ABSTRACT

The digital cultural heritage (CH) domain is rapidly evolving through the adoption of digital infrastructures, immersive media, and data-centric technologies. These advances enable new forms of cultural engagement, such as adaptive narratives, personalised itineraries, and hybrid physical–digital experiences, while also supporting conservation activities through quantitative monitoring, structural interpretation, and preventive planning. Despite this potential, CH remains a challenging application field due to heterogeneous, often sparse data, non-standardised documentation, ethical constraints, and the need to protect fragile, irreplaceable assets. Within this context, two research directions are both crucial and commonly addressed in isolation:

- enhancing cultural heritage and improving users' enjoyment;
- guaranteeing predictive maintenance and preservation of cultural assets.

This dissertation addresses these challenges by proposing a unified framework that integrates the Internet of Things (IoT), Artificial Intelligence (AI), and physically-grounded modelling to support both user-facing enhancement services and expert-facing conservation workflows. The framework is designed as a modular architecture composed of four functional layers: a Data Acquisition Layer for collecting heterogeneous data streams and digital models; a Knowledge-Base Layer for organising, storing, and reusing information across tasks; an Inference Engine Layer for executing learning- and physics-based pipelines; and an Application Layer for visualisation, interaction, and decision support. A core contribution is enabling the processing of complex 3D geometries via Blender APIs, allowing digital replicas of cultural assets to be automatically preprocessed and converted into simulation-ready representations for Scientific Machine Learning (SciML) workflows. Within the inference layer, the dissertation focuses on Physics-Informed Neural Networks (PINNs) and Reduced Order Models (ROMs) as complementary tools to handle data scarcity, enforce physical consistency, and reduce computational costs in high-dimensional differential problems.

The unified framework is assessed through two application scenarios that instantiate the same layered architecture to address both visitor-facing enhancement and expert-facing conservation requirements. On the enhancement side,

the framework integrates a context-aware recommendation pipeline coupled with conversational interaction and non-linear digital storytelling. User context is represented through a novel modality, defined as embedded context, and exploited to generate personalised cultural suggestions that reflect both user preferences and situational constraints. This workflow is evaluated through offline accuracy analysis and an in situ study conducted during real cultural visits, where user satisfaction supports its feasibility in realistic operating conditions. On the conservation side, the framework supports predictive maintenance workflows grounded in physics-based learning. The experimental validation investigates the combined use of Physics-Informed Neural Networks (PINNs) and Reduced Order Models (ROMs) for parameterised differential problems, highlighting how reduced models can accelerate simulations and enable efficient exploration of physical parameters related to degradation and structural dynamics. It also demonstrates PINNs' ability to solve direct problems by integrating observational data with governing equations under incomplete or noisy measurements. In addition, the dissertation introduces a methodological contribution to time-dependent differential problems: a time-discrete, step-by-step PINN strategy that embeds classical numerical time-integration schemes into the training objective, thereby strengthening temporal causality and improving robustness for simulations required for degradation forecasting.
The dissertation is structured to reflect the dual focus on enhancement and conservation within a shared digital ecosystem. Chapter 1 introduces the motivations and objectives. Chapter 2 presents the proposed architecture and its integration of data acquisition, AI, and physics-based methods. Chapter 3 focuses on cultural experience enhancement through embedded context and a novel AI-based context-aware recommender system. Chapter 4 develops the predictive maintenance task, showing how complex 3D assets are integrated into PINN-based simulations through automated geometry processing, together with network identification and validation. In addition, a real scenario application is described. Chapter 5 addresses limitations of continuous-in-time PINNs for evolutionary problems and introduces the step-by-step, time-discrete PINN approach, validated on a non-linear benchmark selected to emphasise temporal causality and long-horizon stability. Chapter 6 summarises the contributions and presents the conclusions.