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Research Article

Intelligent Systems in the Service of Cultural Heritage: The CARE Architecture for Concept-Aligned Ceramics Restoration

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Abstract

The restoration of archaeological ceramics is an intricate process built upon a rigorous system of concepts that bridge foundational theory and practical conservation. Building on previous efforts to systematize key terminology, this paper emphasizes the critical need for an unambiguous conceptual framework capable of guiding intervention goals and facilitating objective quality assessments. We present the CARE architecture (*Concept-Aligned Restoration with Evidence*), a research program designed for the seamless integration of advanced intelligent systems into the restoration workflow. Unlike generic AI approaches, CARE maintains the semantics of archaeology, museology, and conservation science as its core domain. We detail how contemporary intelligent tools—including graph neural networks, multimodal models, and differentiable simulation—can support documentation, automated fragment reassembly, condition diagnostics, and intervention planning while strictly adhering to the principles of reversibility and respect for cultural values. Central to this proposal is the CERAMON knowledge graph, a concept-oriented framework fully aligned with international standards such as CIDOC CRM. Particular emphasis is placed on risk-aware decision-making models and generative reconstructions of missing elements operating under mathematically grounded uncertainty. We introduce a set of specialized metrics—indices for semantic authenticity (S), irreversibility risk (Q), and intervention footprint (I)—designed to translate ethical principles into measurable data. This work addresses a multidisciplinary audience, seeking to align the progress of intelligent systems with human expertise, ethical governance, and the enhancement of public trust in the digital preservation of cultural heritage.

Keywords

Ceramics Restoration, Archaeological Heritage, Care Architecture, Ceramon Ontology, Machine Learning, Graph Neural Networks (GNN), Digital Documentation

1. Introduction

Restoration is far more than a mere technical exercise; it is an inherently conceptual and evaluative process. Its methodology dictates that objectives and quality criteria be rigorously defined before any physical intervention begins [1]. Prior research has already established the foundational framework for the restoration of archaeological ceramics, identifying key categories such

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as attribute, type, variant, property, quality, function, condition, intervention goal, and outcome assessment [2]. However, the central challenge remains the "operationalization" of these theoretical categories. Any ambiguity in translating theory into practice risks irreversible errors and the potential loss of an artifact's cultural and historical value.

Simultaneously, advancements in machine perception and statistical learning have reached a point where they can recognize complex visual patterns, analyze 3D geometry, extract material characteristics, and reason through structured knowledge bases. These breakthroughs pave the way for a new generation of tools designed to augment the expert judgment of restorers and archaeologists. Such systems enhance documentation, ensure reproducibility, and mitigate the risk of inappropriate interventions. This paper bridges the conceptual apparatus of restoration theory with intelligent systems capable of making these notions operational. We propose a human-centered, auditable architecture—one that is strictly governed by restoration ethics and aligned with the overarching goals of archaeology and museology.

2. Recent Advances in Intelligent Systems Applicable to Restoration

Several technical milestones have emerged with direct relevance to the restoration of ceramics:

1) Multimodal Integration and Documentation. Large multimodal models now bridge the gap between imagery, text, and 3D representations [3]. They can synthesize field notes, generate descriptions, and link visual attributes to scholarly literature—capabilities that significantly streamline documentation and typological analysis.
2) Self-Supervised and Contrastive Learning. Applied to images and 3D scans, these methods improve recognition accuracy in scenarios where labeled data is scarce—a pervasive challenge in museum collections [4]. By leveraging unlabeled datasets, they effectively overcome the "small data" bottleneck.
3) Graph Neural Networks (GNNs) for Fragment Reassembly. GNNs enable automated reassembly by modeling the geometric and decorative compatibility of fragments as graph structures [5]. These models can rank potential joins and provide an explicit estimation of uncertainty for each connection.
4) Differentiable Simulation and Scientific Machine Learning (SciML). By unifying physical laws with data-driven approaches, SciML tools can predict complex phenomena in porous ceramics, such as salt migration and moisture transport [6, 7]. This allows for the simulation of treatment outcomes under varying environmental conditions.
5) Knowledge Graphs and Ontologies. These frameworks facilitate the seamless integration of disparate data sources, ranging from excavation records to laboratory reports Alignment with CIDOC CRM and related standards ensures semantic interoperability and the long-term preservation of knowledge [8, 9].
6) Probabilistic Methods and Conformal Prediction. These techniques allow for the rigorous quantification of uncertainty in model outputs [10]. Such precision is critical for risk-informed decision-making in restoration, where the consequences of intervention are often high.

Rather than replacing curatorial intuition, these capabilities enhance the consistency and transparency of both routine and complex decisions, provided they are closely integrated with human expertise and the ethical standards of restoration.

3. Impact on Restoration Practice: A Concept-Aligned Architecture

We propose an architecture entitled CARE (*Concept-Aligned Restoration with Evidence*). CARE is designed to interlink domain knowledge, computational models, and practical interventions within the conceptual framework of restoration and conservation science.

3.1. Knowledge and Semantics: From Terminology to Computation

The core of the system is CERAMON, a lightweight ontology and knowledge graph for ceramic restoration, aligned with CIDOC CRM where applicable. CERAMON encodes the following categories:

1) Attributes: Measurable data such as rim diameter, wall thickness, paste composition, and pigment spectra.
2) Types and Variants: Typological classes situated within specific temporal and cultural contexts.
3) Properties and Qualities: Structural integrity, porosity, surface adhesion, and the legibility of decoration.
4) Functions: Both original utility and contemporary museum functions (exhibition, education, or scientific reference).
5) Conditions: Manifestations of decay, such as efflorescence, fractures, abrasion, and bio-contamination.
6) Interventions: Adhesives, consolidants, desalination protocols, filling materials, and stabilization methods.
7) Goals and Constraints: Authenticity, reversibility, minimal intervention, and documentation requirements.

By explicitly representing these concepts, models can reason within the same categorical framework as specialists, thereby enhancing interpretability and auditability [11].

3.2. Documentation and Diagnostics

Intelligent support significantly upgrades baseline documentation processes:

1) Multimodal Acquisition: Integrating high-resolution

photography, RTI, micro-CT, Raman/XRF spectra, and 3D scans. Models can segment surfaces, annotate motifs, and detect anomalies.
2) Provenance Linking: Automated entity resolution between field journals, museum registers, and scholarly publications via the knowledge graph [12], subject to human verification.
3) Condition Inference: Pattern recognition to identify salt deposits, crack networks, and pigment loss, accompanied by calibrated uncertainty intervals.

3.3. Reassembly and Reconstruction

The reassembly of fragments is a classic challenge in ceramic restoration, addressed here through a combination of geometric and graph-based methods [13, 14]. Modern models introduce:

1) Join Probability Ranking: Evaluating connections based on geometric compatibility, curvature, decorative continuity, and edge wear.
2) Uncertainty-Aware Proposals: Displaying multiple potential joins with associated confidence measures, rather than imposing a single, definitive solution.
3) Generative Reconstruction: Modeling missing sections under strict typological and physical plausibility constraints. The system can present several reconstruction variants based on different hypotheses, allowing for the assessment of divergent interpretations.

3.4. Intervention Planning as Risk-Informed Decision-Making

A restoration plan can be formalized as a constrained optimization problem under uncertainty. Let an intervention sequence be $a_{1:T}$ from a set of actions A encompassing cleaning methods, adhesives, fillers, and environmental parameters. The objective function is defined as:

$\max_{(a_{1:T} \in A)} \alpha \cdot F\_semantic - \beta \cdot R\_irreversible - \gamma \cdot C\_intrusiveness - \delta \cdot U\_model$

subject to ethical constraints and material safety limits, where:

1) F_semantic assesses the alignment of the plan with stated goals in CERAMON, such as decorative legibility or display stability.
2) R_irreversible represents the probability of irreversible changes, derived from treatment history and material science simulations.
3) C_intrusiveness measures the impact of added materials, surface alterations, and the visual dominance of fills.
4) U_model is the aggregated model uncertainty across all predictions.

This representation allows the restorer to adjust weights (α, β, γ, δ) based on context, enabling an interactive exploration of trade-offs. The final decision remains the prerogative of the human expert.

3.5. Quality Assessment and Auditing

A rigorous evaluation closes the loop between theory and practice through a set of interpretable metrics:

1) Semantic Authenticity Index (S): The degree to which the restored state fulfills the objectives declared in CERAMON.
2) Irreversibility Risk Index (Q): The probability that interventions cannot be undone without significant loss of original substance.
3) Intervention Footprint (I): The ratio of added materials and altered surface area, normalized by the object's dimensions.
4) Uncertainty Transparency (T): The proportion of model outputs provided with calibrated intervals and their utilization in the decision-making process.
5) Documentation Completeness (D): A measure of data modality coverage and adherence to reporting standards.

These indicators are calculated automatically where feasible and subsequently validated by experts. They are integrated into the object record to facilitate future audits and long-term preservation monitoring.

4. Interdisciplinary Potential

The CARE architecture integrates several distinct fields of study:

1) Archaeology: Provides the typologies, contexts, and cultural interpretations that the knowledge graph encodes for computational use.
2) Restoration and Material Science: Supply treatment protocols and physical models, which Scientific ML refines based on empirical data.
3) Computer Vision and Graph Learning: Support complex 3D reassembly and reconstruction, while uncertainty quantification ensures risk-informed decision-making.
4) Museology: Contributes value frameworks, display constraints, and audience engagement goals. These parameters shape the F_semantic metric and reporting standards.
5) Ethics and Policy: Define boundaries for intervention, access control, and community consultation protocols.

A museum-based pilot project focusing on a specific corpus—such as regional painted ceramics—could unite these disparate teams. A shared data model and common metrics allow each group to contribute without diluting their respective disciplinary standards.

5. Ethical, Regulatory, and Social Considerations

Working with cultural heritage demands extreme caution. Intelligent tools must adhere to the same foundational principles as traditional restoration:

1) Human-in-the-loop: Systems assist rather than decide.

Interfaces must highlight options, evidence, and uncertainty rather than prescriptive "solutions."
2) Respect for Cultural Values: All reconstructions are labeled as hypothetical. Where multiple interpretations exist, the system presents variations rather than a singular "canonical" version.
3) Reversibility and Minimal Intervention: Decision models treat risk as a central factor. Generative outputs serve to visualize possibilities before any physical action is taken.
4) Transparency and Auditing: Every step is logged. Data provenance and model versions are recorded in the knowledge graph. Digital reconstructions must carry visible markers during public exhibition.
5) Data Governance: Sensitive provenance details and personal data in excavation records are rigorously protected. Access policies reflect legal and communal requirements.
6) Environmental Sustainability: Computational planning accounts for energy consumption. Resource-heavy training is distributed across institutions and reused via centralized model hubs.

6. Application Scenarios

The following two case studies illustrate the practical implementation of the CARE approach in conservation environments.

Scenario A: Reassembly of a Hellenistic Amphora

Fragments are digitized via 3D scanning and high-resolution photography. The model generates a ranked list of potential joins, each accompanied by confidence intervals. Decorative bands and surface curvature are virtually aligned to verify morphological plausibility. Three candidate assemblies are presented with detailed ranking justifications. Once the restorer selects a preferred configuration, the system provides generative proposals for loss compensation, constrained by typological accuracy and minimal visual dominance. The system presents two variants and calculates expected reversibility indices for different filling materials. The final decision, made by the restorer, is fully documented within the digital record.

Scenario B: Mitigation of Salt Efflorescence

Non-invasive spectroscopy is employed to measure salt concentration and depth profiles. The treatment planning model simulates desalination using various solvents and cycles, utilizing physics-informed surrogates. Weighting factors in the objective function emphasize low intrusiveness and high reversibility. The system proposes a conservative protocol and estimates the probability of incomplete desalination. The restorer approves a limited trial on undecorated areas, subsequently updating the intervention plan based on the observed empirical outcomes.

7. Methods and Research Roadmap

We propose a three-year research program organized into four integrated Work Packages (WP):

1) *WP1: CERAMON Knowledge Graph.* Developing a CIDOC CRM-aligned schema for attributes, types, and interventions. This includes data migration with curated links to field notes and the implementation of logical inference tools to detect documentation gaps.
2) *WP2: Multimodal Acquisition and Reassembly.* Designing pipelines for images, 3D scans, and spectroscopy. Developing self-supervised encoders for fragment descriptors and GNN-based models for uncertainty-aware join ranking. Validation will utilize benchmarks of both synthetic and authentic fragment sets.
3) *WP3: Risk-Informed Planning and Simulation.* Creating surrogate models for moisture and salt transport, calibrated via laboratory tests. Implementation of interactive optimization with adjustable weights for ethical constraints and the integration of conformal prediction for calibrated uncertainty bounds.
4) *WP4: Evaluation and User Experience.* Collaborative interface design with restorers and curators. Validation of the S, Q, I, T, D metrics and user studies focusing on interpretability, trust, and workflow efficiency.

8. Perspectives: Towards Universal Heritage Assistants

The potential emergence of Artificial General Intelligence (AGI) suggests a future where systems can process multilingual excavation diaries, correlate them with global typological corpora, and simulate restoration outcomes under diverse conditions. However, even the most advanced systems will require "conceptual anchors" to ensure transparency and reproducibility.

The conceptual framework of restoration provides these anchors. Human intelligence will remain central to setting objectives, interpreting cultural significance, and safeguarding heritage values. Intelligent systems will alleviate the burden of routine tasks, enabling researchers to address new questions—from identifying latent patterns in regional decorative styles to predicting preservation trajectories amidst climate change. Recent advances in AI-based generative reconstruction of ceramic patterns [15] further illustrate how intelligent systems can complement human expertise in cultural heritage preservation.

Abbreviations

CARE	Concept-Aligned Restoration Environment
ICOM-CC	International Council of Museums – Committee for Conservation
GNN	Graph Neural Networks
CIDOC CRM	International Committee for Documentation – Conceptual Reference Model
GNNs	Graph Neural Networks
SciML	Scientific Machine Learning
RTI	Reflectance Transformation Imaging
micro-CT	Micro-Computed Tomography
Raman/XRF	Raman Spectroscopy / X-Ray Fluorescence

Author Contributions

Tatyana Nikolaevna Krasnova: Conceptualization, Methodology, Supervision, Writing – original draft

Conflicts of Interest

The author declares no conflicts of interest.

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Biography

Tatiana Nikolaevna Krasnova is a fellow of the Russian Research Institute for Cultural and Natural Heritage named after D. S. Likhachev (Institute of Heritage). After graduating from the Kharkov Art and Industry Institute, she worked at the Restoration Center in Kharkov and taught restoration at the Institute. She headed the Kharkov Scientific and Methodical Center for the Protection of Cultural Heritage. 30 years of work experience in the field. She is a participant of many conferences, author of more than 65 scientific articles and 1 monograph "Research, Restoration and Preservation of Museum Ceramics", awarded the Diploma "Best Monograph" for 2017 by the National Academy of Sciences of Ukraine

Research Field

Tatyana Nikolaevna Krasnova: materials and technology of ceramics manufacturing, materials in the restoration of ceramics, types and causes of fracture of ceramic materials, methods of preservation of archaeological ceramics, theory of restoration