

ARTIFICIAL INTELLIGENCE APPLICATIONS IN ARCHAEOLOGICAL RESEARCH

Dr. Aditi Sharma

Assistant Professor

Department of Archaeology and Digital Heritage Studies

School of Humanities and Social Sciences

University of Archaeological and Cultural Studies, New Delhi, India

Abstract

Artificial intelligence has emerged as an important set of methods for archaeological research because contemporary projects generate large and diverse collections of information from satellite imagery, airborne laser scanning, excavation records, photographs, field notes, museum catalogues, inscriptions, geophysical surveys, and laboratory analysis. These data sources contain patterns that are difficult to review manually at scale. Artificial intelligence can assist researchers in locating potential sites, recognizing archaeological features, classifying objects, reconstructing incomplete texts, organizing digital collections, and identifying relationships across complex cultural landscapes. Its value lies in supporting systematic investigation while preserving the interpretive judgment of archaeologists.

This review-based study examines major applications of artificial intelligence in archaeological research, with attention to machine learning, computer vision, natural language processing, spatial analysis, predictive modelling, photogrammetry, and digital heritage management. The paper considers how AI tools can be used for archaeological prospection, remote-sensing interpretation, artifact classification, epigraphic analysis, excavation documentation, conservation monitoring, and public communication. It also examines methodological concerns related to training data, false positives, bias, transparency, intellectual property, community rights, sensitive site disclosure, and the need for field validation.

The analysis indicates that AI should be understood as a research-support system rather than an autonomous substitute for archaeological reasoning. Reliable use depends on high-quality datasets, clearly defined research questions, transparent model design, uncertainty reporting, reproducible workflows, expert review, local knowledge, and ground-truth verification. When applied responsibly, AI can improve the speed, scale, consistency, and accessibility of archaeological inquiry while helping institutions document and protect cultural heritage in changing landscapes.

Keywords: Artificial intelligence; Archaeological research; Machine learning; Remote sensing; Computer vision; Cultural heritage; Site detection; Artifact classification; Digital archaeology; Heritage conservation

1. INTRODUCTION

Archaeology investigates past human life through material remains, built environments, landscapes, biological evidence, written records, and cultural memory. The discipline has always adopted new recording and analytical technologies, including photography, aerial survey, geographic information systems, radiocarbon dating, digital databases, three-dimensional modelling, and remote sensing. Artificial intelligence extends this technological development by offering computational methods that can detect regularities, classify complex information, estimate probabilities, and support decisions across large datasets. Its

growing relevance reflects both the expansion of digital archaeological evidence and the need to manage research tasks that exceed the capacity of manual review alone.

Archaeological work increasingly involves high-resolution imagery, lidar-derived terrain models, multispectral satellite data, drone surveys, geophysical measurements, digital excavation registers, artifact photographs, and online archive collections. A single survey project may produce millions of pixels, thousands of images, and many layers of spatial information. These materials are valuable but can be difficult to interpret consistently, particularly when researchers must distinguish cultural traces from natural

formations, later disturbances, vegetation patterns, modern infrastructure, or image noise. Machine learning and computer vision can help identify candidate features and make the initial screening process more efficient.

The use of AI is not limited to finding sites. Algorithms can assist with pottery and lithic classification, fragment matching, inscription restoration, language analysis, predictive modelling of settlement locations, reconstruction of damaged objects, documentation of excavation contexts, and analysis of visitor engagement with heritage collections. Natural language processing can organize historical documents and excavation reports, while computer vision can support rapid cataloguing of artifacts. In conservation settings, AI can help compare repeated images to identify surface changes, moisture patterns, cracks, vegetation growth, or unauthorized interventions at heritage places.

However, archaeological evidence is rarely complete, neutral, or uniformly distributed. It is shaped by preservation conditions, earlier research priorities, colonial collecting practices, modern land use, legal restrictions, and the availability of digital records. AI systems trained on uneven datasets may reproduce these gaps and present uncertain results with excessive confidence. For this reason, the adoption of AI requires methodological discipline. Archaeologists must define what the model is expected to do, document the training data, assess error patterns, test results in the field, and ensure that technology does not override cultural context or community perspectives. This paper examines these issues through a structured review of AI applications in archaeological research.

2. LITERATURE REVIEW

The literature on AI in archaeology describes a shift from isolated computational experiments toward integrated workflows that combine domain expertise with automated analysis. Earlier digital archaeology focused largely on database construction, geographic information systems, and visualization. Recent work has expanded toward machine learning models capable of recognizing visual patterns, grouping similar objects, identifying anomalies, and estimating the likelihood that a location or image contains archaeological

evidence. These approaches are especially valuable where the volume of available data is high and researchers need a transparent way to prioritize further investigation.

Remote-sensing research has been one of the most visible areas of development. Satellite imagery, aerial photographs, lidar, thermal data, and drone-based surveys can reveal crop marks, earthworks, building outlines, ancient roads, terracing, burial mounds, and settlement traces. Artificial intelligence supports this process by classifying land-cover patterns, segmenting images, detecting repeated shapes, and ranking locations that may require field inspection. Studies emphasize that these methods work best when automated detection is combined with archaeological interpretation, environmental knowledge, and on-the-ground validation.

Another major strand of research concerns artifact and collection analysis. Computer vision models can be trained to recognize material categories, decorative motifs, manufacturing traces, and morphological features in images of ceramics, coins, tools, sculptures, or architectural fragments. Such systems may reduce repetitive cataloguing work and help researchers compare distributed collections. Yet classification outputs depend strongly on the quality, diversity, and documentation of training images. A model that performs well on one collection may fail when image conditions, object types, or regional traditions change.

Recent scholarship also addresses text, illustration, and interpretive risks. AI-based language models and image-generation systems can create plausible but inaccurate historical content, including anachronistic reconstructions and fabricated source claims. Archaeological interpretation must therefore remain evidence-led. The literature increasingly argues for human-AI collaboration, reproducible research practices, ethical data governance, and clear separation between model-generated suggestions and verified archaeological conclusions.

2.1 FOUNDATIONS AND SCOPE OF AI IN ARCHAEOLOGY

Artificial intelligence in archaeology refers to computational methods that learn from examples, identify patterns, generate structured predictions, or support complex

information processing. The most common approaches include supervised machine learning, unsupervised clustering, deep learning, computer vision, natural language processing, spatial modelling, and rule-based systems. Each method serves a different purpose. Supervised learning uses labeled examples to classify or detect known categories, while unsupervised methods explore hidden groupings in data without predefined labels. Deep learning is particularly useful for images, lidar visualizations, and large-scale object-recognition tasks.

The scope of AI includes both research and heritage-management functions. In research, AI can assist with the identification of potential archaeological sites, recognition of artifact classes, analysis of spatial relationships, reconstruction of incomplete textual material, and synthesis of digital archives. In heritage management, it can support monitoring, risk assessment, documentation, emergency response, and prioritization of conservation activity. These applications do not eliminate the need for survey, excavation, laboratory analysis, or archival reading. Instead, they help researchers focus attention on patterns that may otherwise remain unnoticed.

A central principle is that AI outputs are probabilistic and context-dependent. A prediction should not be treated as proof that a buried site, artifact category, or historical interpretation is correct. Rather, it is a reason to examine the evidence further. Archaeological workflows must therefore include confidence scores, documentation of model limitations, validation procedures, and opportunities for expert or community review. The value of AI grows when it is embedded within a transparent research design rather than used as a black-box source of conclusions.

2.2 MAJOR APPLICATION AREAS

AI applications in archaeology can be grouped into several linked areas. Landscape-scale analysis uses remote sensing and spatial modelling to recognize possible features and select survey targets. Object-level analysis applies computer vision and statistical learning to photographs, scans, and measurements of artifacts. Documentary analysis uses natural language processing to search, transcribe,

translate, and organize historical and archaeological texts. Conservation applications use repeated images and sensor data to identify change over time. Together, these methods create a broader digital evidence environment in which different data types can be compared more systematically.

The strongest applications are those that begin with a precise archaeological question. For example, a model may be designed to identify circular mounds in a defined landscape, distinguish particular ceramic fabric groups in a catalogued collection, or locate damaged areas in a digital model of a monument. Broad claims that AI can discover the past without clear research design are not reliable. Algorithms need specific labels, relevant comparison data, and an explanation of why observed patterns matter archaeologically.

The literature also notes the importance of data stewardship. Archaeological datasets may contain sensitive geographic coordinates, ancestral knowledge, images of sacred objects, or documentation linked to living communities. Open data can improve reproducibility, but unrestricted release may increase risks of looting, commercialization, or cultural harm. Responsible AI therefore requires controlled access arrangements, metadata standards, respectful consultation, and decisions about what should not be made automatically discoverable.

3. OBJECT OF STUDY

The primary object of this study is to examine how artificial intelligence applications can support archaeological research while maintaining the evidentiary, ethical, and interpretive standards of the discipline. The paper focuses on AI-assisted processes that help researchers identify, document, classify, compare, and monitor archaeological evidence across fieldwork, archives, museum collections, and heritage landscapes.

The study considers the relationship between algorithmic outputs and archaeological validation. It examines how data quality, model selection, labeling practice, interpretability, uncertainty, and human review influence the reliability of AI-supported research. Particular attention is given to the difference between an automated prediction and an archaeological conclusion. A predicted site, object type, or textual restoration must be

evaluated through contextual evidence rather than accepted solely because a model produces a high score.

A further objective is to identify practical conditions for responsible implementation. These include interdisciplinary collaboration, standardized documentation, field verification, transparent reporting, safeguards for sensitive data, community participation, and preservation of research records. The study therefore treats AI not only as a technical innovation but also as a governance issue for archaeology and cultural heritage.

3.1 LANDSCAPE AND SITE DETECTION

- Use of satellite imagery, drone photographs, lidar, thermal data, and historical maps to identify potential archaeological features.
- Image classification and semantic segmentation for detecting mounds, walls, terraces, pathways, canals, tombs, and settlement traces.
- Predictive modelling to estimate areas where archaeological remains are more likely to occur based on terrain, soils, water, visibility, and known site patterns.
- Automated comparison of multi-temporal images to identify recent disturbance, erosion, agricultural encroachment, or damage to heritage landscapes.
- Integration of model outputs with archaeological survey, local environmental knowledge, and ground-truth verification.

3.2 ARTIFACT, TEXT, AND DIGITAL COLLECTION ANALYSIS

- Computer-vision methods for recognizing artifact categories, decorative motifs, materials, typological features, and manufacturing traces.
- Image-based cataloguing and similarity search for ceramics, coins, lithics, sculptures, architectural fragments, and museum objects.
- Natural language processing for indexing excavation reports, archival documents, field notes, inscriptions, and historical records.
- AI-assisted restoration and attribution of damaged or incomplete inscriptions, with

results reviewed by epigraphic and linguistic specialists.

- Three-dimensional analysis of scanned artifacts and structures to support documentation, comparison, reconstruction, and conservation planning.

3.3 GOVERNANCE, VALIDATION, AND ETHICAL DIMENSIONS

- Documentation of data provenance, labels, algorithms, parameters, model versions, and evaluation measures used in each research project.
- Field validation and expert review before potential sites, object identifications, or reconstructed texts are treated as verified findings.
- Assessment of bias arising from incomplete records, uneven survey history, colonial archives, limited training samples, and variable image quality.
- Protection of sensitive site coordinates, sacred knowledge, community-held data, and vulnerable heritage resources from misuse.
- Clear communication of uncertainty, false positives, false negatives, and the limits of automated interpretation.

4. RESEARCH METHODOLOGY

The present study adopts a review-based, descriptive, analytical, and comparative methodology to examine artificial intelligence applications in archaeological research. The study draws on scholarship in archaeology, remote sensing, machine learning, computer vision, digital humanities, heritage conservation, and research ethics. Secondary material is interpreted through a thematic framework that connects technical capability with archaeological purpose, evidence quality, validation practice, and cultural responsibility. The method does not attempt to measure the performance of a single AI model. Instead, it compares the main types of AI application reported in archaeological research and evaluates their contribution to discovery, documentation, classification, interpretation, preservation, and public access. The analysis also considers the conditions under which AI results may be unreliable, incomplete, or ethically sensitive.

4.1 RESEARCH DESIGN

Component	Description
Research Type	Review-based, descriptive, analytical, and comparative
Approach	AI applications, archaeological interpretation, and heritage governance analysis
Data Source	Research articles, technical guidance, heritage reports, standards, and published case studies
Analysis Method	Thematic synthesis, application mapping, and comparative assessment of strengths and limitations
Focus Area	Site detection, artifact analysis, text processing, digital documentation, conservation, and research ethics

4.2 SOURCES AND ANALYTICAL CATEGORIES

The study considers the following evidence categories for evaluation:

- Published studies on machine learning, computer vision, remote sensing, and spatial analysis in archaeological research.
- Research on digital documentation, artifact databases, epigraphy, photogrammetry, and heritage conservation technologies.
- Ethical guidance on responsible artificial intelligence, research transparency, cultural heritage protection, and data governance.
- Case studies reporting the use of AI in landscape survey, site detection, artifact classification, text restoration, and monitoring.

Each evidence source is analysed based on:

- Archaeological research question and the type of data being processed.
- AI method used, including its training, evaluation, and interpretation requirements.
- Potential contribution to efficiency, consistency, discovery, documentation, or conservation.
- Risks related to bias, uncertainty, data sensitivity, reproducibility, and cultural impact.
- Validation procedures involving archaeologists, field survey, laboratory analysis, or community knowledge.

5. DATA ANALYSIS

The reviewed evidence shows that AI is most effective when it is used to manage scale rather than to replace archaeological inquiry. Remote-sensing projects may cover large regions where manual inspection of every image tile is impractical. In these situations, computer vision can screen imagery and identify candidate areas for expert review.

This shortens the initial search process, but the final identification of a site still requires contextual interpretation, comparison with other data layers, and, where possible, field inspection. A useful workflow therefore treats model output as a ranked list of questions for archaeologists rather than a finished map of confirmed sites.

Landscape applications demonstrate the importance of data resolution and environmental context. Lidar can reveal microtopography beneath vegetation, whereas multispectral imagery may highlight crop stress or soil variation associated with buried features. Historical maps can preserve traces of landscapes that have been altered by urban growth or mechanized agriculture. AI models can combine these sources and recognize patterns across them, but their performance varies with season, terrain, vegetation, image quality, and the visibility of archaeological traces. A model trained on one environmental zone may not transfer reliably to another without new examples and recalibration.

Artifact analysis provides a second important domain. Digital photographs, structured-light scans, and three-dimensional models make it possible to compare object attributes at a scale not possible in traditional cataloguing. Algorithms can support the grouping of similar ceramics, the recognition of coin types, the identification of repeated motifs, and the detection of fragments that may belong together. The analytical benefit is strongest when the datasets include reliable object metadata and when specialist knowledge informs the categories used for training. Poorly documented collections may lead to misleading groupings because the model learns the habits of a cataloguing system rather than the material history of the objects.

Textual and inscriptional applications show both promise and limits. Machine learning can assist with character recognition, pattern matching, language classification, and suggestions for restoring damaged passages. These tools can help researchers search large corpora and compare alternative readings, particularly when inscriptions are fragmentary. Yet archaeological texts contain historical, linguistic, and material contexts that cannot be reduced to character probabilities. A plausible restoration may be wrong when it conflicts with chronology, find context, script style, or regional vocabulary. AI-assisted text work must therefore retain records of the original surface, alternative readings, and the reasoning used by specialists.

The analysis also highlights a recurring concern about model transparency. Some high-performing systems are difficult for non-specialists to interpret. In archaeology, where conclusions may affect heritage designation, conservation decisions, public narratives, and community rights, opaque outputs are problematic. Researchers should report the purpose of the model, the source and balance of the training data, the performance measures used, common error types, and the circumstances in which the model should not be trusted. Maps and catalogues should distinguish between verified information and AI-generated predictions so that later users do not treat preliminary results as established facts.

Finally, AI creates new responsibilities for data governance. Coordinates of undocumented or vulnerable sites can facilitate looting when widely released. Images and descriptions may concern sacred places or culturally restricted materials. Training data from museums and archives may reflect histories of unequal ownership or access. For these reasons, digital archaeology needs rules about consent, controlled access, attribution, benefit sharing, and consultation with relevant communities. Responsible AI is not only a matter of technical accuracy; it is also a matter of protecting cultural meaning and preventing avoidable harm.

6. DISCUSSION

The findings indicate that artificial intelligence can strengthen archaeological research when it is used within a human-centered evidence

framework. AI can make large datasets more searchable, help researchers identify patterns, and support more consistent documentation. It can also enable non-invasive approaches that reduce the need for unnecessary excavation. However, archaeological value does not come from speed alone. The discipline depends on contextual reasoning, stratigraphic relationships, material analysis, chronology, historical knowledge, and dialogue with communities. AI contributes most effectively when it directs attention to evidence that must then be interpreted through these wider practices.

One important issue is the tendency to confuse prediction with discovery. A computer-vision system may identify a feature that resembles a known type of mound or wall, but resemblance is not confirmation. Natural formations, modern earthworks, agricultural marks, and image artifacts may generate false positives. Conversely, poorly preserved or uncommon sites may not be detected at all. Models must be assessed not only by average accuracy but also by the consequences of their errors. In heritage protection, a false negative may leave a site unrecorded, while a false positive may divert limited survey resources. Error analysis should therefore be part of archaeological reporting.

A second issue concerns the role of training data. Many archaeological datasets are geographically uneven because some regions, periods, and object types have received more intensive documentation than others. Models trained on well-recorded areas may reinforce the visibility of already prominent heritage while overlooking underrepresented histories. Collaborative data creation, multilingual metadata, inclusion of local research, and careful labeling protocols can help reduce this imbalance. Yet complete neutrality is not possible; researchers must acknowledge how data histories shape the outputs of AI systems. The discussion also emphasizes methodological reproducibility. Archaeological claims supported by AI should be accompanied by sufficient documentation for another research team to understand or test the process. This includes the data source, pre-processing steps, model architecture or software, parameter choices, evaluation method, uncertainty estimates, and validation

results. Where data cannot be fully shared because of site sensitivity or community restrictions, researchers should still provide a clear account of why access is limited and how ethical safeguards were applied.

Finally, the future of AI in archaeology will depend on collaboration. Archaeologists, computer scientists, surveyors, archivists, conservators, museum professionals, legal experts, and community representatives have different but necessary forms of knowledge. Programs developed without archaeological input may classify the wrong features or ignore contextual evidence. Archaeological projects that use AI without technical expertise may misinterpret model outputs. A collaborative approach can create systems that are scientifically useful, culturally respectful, and transparent about what they can and cannot establish.

7. CONCLUSION

This study concludes that artificial intelligence has significant potential to support archaeological research across landscape survey, site detection, artifact classification, text analysis, digital documentation, and heritage conservation. AI can assist researchers in processing large data volumes, recognizing patterns, organizing complex collections, and directing attention to areas that require further investigation. These advantages are particularly important in contexts where cultural landscapes are extensive, rapidly changing, or difficult to document through manual methods alone.

The analysis also demonstrates that AI outputs are not self-validating archaeological facts. They depend on data quality, research design, model choices, environmental conditions, and the historical biases of existing records. Reliable use requires field verification, expert review, uncertainty reporting, reproducible workflows, and careful distinction between prediction and confirmation. The strongest projects are those that combine automated methods with archaeological interpretation and local knowledge.

Future applications should place ethical responsibility alongside technical innovation. This means protecting sensitive locations,

respecting community rights, documenting data provenance, addressing bias, and preventing unsupported generated content from entering archaeological interpretation. By adopting transparent and collaborative practices, archaeology can use AI to expand research capacity while preserving the discipline's commitment to evidence, context, cultural respect, and public accountability.

8. RECOMMENDATIONS

Based on the study, the following recommendations may strengthen the responsible use of artificial intelligence in archaeological research:

- Define clear archaeological research questions before selecting an AI tool or model.
- Use documented, diverse, and contextually appropriate datasets for training and testing.
- Treat model results as research leads that require expert review and field or laboratory validation.
- Report accuracy measures, false positives, false negatives, uncertainty, and known limitations in published work.
- Maintain transparent records of data sources, labeling decisions, software, parameters, model versions, and validation procedures.
- Combine automated analysis with archaeological expertise, local environmental knowledge, and community participation.
- Protect sensitive site coordinates, sacred knowledge, and vulnerable heritage information through appropriate access controls.
- Develop ethical protocols for use of museum, archive, indigenous, and community-held cultural data.
- Avoid presenting AI-generated images, reconstructions, or text as verified evidence without clear labeling and source-based review.
- Support interdisciplinary training so that archaeologists understand AI limitations and technical teams understand archaeological context.

9. REFERENCES

1. Argyrou, A., and Agapiou, A. (2022). A review of artificial intelligence and remote sensing for archaeological research. *Remote Sensing*, 14(23), 6000. <https://doi.org/10.3390/rs14236000>

2. Bickler, S. H. (2021). Machine learning arrives in archaeology. *Advances in Archaeological Practice*, 9(2), 186-191. <https://doi.org/10.1017/aap.2021.6>
3. Casini, L., Marchetti, N., Montanucci, A., Orrù, V., and Roccetti, M. (2023). A human-AI collaboration workflow for archaeological sites detection. *Scientific Reports*, 13, 8699. <https://doi.org/10.1038/s41598-023-36015-5>
4. Orengo, H. A., and Garcia-Molsosa, A. (2019). A brave new world for archaeological survey: Automated machine learning-based potsherd detection using high-resolution drone imagery. *Journal of Archaeological Science*, 112, 105013. <https://doi.org/10.1016/j.jas.2019.105013>
5. Traviglia, A., and Torsello, A. (2017). Landscape pattern detection in archaeological remote sensing. *Geosciences*, 7(4), 128. <https://doi.org/10.3390/geosciences7040128>
6. Guyot, A., Lennon, M., Lorho, T., and Hubert-Moy, L. (2021). Combined detection and segmentation of archaeological structures from LiDAR data using a deep learning approach. *Journal of Computer Applications in Archaeology*, 4(1), 1-19. <https://doi.org/10.5334/jcaa.64>
7. Evans, D. H., Pottier, C., Fletcher, R., Hensley, S., Tapley, I., Milne, A., and Barbetti, M. (2007). A comprehensive archaeological map of the world's largest preindustrial settlement complex at Angkor, Cambodia. *Proceedings of the National Academy of Sciences*, 104(36), 14277-14282. <https://doi.org/10.1073/pnas.0702525104>
8. Evans, D. H., Fletcher, R. J., Pottier, C., Chevance, J.-B., Soutif, D., Tan, B. S., Im, S., Ea, D., Tin, T., Kim, S., Cromarty, C., De Greef, S., Hanus, K., Bâty, P., Kuszinger, R., Shimoda, I., and Boornazian, G. (2013). Uncovering archaeological landscapes at Angkor using lidar. *Proceedings of the National Academy of Sciences*, 110(31), 12595-12600. <https://doi.org/10.1073/pnas.1306539110>
9. Chase, A. F., Chase, D. Z., Weishampel, J. F., Drake, J. B., Shrestha, R. L., Slatton, K. C., Awe, J. J., and Carter, W. E. (2011). Airborne LiDAR, archaeology, and the ancient Maya landscape at Caracol, Belize. *Journal of Archaeological Science*, 38(2), 387-398. <https://doi.org/10.1016/j.jas.2010.09.018>
10. Parcak, S. H. (2019). *Archaeology from Space: How the Future Shapes Our Past*. New Haven: Yale University Press.
11. McCoy, M. D. (2017). Geospatial big data and archaeology: Prospects and problems too great to ignore. *Journal of Archaeological Science*, 84, 74-94. <https://doi.org/10.1016/j.jas.2017.06.003>
12. Opitz, R. S., and Cowley, D. C. (Eds.). (2013). *Interpreting Archaeological Topography: 3D Data, Visualisation and Observation*. Oxford: Oxbow Books.
13. Campana, S. (2017). Drones in archaeology: State-of-the-art and future perspectives. *Archaeological Prospection*, 24(4), 275-284. <https://doi.org/10.1002/arp.1569>
14. Kokalj, Ž., Hesse, R., Doneus, M., and Verhoeven, G. (2019). *Airborne Laser Scanning Raster Data Visualization: A Guide to Good Practice*. Ljubljana: Založba ZRC.
15. Magnani, M., and Clindaniel, J. (2025). Artificial intelligence and the interpretation of the past. *Advances in Archaeological Practice*. <https://doi.org/10.1017/aap.2025.10110>
16. Magnani, M., and Clindaniel, J. (2023). Artificial intelligence and archaeological illustration. *Advances in Archaeological Practice*, 11(4), 452-460. <https://doi.org/10.1017/aap.2023.25>
17. Assael, Y., Sommerschild, T., Shillingford, B., Bordbar, M., Pavlopoulos, J., Chatzipanagiotou, M., Androutsopoulos, I., Prag, J., and de Freitas, N. (2022). Restoring and attributing ancient texts using deep neural networks. *Nature*, 603, 280-283. <https://doi.org/10.1038/s41586-022-04448-z>
18. Kansa, E. C. (2012). Openness and archaeology's information ecosystem. *World Archaeology*, 44(4), 498-520. <https://doi.org/10.1080/00438243.2012.737575>
19. Richards, J. D. (2017). Twenty years preserving data: A view from the UK Archaeology Data Service. *Advances in Archaeological Practice*, 5(3), 227-237. <https://doi.org/10.1017/aap.2017.11>
20. Morgan, C., and Eve, S. (2012). DIY and digital archaeology: What are you doing to participate? *World Archaeology*, 44(4), 521-537. <https://doi.org/10.1080/00438243.2012.741810>
21. UNESCO. (1972). *Convention Concerning the Protection of the World Cultural and Natural Heritage*. Paris: UNESCO.

22. UNESCO. (2021). *Recommendation on the Ethics of Artificial Intelligence*. Paris: UNESCO.
23. ICOMOS. (1990). *Charter for the Protection and Management of the Archaeological Heritage*. Lausanne: International Council on Monuments and Sites.
24. European Commission. (2019). *Ethics Guidelines for Trustworthy AI*. Brussels: European Commission.
25. National Institute of Standards and Technology. (2023). *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*. Gaithersburg, MD: NIST.