

Data-Driven Interpretation of Structural Seismic Response for Interdisciplinary Seismology Applications

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COST Action CA24101 – FuSe | Working Groups: WG1 · WG3 · WG4 · WG5



Introduction & Motivation

Background

Seismic events generate complex interactions between ground conditions, local site effects, and structural behaviour. While seismology focuses on wave propagation and geophysical processes, earthquake engineering addresses structural response and performance.

A critical interdisciplinary gap limits our ability to extract full physical insights from seismic observations at and around engineered structures.

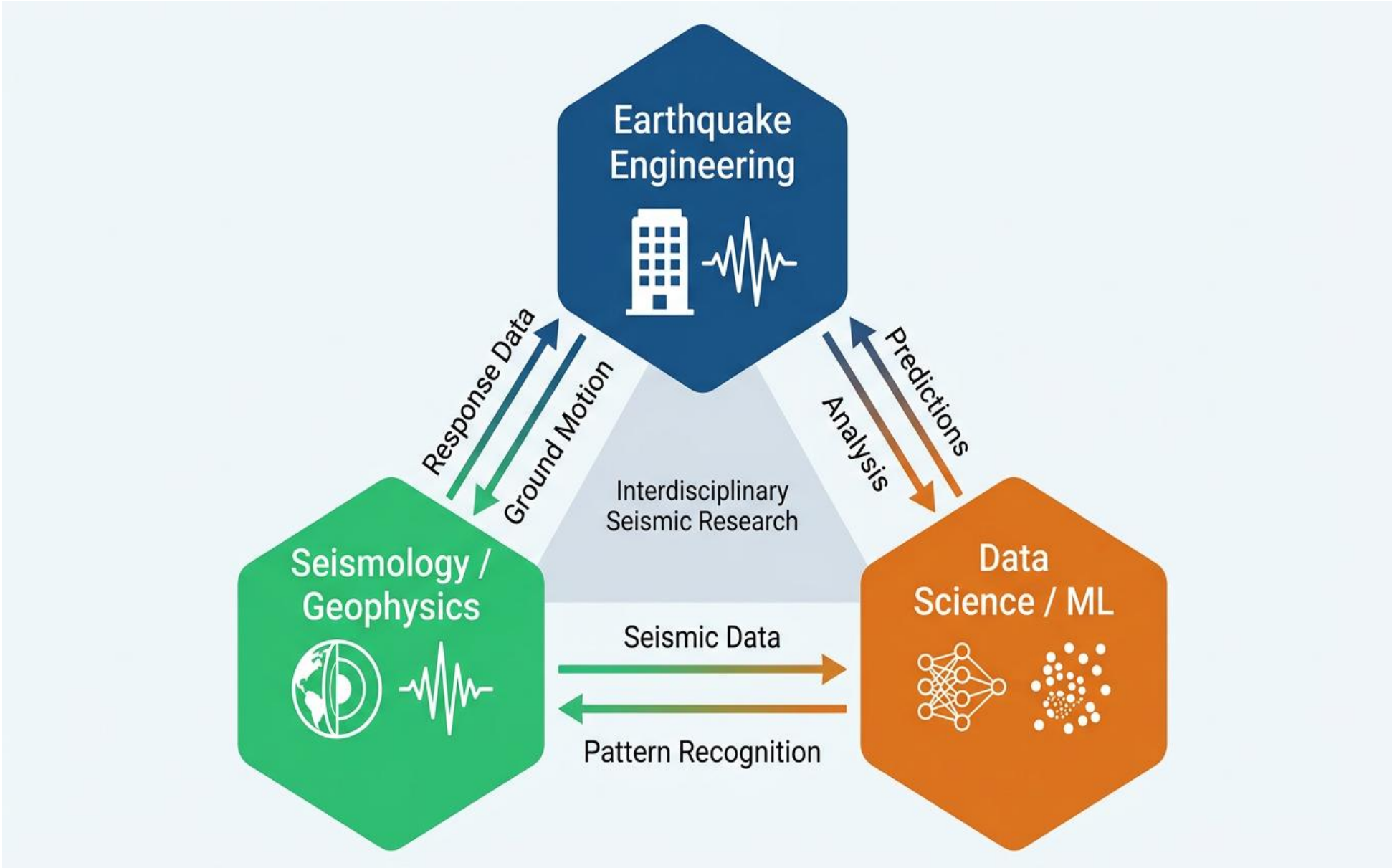
Research Opportunity

Data-driven and ML/AI methods offer powerful tools to bridge this gap connecting structural monitoring data, site characterization, and seismological observations within a unified framework.

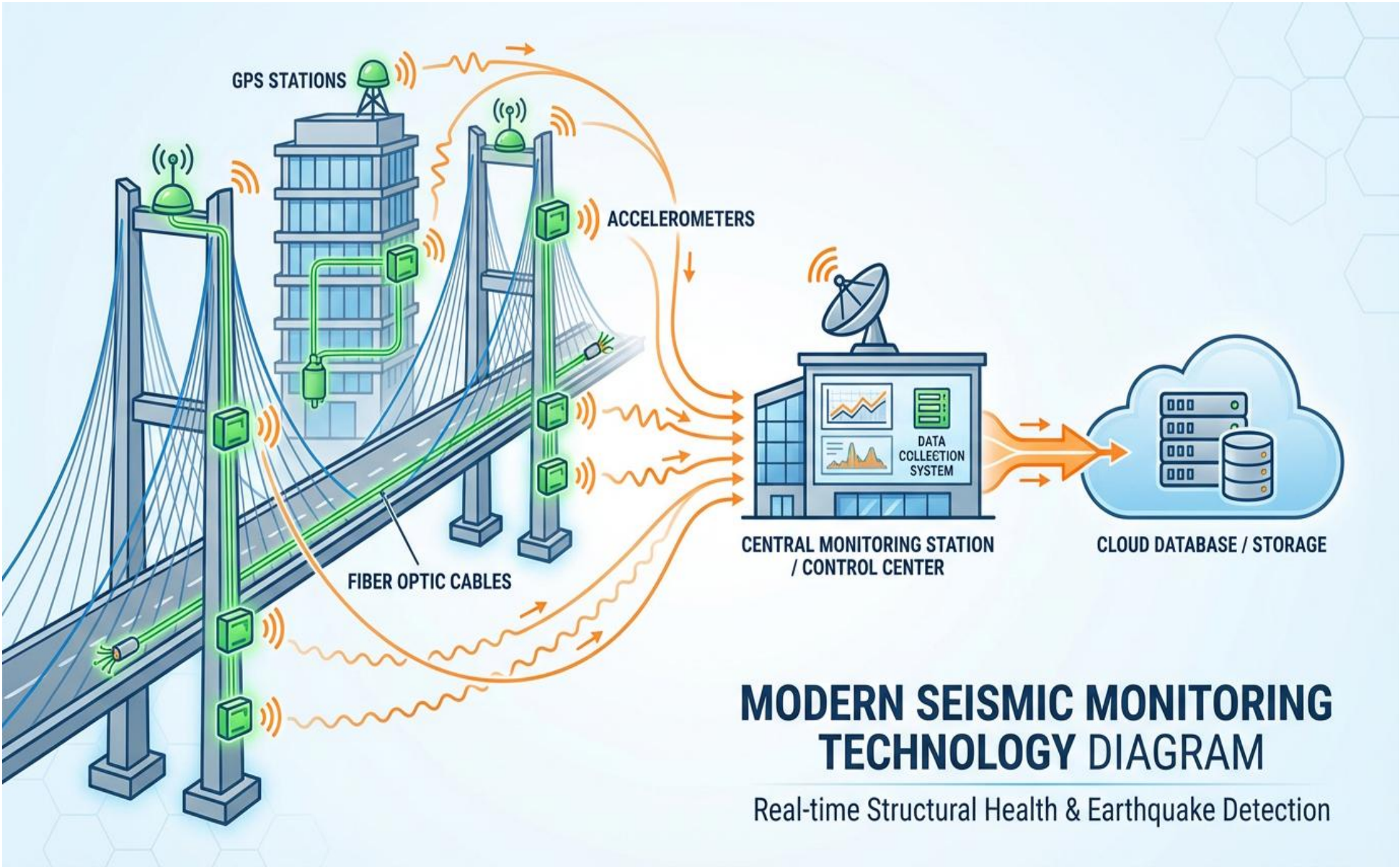
Research Aims

1. Develop a conceptual framework linking site effects, ground-motion parameters, and structural seismic response
2. Identify how ML/AI can classify response behaviour and explore seismic input–structure relationships
3. Show how engineering observations complement seismological and geophysical data for fundamental physics investigation
4. Support interdisciplinary collaboration within COST Action CA24101 – FuSe

Interdisciplinary Research Framework



Structural Monitoring Concept



Key Methodological Components

1. Site Effects & Ground Motion

- Ground-motion parameters: PGA, PGV, spectral accelerations $S_a(T)$
- Local site amplification and soil-structure interaction characterisation
- Shear-wave velocity profiles (VS30) and site classification
- Strong-motion databases: KiK-net, COSMOS, European SM networks

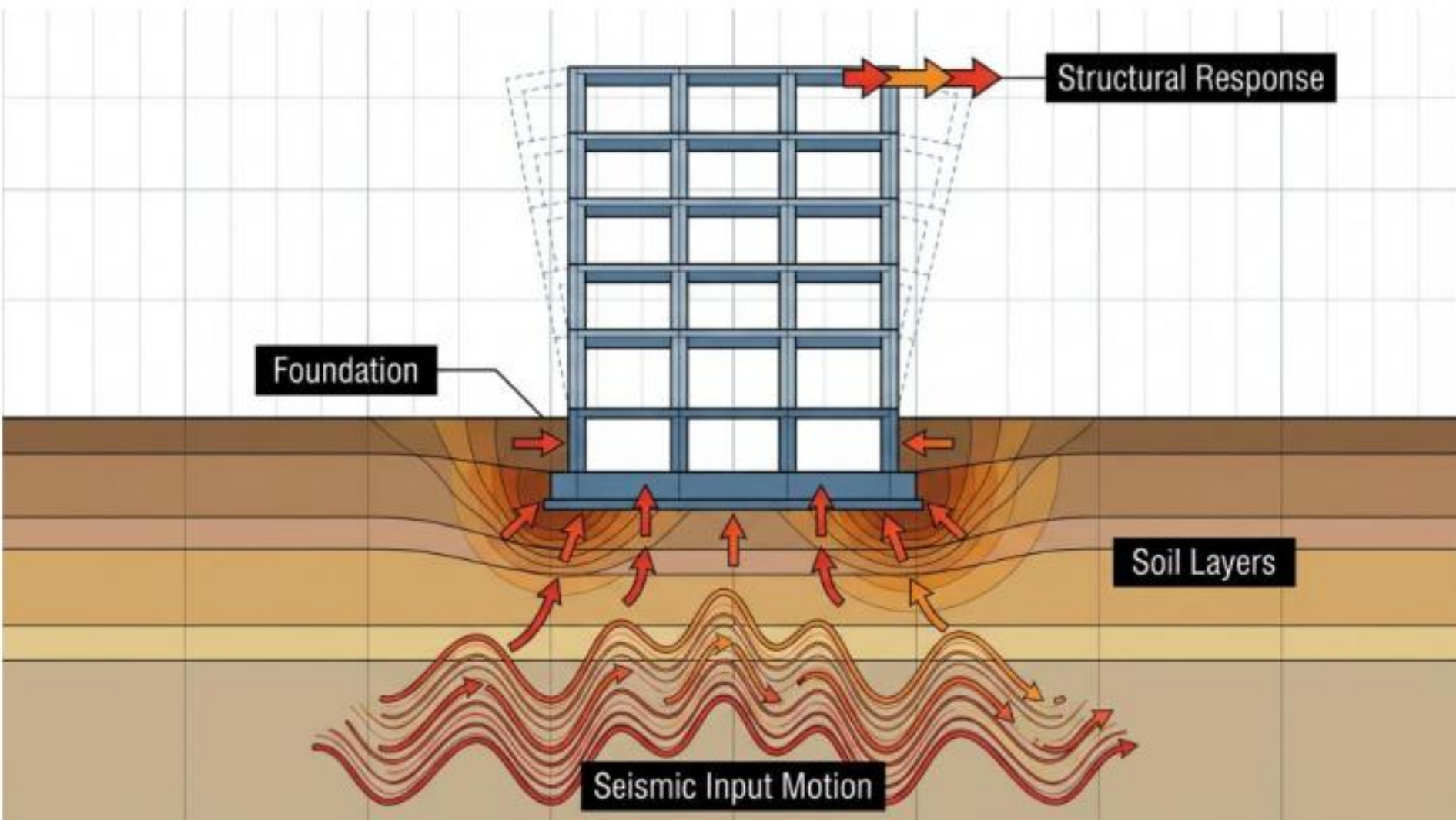
2. Structural Response Indicators

- Peak roof drift ratio (PRDR) and inter-storey drift (ISD)
- Floor acceleration and velocity time histories from instrumented buildings
- Structural period, damping ratio, and identified modal properties
- Real-time sensor data from bridges, buildings, and geotechnical arrays

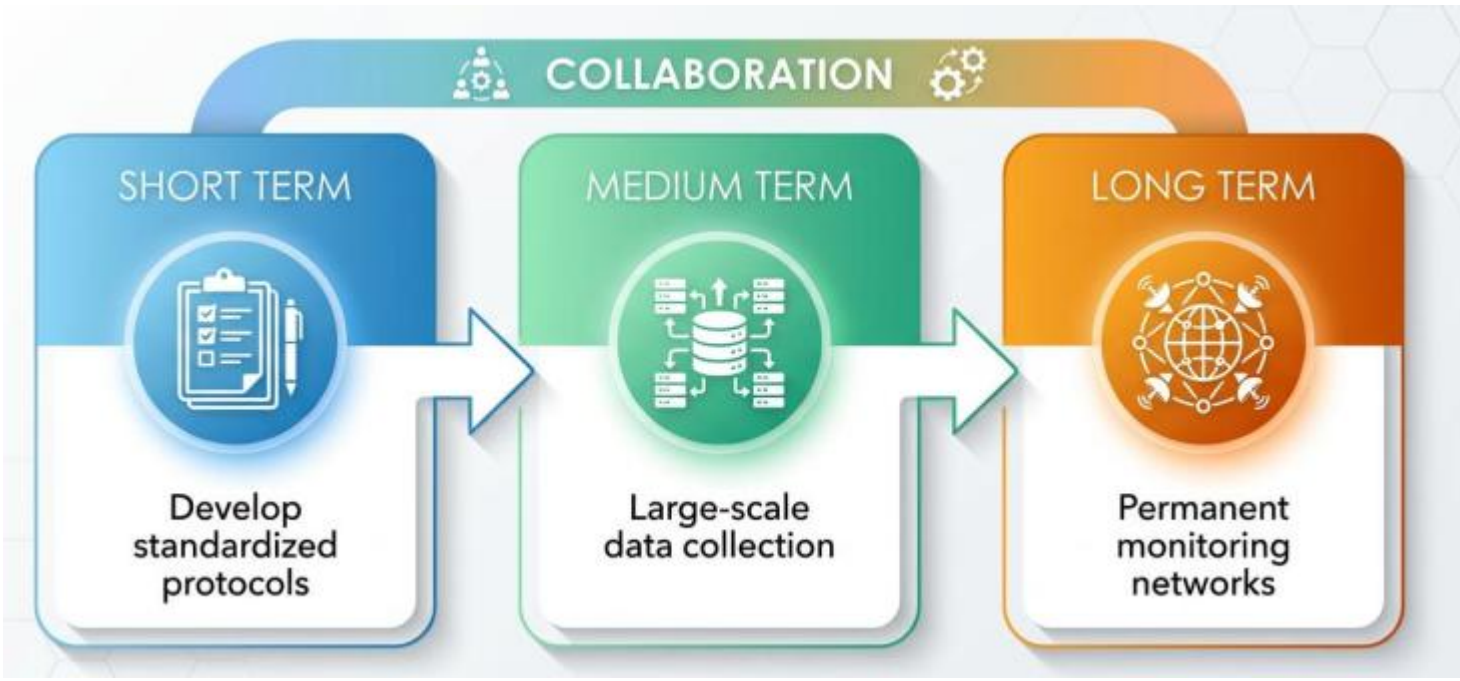
3. ML/AI Methods & Interpretation

- Physics-informed deep learning: BiLSTM, CNN, Transformer (Phy-Seisformer)
- Tree-based models (XGBoost, LightGBM) with SHAP explainability analysis
- Transfer learning between buildings and across seismic environments
- Uncertainty-aware surrogates and probabilistic response reconstruction

Soil-Structure Interaction



Research Progression Roadmap



Expected Contributions

- Conceptual interdisciplinary framework connecting seismology, geophysics, and earthquake engineering
- Methodology for integrating structural monitoring into seismological data interpretation
- Data-driven approach to identify seismic input–structure relationship patterns
- Foundation for empirical validation using real monitoring datasets

Relevance to CA24101 – FuSe

- Uses civil structures as natural physics laboratories — the core FuSe concept
- Directly supports WG1 (physics tests), WG3 (site effects), WG4 (monitoring), WG5 (data integration)
- Aligns with the Training School theme: connecting Earth sciences, engineering, and fundamental physics
- Promotes collaboration between engineers, seismologists, geophysicists, and data scientists

Future Directions

- Validation using KiK-net, COSMOS, and European strong-motion databases
- Integration with FEM and simplified lumped-mass numerical models (hybrid data-physics approach)
- Extension to multi-hazard scenarios and spatial seismic risk assessment
- Joint experimentation with FuSe Working Groups for field data access and joint publications

Selected References

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- [5] COST Action CA24101 – FuSe. (2024). Testing Fundamental Physics with Seismology. <https://www.cost.eu/actions/CA24101/>

Acknowledgements

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