation. Domain-adapted encoders trained on vehicle responses form invariant features across vehicles and spans, adversarial and hierarchical learning support condition inference without direct instrumentation, and regression with dynamic time warping has been used on vehicle-induced signals for unsupervised damage assessment [18,34,40,88].

Research threads that test new computation forms and system views also appear. Unsupervised quantum machine learning has been proposed for vibration signals, and digital-twin models combine feature fusion with unsupervised learning to maintain virtual representations of bridges in service [138]. Outlier ensembles and deep clustering variants continue to serve as robust anomaly detectors under noise, while novelty indices and symbolic representations remain useful for online early-damage indication [3,14,38,139].

Recent contributions on context-free forecasting and spatio-temporal sparse integration aim to manage evolving data streams without dense labeling [25,86]. Hybrid detection informed by mechanical models creates links between numerical predictions and learned features, as seen in computer aided engineering (CAE)-aided encoders and deep one-class detection for *in-situ* bridges [136,140].

Score-guided regularization and covariance-based metrics have improved transparency in decision rules, and correlation-based assessment supplies indicators such as stiffness trends from periodic monitoring data [30,68,118,141]. Long-standing statistical work on unsupervised diagnosis for composite beams and civil structures established the idea of tracking response-surface change without labels, an idea that remains visible in modern latent-feature designs [78,80]. The overall direction points toward adaptable, integrated and interpretable systems that operate under minimal supervision while coping with missing data, environmental variation and multiple sensing modes. Continued refinement of normalization, generative modeling and edge deployment indicates sustained movement toward field-ready unsupervised monitoring.

Table 3 indicates that deployment-oriented progress is increasingly driven by methods that explicitly address missing data, cross-domain shifts, uncertainty reporting, and computational constraints rather than focusing only on isolated detection accuracy. A consistent contrast across these studies is that models with strong predictive or reconstruction capacity still require careful calibration of thresholds and uncertainty to avoid overconfident alarms under drift, while lightweight edge implementations must trade representation richness for power, memory, and latency limits. The table also highlights that transfer learning and domain adaptation are becoming central for network-wide monitoring, where the cost of per-site tuning can dominate operational budgets. These trends reinforce that future advances are likely to be judged by reliability under field variability, resilience to imperfect data streams, and feasibility of continuous operation rather than by peak accuracy on a single controlled dataset.

Table 3: Summary of studies on deployment, transfer learning, missing data, uncertainty, and forecasting in unsupervised structural health monitoring.

Reference	Aim of the Study	Findings	Remarks
Mousavi et al. [138]	Presented a Digital-Twin framework for real-time bridge damage detection that fused multi-domain features in a fusion autoencoder and evaluated with synthetic anomalies generated by a transformer-based GAN.	Detected subtle anomalies on Australia's Werrington Bridge better than conventional unsupervised DL and identified and localized all real damage cases on Austria's S101 Bridge without additional tuning.	Demonstrated that feature fusion plus realistic synthetic anomalies strengthened evaluation and reduced reliance on costly lab testing.
Zheng et al. [9]	Proposed a missing-data imputation method that pretrained an imputer on a source domain and adapted it to a target bridge via a generator that learned the target missingness pattern.	Reduced imputation errors on pedestrian-bridge monitoring data relative to the pretrained baseline without assuming prior knowledge of missingness.	Enabled practical recovery of SHM streams by adapting to real missing-pattern structures unsupervisedly.

(Continued)

Table 3 (continued)

Reference	Aim of the Study	Findings	Remarks
Xie et al. [8]	Developed an enhanced generative-adversarial imputation network that operated fully unsupervised even when all sensors had incomplete data.	Achieved high-quality imputation in time and frequency domains on the Dowling Hall footbridge data by integrating self-attention and skip connections into the generator.	Addressed a challenging, real-world regime where no complete sensors existed for supervision.
Yang et al. [142]	Trained an unsupervised damage detector directly on current guided-wave measurements and introduced noise-augmentation strategies to avoid learning to reconstruct damaged signals.	Improved separability in latent space and achieved better detection for low-SNR inputs while providing a procedure to choose optimal noise intensity.	Eliminated the dependence on long historical baselines and stayed effective when the training set contained many damaged waves.
Chen et al. [139]	Combined a BiLSTNet-A forecaster with temperature-driven moving PCA to form a hybrid unsupervised anomaly detector using only intact strain data.	Demonstrated better robustness to temperature loading with the DL forecaster and complementary strengths when fused with Td-MPCA on long-span bridge data.	Showed that hybridization of learned forecasting and classical normalization improved reliability under strong EOC shifts.
Shi et al. [143]	Proposed contrastive and self-supervised representation learning for open-set damage classification in SHM under incomplete and imbalanced vibration data, targeting scenarios where unknown damage states may appear during deployment.	Reported that learned representations improved robustness to missing data and imbalance while supporting open-set decision making that distinguishes known from previously unseen damage patterns.	Strengthened the link between representation learning and operational SHM by explicitly addressing incomplete data and open-set conditions that are common in long-term monitoring archives.
Deng et al. [90]	Automated bridge-scale data cleaning by converting to wavelet images, extracting CNN features, and clustering to pseudo-label anomalies for refinement.	Reached ~98% accuracy across classes and removed manual prescreening, enabling scalable maintenance of very large monitoring archives.	Positioned unsupervised cleaning as a prerequisite for dependable downstream detection and localization.

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Table 3 (continued)

Reference	Aim of the Study	Findings	Remarks
Gao et al. [25]	Proposed a PSA-CGAN framework to forecast long, context-free time series for SHM where pre- and post-context were unavailable or missing.	Accurately predicted accelerations for near- and far-forecasting on two bridges and tracked progressively changing damage trends in real time.	Addressed practical forecasting scenarios with missing context to support proactive decision-making.
Hoda et al. [87]	Realized FPGA-based, unsupervised SHM in the field by extracting the first principal component in hardware and forming a normalized novelty index.	Matched software baselines and classified damage levels in real time during controlled loading of a decommissioned bridge.	Confirmed feasibility of task-specific, low-power SHM deployments that bypass cloud computation.
Kashyap et al. [37]	Demonstrated an unsupervised TinyML pipeline for GW-SHM that ran on an Artix-7 FPGA and detected disbonds/delaminations under 0–90°C.	Achieved reasonably high accuracy with very lightweight models while handling temperature variability without pre-computed labels.	Provided an end-to-end embedded edge solution from data acquisition to inference for scalable deployments.
Liu et al. [18]	Introduced HierMUD, a hierarchical multi-task unsupervised domain adaptation framework to transfer damage detection, localization, and quantification models from one bridge to another.	Reached average accuracies of ~95% for detection and 93% for localization and delivered low quantification error while reweighting more shifted tasks.	Tackled multi-task domain shifts systematically to enable network-wide drive-by SHM with no target labels.
Jiang et al. [7]	Proposed a GAN-based strain imputation method that captured spatiotemporal relationships across sensors and did not require intact, complete training sets.	Provided accurate imputations for single and multiple missing sensors on a real concrete bridge, outperforming correlation-based baselines.	Offered a robust alternative to model-based imputation when inter-sensor correlations were difficult to model explicitly.

7 Discussion and Future Implications

This review indicates a steady shift from isolated algorithm trials toward integrated monitoring pipelines that can cope with variable environments, gaps in data, and limited labels. Three families shape current use, namely clustering, novelty detection, and representation learning. Clustering remains common because it groups operating states while exposing departures from routine behavior. Novelty detection suits long records that mainly capture undamaged conditions. Representation learning with autoencoders and related encoders supplies compact features and reconstruction measures that are less sensitive to seasonal drift. A clear theme across studies is the need to manage environmental and operational variability.

Kernel mappings, metric learning, and healthy subspace or hypersphere models appear frequently, often in combination with simple thresholding. Results from bridges and dams show that careful normalization before decision making can stabilize alarms across seasons, and several papers report that distance measures tuned to local conditions match or exceed deeper models in stability. Another consistent pattern is the use of transfer across sites. Domain adaptation is now routine in drive-by monitoring and in large civil assets, such as high arch dams, where conditions change after major events. These methods cut down on site specific tuning and make population based assessments possible. Related work uses shared latent spaces to compare nominally similar structures, which suits regional programs and fleets. Generative modeling and data cleaning have moved closer to the core of SHM pipelines. Imputation networks fill gaps that arise in long campaigns, while convolutional cleaning and outlier removal improve the reliability of later stages. Sequential encoders add support for damage localization under dynamic excitation. These additions matter in records with outages and noise, which are common in field settings.

Streaming operation is another focus. Online novelty indices, moving windows, and incremental encoders have been validated on rail bridges and laboratory structures. Edge and embedded implementations suggest that real time processing is feasible within power and bandwidth limits, which supports continuous monitoring without large data transfers. This trend links algorithm design with deployment constraints. Evaluation practice is improving. The reviewed literature still spans highly heterogeneous datasets, sensing layouts, damage definitions, and reporting conventions, which makes direct comparison of numerical performance across papers inherently uncertain even when the same model family is used. Differences in sampling rates, monitoring duration, environmental range, and the availability of true "ground-truth" damage states can shift reported scores substantially, while metrics such as accuracy, F1, ROC, and precision–recall may not be directly comparable when anomaly prevalence and thresholding rules differ. This heterogeneity reinforces the value of shared benchmarks and standardized evaluation protocols, including multi-season tests, open splits, and consistent reporting of false-alarm behavior under environmental drift, so that future studies can provide clearer evidence of generalization and operational reliability.

Receiver operating characteristic curves and precision–recall analysis appear often, which helps tune thresholds under class imbalance and changing environments. Studies that use public benchmarks, such as the Z24 bridge, allow direct comparisons between one class models, clustering, and autoencoder based methods. Reports continue to advise caution, since metrics can overstate performance if normalization and drift are not tested across seasons. Interpretability and decision clarity remain priorities for field use. Many authors favor compact features with simple rules, provided that preprocessing removes the main drivers of variability. Where deeper models are adopted, probabilistic layers and uncertainty estimates help operators judge alarm strength. The overall picture points to SHM systems that combine clear features, site adaptation, and streaming readiness, so that alarms remain reliable when sensors age, networks change, and operating patterns shift.

8 Conclusion

This study aims to assemble a systematic and bibliometric review of recent unsupervised learning methods in structural health monitoring, addressing a gap left by prior reviews that treated single sensors or narrow algorithm classes. It maps how clustering, novelty detection, and representation learning have been applied across structures and sensing modes, and how researchers handle environmental drift, missing data, and site transfer. The review also compiles evaluation choices and adoption patterns across field and laboratory studies.

Unsupervised learning in SHM clusters into three main uses, namely grouping of operating states, boundary-based alarms for healthy behavior, and compact representations through autoencoders and related encoders. Environmental and operational variation is managed most effectively when normalization and distance learning are placed before decisions, with healthy subspace and hypersphere models providing clear boundaries. Transfer across sites has matured, with domain adaptation supporting drive-by settings and large civil assets, which reduces tuning costs and enables fleet level assessment. Generative imputation and data cleaning are now core steps in long term records, since outages and noise would otherwise bias features and thresholds. Streaming readiness is improving through online indices, incremental encoders, and edge implementations, while evaluation practice increasingly relies on receiver operating characteristic and precision-recall analysis.

Practical deployment remains tightly linked to sensor reliability, data continuity, and operational scalability. Long-term monitoring campaigns often face sensor aging, intermittent dropouts, calibration drift, and changing network configurations, and these issues can mimic damage signatures if preprocessing and thresholds are not robust to such non-structural disturbances. Dense networks also raise computational and bandwidth constraints, which makes the reliability-complexity trade-off decisive when selecting models for field use. Edge and embedded implementations, together with compact feature representations, are therefore important not only for latency reduction but also for reducing dependence on continuous data transfer and centralized storage. These considerations reinforce that reliable SHM decisions depend on end-to-end feasibility, including the stability of sensing hardware, the resilience of the pipeline to missing data and environmental drift, and the interpretability of alarm logic for operators.

Finally, future work should prioritize multi season field trials with open data and code, shared protocols for normalization and domain shift tests, and side by side comparisons that include simple baselines. Further study on uncertainty reporting and alarm calibration will support decision making, and hardware aware designs will help connect research outcomes with continuous operation in bridges, dams, offshore assets, and similar systems.

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