



Research Article

From Data to Decisions: Closing the Communication Gap in Structural Health Monitoring of Dams

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Abstract

Advances in data science have enabled the large-scale acquisition of structural information in large dams through modern monitoring systems, fostering the development of predictive models, analytical platforms, and advanced visualization tools that provide increasingly detailed diagnostics of structural behavior. Nevertheless, despite this high level of technical sophistication, a critical limitation persists: the difficulty of translating complex analytical outputs—such as time series, dashboards, and multivariate indicators—into information that is clear, relevant, and actionable for operational and strategic decision-making. This paper contends that the primary constraint on the effectiveness of data-driven initiatives in Structural Health Monitoring is not technical but human, arising from a persistent communication gap between data analysts and structural safety managers that hinders the transformation of analytical results into consistent and timely decisions. Consequently, the interpretation of monitoring outputs often remains subjective, weakly standardized, and highly dependent on individual expertise, potentially undermining the reliability of operational responses. Drawing on recent studies and practical evidence from dam monitoring, this work analyzes the underlying causes and manifestations of this gap, evaluates its implications for structural safety, and proposes a set of mitigation strategies, including the standardization of technical language, the development of interdisciplinary skill profiles, the redesign of decision-oriented visualizations, and the implementation of protocols that explicitly connect analytical outcomes with defined operational actions.

Keywords

Structural Health Monitoring, Large Dams, Decision-Oriented Monitoring, Data-to-Decision Gap, Human Factors

1. Introduction

Technological advances in the field of Structural Health Monitoring (SHM) have significantly transformed the way large dams are observed and evaluated. Since its earliest formulations, SHM has been conceived not merely as instrumentation and analysis, but as an integrated process encompassing data acquisition, diagnosis, and decision-oriented inference [10]. Structures that were traditionally monitored through pe-

riodic inspections and discrete measurements can now be observed continuously, systematically, and across multiple dimensions [15]. The deployment of diverse sensor networks, together with the development of digital platforms for data visualization, automated analysis, and predictive modeling, has enabled the management of large volumes of structural information in near real time.

This enhanced observational capacity, supported by large-

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scale data processing algorithms and advanced analytical tools [8, 13], offers substantial opportunities to improve structural diagnostics, preventive maintenance strategies, and response mechanisms during critical events [6]. In principle, these technological capabilities should lead to more informed, timely, and reliable decision-making processes in dam safety management.

However, this digital transformation has not been accompanied by an equivalent evolution in the mechanisms used to interpret, communicate, and operationalize the knowledge generated by these systems. Data—regardless of their sophistication—have limited practical value if they cannot effectively support timely and well-founded decisions. In many monitoring programs, the growing volume of technical information does not necessarily translate into meaningful improvements in operational practice.

Consequently, the core obstacle often lies not in the available technology itself, but in the gap between those who produce the analytical outputs (data analysts, modelers, and monitoring specialists) and those responsible for acting upon them (structural engineers, dam operators, consultants, and regulatory authorities). This communication gap can hinder the transformation of analytical insights into clear operational guidance.

Within this context, the communication gap between data generation and decision-making emerges as one of the most significant challenges for the effective implementation of Structural Health Monitoring systems in critical infrastructure. The objective of this paper is to analyze the nature of this gap, examine its practical manifestations in dam monitoring practice, and propose strategies aimed at improving the translation of analytical information into decision-oriented knowledge.

2. Underlying Causes of the Human-technical Gap in Structural Data Interpretation

2.1. Complexity and Lack of Standardization in Results

At present, no universally standardized framework exists in dam Structural Health Monitoring (SHM) for presenting and interpreting analytical results. Consequently, different technical teams may interpret the same graphs, indicators, or datasets in different ways.

A central cause of this problem lies in the intrinsic complexity of modern analytical outputs. Techniques such as machine learning algorithms [5], multivariate statistical models, and finite element simulations often produce sophisticated indicators—time- and frequency-domain patterns, damage indices, or trend analyses—that do not always have an immediate engineering interpretation [10]. This challenge has been specifically documented in data-driven models for dams, where

strong predictive performance does not, in itself, ensure interpretability or direct operational utility [7].

This difficulty is compounded by the absence of a shared technical language to communicate such findings. Different specialists may classify or describe the same phenomenon using different criteria, generating ambiguity in the diagnostic process. For example, the categorization of structural conditions or anomalous behavior may vary according to the analyst's methodological framework.

A recent study proposes that data should be treated as a “language” with its own syntax and semantics [12]. From this perspective, the absence of shared grammars and standardized protocols for data collection and interpretation leads to inconsistencies in analysis.

2.2. Subjective Decisions and Cognitive Biases

Closely related to the previous issue, the human factor introduces variability into the interpretation of monitoring data. Analytical decisions—including variable selection, preprocessing methods, anomaly thresholds, and model calibration—are frequently influenced by professional judgment rather than strictly standardized procedures [9].

As a result, two analysts working with the same dataset may reach different conclusions if they do not share common interpretive criteria. Similar variability has been documented even in traditional visual inspections, where safety ratings assigned to the same facility may differ among engineers due to differences in training and experience.

Human cognitive limitations further contribute to this variability [1]. No analyst or model operates with complete information, and every interpretive framework involves simplifications. Consequently, relevant signals may be overlooked or misinterpreted. For instance, a statistically significant increase in seepage may be dismissed as random noise based on prior experience, while normal seasonal variations may be incorrectly interpreted as structural deterioration.

Such situations illustrate that the communication gap is not only a matter of transmitting information but also of how human judgment shapes the meaning attributed to analytical results.

2.3. Deficient Interdisciplinary Communication

Data science initiatives in dam SHM typically involve multiple professional domains, including data scientists, geotechnical and structural engineers, field technicians, consultants, and regulatory authorities. In such environments, effective communication is essential for translating analytical findings into operational decisions.

However, data analysts often produce results expressed in statistical or algorithmic terms that are difficult for engineering teams to relate to practical actions, such as modifying inspection schedules or adjusting monitoring protocols. Con-

versely, engineers may not always clearly communicate operational needs or safety priorities, leading to analyses that fail to address the most relevant questions.

This disconnect weakens the translation of data into actionable knowledge. In complex SHM systems, poorly coordinated human interaction has been shown to introduce redundancies and interpretive inconsistencies that can affect diagnostic reliability [14].

In dam safety practice, the problem is often exacerbated by fragmented information flows. Instrumentation records, inspection reports, and analytical models are frequently managed in separate systems that do not communicate effectively. As noted by dam operators, monitoring information often remains distributed across spreadsheets, reports, and independent databases, hindering an integrated understanding of structural behavior [3].

When information remains fragmented, complex analytical results become detached from the narrative required for informed safety decisions.

2.4. Data Overload and Visualization Limitations

Paradoxically, the rapid growth of monitoring technologies has introduced a new challenge: the risk of data overload. Modern acquisition systems—including telemetry networks, drones, satellite observations, and automated dataloggers—generate information at volumes that can exceed the analytical capacity of engineering teams [11].

Without effective tools for filtering, summarizing, and visualizing data, the abundance of information may hinder rather than support decision-making. Many organizations still rely on spreadsheets or fragmented workflows to manage instrumentation datasets, making it difficult to identify complex patterns or emerging anomalies in real time.

Industry reports highlight that one of the main challenges faced by dam owners is not only storing monitoring data but extracting clear insights from it. Static charts or extensive data tables often fail to convey the operational significance of the information.

When complex datasets are not translated into clear indicators—such as alert conditions, response indices, or decision-oriented summaries—the likelihood of delayed or inadequate action increases. In this sense, ineffective visualization interfaces further deepen the communication gap between analytical outputs and operational interpretation.

3. Consequences of the Communication Gap in SHM Decision-making

The communication gap described above represents a tangible risk for both structural safety and the effectiveness of monitoring programs.

A primary consequence occurs when analytical results cannot be translated into operational decisions. Monitoring systems implemented at considerable cost may generate alerts that are poorly understood or misinterpreted, resulting in either false negatives—overlooking early signs of deterioration—or false positives that trigger unnecessary alarms. Both situations undermine effective risk management.

Research has shown that delayed responses to vulnerable components, incorrect prioritization of maintenance tasks, and poor communication among stakeholders can contribute to cascading structural failures [2]. In dam engineering, this implies that variations in critical monitoring parameters may fail to prompt timely corrective measures if their significance is not correctly interpreted.

Another consequence is the inefficient use of monitoring technologies. When monitoring programs do not produce clearly actionable insights, their value may be questioned by operators or regulatory authorities. In some documented cases, advanced instrumentation systems have been partially or entirely discontinued after only a few years of operation because the information generated was not effectively integrated into decision-making processes.

Such situations represent not only a loss of financial investment but also a regression toward less sensitive monitoring approaches. The communication gap therefore directly influences the perceived credibility of data-driven monitoring solutions.

No amount of information generated by the monitoring system can compensate for the effects of erroneous human decisions or the lack of timely action.

At an organizational level, repeated difficulties in interpreting analytical outputs may foster skepticism toward advanced analytical techniques. Over time, this skepticism can create resistance to innovation, limiting the adoption of new monitoring methodologies.

In extreme situations, the disconnect between analytical information and operational action may indirectly contribute to safety incidents. Studies on human factors consistently show that structural failures typically result from chains of technical and organizational deficiencies rather than from a single cause.

Ultimately, monitoring data only enhance safety when they are correctly interpreted and translated into timely action. The risks associated with the communication gap can therefore be grouped into three interconnected dimensions: safety risks, operational inefficiencies, and declining trust in monitoring systems.

4. Strategies to Close the Communication Gap

Bridging the human–technical gap in SHM requires strategies that address both technical and organizational dimensions of monitoring practice.

A fundamental step involves improving the standardization

and clarity of how monitoring results are communicated. Recent initiatives have emphasized the importance of developing a “common grammar” for structural monitoring data. This includes standardized naming conventions for variables, unified metrics, and consistent definitions of structural states or anomalous behavior [10]. These practices align with recommendations from recent reviews, which emphasize the need for standardized monitoring indices and shared interpretation criteria to ensure consistency in the assessment of structural behavior.

For example, the nomenclature of piezometric sensors may follow standardized conventions based on sensor type, location, measurement method, and units. Similarly, predefined reference thresholds can facilitate consistent interpretation of parameters such as crest displacement or seepage indicators.

Equally important is ensuring transparency in the analytical process. Documenting preprocessing procedures, model selection, and analytical assumptions enhances traceability and allows other specialists to understand and evaluate the reliability of the results.

Strengthening interdisciplinary collaboration also plays a crucial role. Engineers involved in dam monitoring should develop basic competencies in data science concepts, while data analysts should acquire familiarity with dam engineering principles and operational constraints. Collaborative environments—such as cross-functional teams or joint diagnostic reviews—help ensure that analytical findings are interpreted within the physical and operational context of the structure.

Another key dimension involves improving visualization and data management tools. Advances in digital platforms now allow complex datasets to be integrated and presented in intuitive formats. For instance, digital twin platforms can combine three-dimensional models with real-time monitoring data, enabling engineers to visualize structural responses directly within the spatial representation of the dam.

Modern dashboards can also integrate multiple sources of information—including instrumentation data, satellite observations, and environmental variables—within a single decision-oriented interface. Centralized monitoring portals facilitate collaboration among teams responsible for operation, maintenance, and structural assessment.

Interactive visualizations that combine instrumentation records, analytical models, inspection results, and environmental data improve the detection of trends, anomalies, and correlations among variables. In this sense, visualization tools can be understood as extensions of human cognition, enabling experts to interpret large volumes of information more effectively.

Finally, organizational practices must support the effective use of monitoring information. Establishing predefined response protocols linked to monitoring indicators helps ensure that analytical results trigger appropriate operational actions. The Trigger Action Response Plan (TARP) methodology exemplifies this approach by explicitly linking monitoring parameters to alert levels and predefined operational actions [4].

Periodic review exercises can also strengthen institutional learning by allowing teams to reassess past decisions using historical data.

Through these combined measures—standardization, interdisciplinary collaboration, improved visualization, and organizational learning—the gap between analytical outputs and operational decision-making can be progressively reduced.

5. Conclusion

In the field of Structural Health Monitoring of dams, recent technological developments have made it possible to overcome many of the traditional limitations associated with data acquisition, storage, and analysis. Advanced sensor networks, analytical platforms, and digital tools now allow engineers to observe structural behavior with an unprecedented level of detail. However, despite these technical advances, the final stage of the monitoring process—the translation of analytical outputs into operational decisions—remains strongly dependent on human interpretation.

This paper has examined how several interacting factors contribute to a persistent communication gap in SHM practice. The lack of standardized frameworks for presenting and interpreting results, the intrinsic complexity of modern analytical outputs, the influence of subjective judgments in data analysis, limitations in interdisciplinary communication, and constraints in current visualization approaches collectively hinder the effective transformation of data into actionable knowledge.

Addressing this challenge requires more than purely technical improvements. Human-centered strategies must play a central role in the evolution of SHM systems. These include the development of shared frameworks for the interpretation and communication of monitoring results, the strengthening of interdisciplinary competencies among engineers and data analysts, and the adoption of visualization platforms that present complex information in formats that are intuitive and operationally meaningful.

Equally important is the establishment of organizational practices that link monitoring information with clearly defined response procedures. When monitoring signals are directly associated with predefined operational actions, the transition from analysis to decision-making becomes more efficient and reliable.

Ultimately, the success of SHM initiatives in dam engineering should not be evaluated solely by the sophistication of analytical tools or the quantity of data generated, but by the extent to which monitoring information effectively supports safer and more informed operational decisions. By narrowing the gap between analytical insight and practical action, the large volumes of data produced by modern monitoring systems can be transformed into meaningful knowledge that contributes to the long-term safety and resilience of dam infrastructure.

Abbreviations

SHM Structural Health Monitoring
TARP Trigger Action Response Plan

Author Contributions

Fabian Restelli: Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing

Conflicts of Interest

The author declares no conflicts of interest.

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