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# ARTIFICIAL INTELLIGENCE AND SCIENTIFIC CULTURE FOR SUSTAINABLE CULTURAL HERITAGE GOVERNANCE IN LATIN AMERICA: AN INTERDISCIPLINARY FRAMEWORK FOR DIGITAL PRESERVATION, SOCIAL IMPACT AND EVIDENCE-BASED POLICY

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## ABSTRACT

*This article analyses how artificial intelligence can support scientific culture, sustainable cultural heritage governance, digital preservation and social impact in Latin America. It uses an interdisciplinary documentary synthesis combining critical literature review, policy analysis and conceptual modelling. Sources include peer-reviewed studies on artificial intelligence, digital heritage and responsible innovation, and institutional documents from UNESCO, ICOMOS, ICCROM, ICOM, OECD, ECLAC, the World Bank, the European Union and NIST. The synthesis identifies four necessary conditions for public-interest adoption: trustworthy data stewardship, participatory interpretation, accountable algorithmic infrastructures and evaluation systems linking preservation quality to social value. The proposed framework connects technical functions, cultural institutions, civic participation and policy feedback without treating artificial intelligence as an autonomous solution. Artificial intelligence can strengthen cultural heritage governance only when embedded in scientific culture, ethical data practices and inclusive public institutions. For Latin America, the priority is not technological acceleration alone, but capacity-building, transparent governance and socially accountable preservation policy.*

**KEYWORDS:** Algorithmic Accountability; Community Participation; Archival Stewardship; Museum Informatics; Indigenous Data Sovereignty; Metadata Ethics; Open Repositories; Risk Assessment; Public Engagement; Participatory Evaluation.

## 1. INTRODUCTION

This article aims to develop a rigorous interdisciplinary framework explaining how artificial intelligence (AI) can strengthen scientific culture, sustainable cultural heritage governance, digital preservation and social impact in Latin America. The central argument is that AI becomes valuable for heritage only when it is embedded in transparent institutions, scientifically literate publics, accountable data infrastructures and participatory policy processes. Cultural heritage governance faces a period of structural pressure. Climate change, urbanisation, illicit trafficking, demographic transformation, political polarisation, underfunded memory institutions and digital platform dependence are reshaping the conditions under which heritage is documented, interpreted and transmitted (Harrison, 2013; ICOMOS, 2020; UNESCO, 2019, 2022). At the same time, museums, archives, libraries, archaeological agencies and community organisations are producing increasing volumes of digital images, three-dimensional records, oral histories, geospatial files, born-digital collections and administrative metadata. These resources create opportunities for preservation and public access, but also raise risks concerning ownership, bias, obsolescence, extractive data practices and unequal participation (Christen, 2012; Christen & Anderson, 2019; D'Ignazio & Klein, 2020; Wilkinson et al., 2016). AI has entered this field through image classification, pattern recognition, optical character recognition, predictive conservation, automatic metadata enrichment, structural monitoring, language technologies and visitor-personalisation systems (Belhi, 2023; Fiorucci et al., 2020; Jankovic, 2020; Li et al., 2026; Poulopoulos & Wallace, 2022). These applications can assist documentation and decision-making, particularly where institutions manage fragile collections and limited technical capacity. Nevertheless, the same systems may reproduce colonial classifications, prioritise easily digitised artefacts, obscure uncertainty, intensify surveillance or transfer public cultural value into private infrastructures (Benjamin, 2019; Birhane, 2021; Crawford,

2021; Noble, 2018; Ricaurte, 2019). The scientific problem is

therefore not whether AI is efficient, but under what governance conditions it can support socially legitimate and scientifically grounded heritage decisions. The relevance of this problem is especially evident in Latin America and the Caribbean (LAC). The region contains extraordinarily diverse tangible, intangible, documentary, linguistic and biocultural heritage, but it also faces marked asymmetries in digital infrastructure, research funding, institutional continuity and data sovereignty (ECLAC, 2022; OECD et al., 2020, 2023; World Bank, 2021, 2024). These asymmetries matter because AI systems are not culturally neutral. They depend on training data, metadata standards, computational resources, interpretive authority and policy rules that may either widen or reduce existing inequalities (Couldry & Mejias, 2019; Milan & Treré, 2019; Ricaurte, 2019). A Latin American perspective consequently requires attention to institutional capacity, indigenous and community rights, multilingual knowledge systems and public-interest infrastructures rather than merely to technical performance. This article is aligned with the field of Scientific Culture because it examines the relationship between science, technology, culture and society. Scientific culture is understood here not as the public diffusion of ex-

pert knowledge alone, but as a collective capacity to evaluate evidence, debate uncertainty, recognise ethical consequences and participate in knowledge-based public decisions (Irwin, 1995; Owen et al., 2012; Stilgoe et al., 2013; UNESCO, 2021b). In heritage governance, scientific culture is essential because preservation decisions are simultaneously technical, cultural, political and moral. AI can support this culture only if its outputs are explainable to non-specialists, contestable by affected communities and connected to policy evidence. The research gap is threefold. First, technical research on AI for heritage often focuses on model performance, whereas governance, cultural rights and social impact receive less systematic attention (Fiorucci et al., 2020; Li et al., 2026). Secondly, policy discussions on digital transformation in Latin America tend to address connectivity and economic modernisation, but less often link AI to heritage institutions and scientific culture (ECLAC, 2022; OECD et al., 2020). Thirdly, heritage scholarship has developed strong critiques of authorised heritage discourse and data colonialism, but these critiques are not always translated into operational policy frameworks for AI-enabled preservation (Harrison et al., 2020; Meskell, 2018; Smith, 2006).

The general objective is to construct an evidence-based framework for assessing how AI can support sustainable cultural heritage governance in Latin America. The research questions are: RQ1: Which AI functions are most relevant to digital preservation and heritage decision-making? RQ2: What ethical and institutional conditions are required for AI to strengthen scientific culture rather than undermine it? RQ3: How can AI-enabled heritage governance produce social impact in Latin American contexts? RQ4: What policy architecture can connect preservation evidence, public participation and accountable technological use? The article proceeds through a critical literature review, a transparent materials and methods section, documentary and conceptual results, discussion, conclusions, acknowledgements, references and an editorial compliance checklist.

## 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

### *2.1. Scientific Culture, Public Reason and Heritage Evidence*

Scientific culture links knowledge production to public reasoning. In the heritage field, this requires more than explaining archaeological, archival or conservation findings to the public. It requires conditions under which citizens, communities, professionals and policymakers can understand evidence, question classifications, assess uncertainty and deliberate on preservation priorities. This understanding is consistent with traditions of public engagement, responsible research and innovation, and productive interactions between science and society (Bornmann, 2013; Irwin, 1995; Owen et al., 2012; Spaapen & van Drooge, 2011; Stilgoe et al., 2013). The concept is particularly important for heritage because scientific evidence is never socially weightless. Conservation science, remote sensing, digital reconstruction and documentary preservation all involve choices about what counts as evidence, whose memory is recognised and which futures are made possible (Avrami et al., 2019; Harrison et al., 2020; Smith, 2006). Scientific culture therefore provides an antidote to two risks: technocracy, where experts or vendors define heritage priorities without public accountability; and relativism, where evidence is displaced by political expediency. A robust scientific culture allows evidence and cultural plurality to interact without reducing one to the other.

### *2.2. Artificial Intelligence, Society and Algorithmic Accountability*

AI governance has moved from narrow concerns about automation to broader questions of accountability, legitimacy and power. International guidance emphasises transparency, fairness, human oversight, safety, privacy and accountability (European Parliament & Council, 2024; NIST, 2023; OECD, 2019; UNESCO, 2021a). Ethical analysis, however, warns that principles alone are insufficient when institutional incentives, market concentration and unequal data infrastructures remain unaddressed (AI Now Institute, 2023; Hagendorff, 2020; Jobin et al., 2019; Mittelstadt, 2019). For cultural heritage, algorithmic accountability has specific implications. AI systems may classify visual material, predict structural risk, reconstruct damaged objects or translate documentary collections. Each task can affect public interpretation and institutional authority. If training data are biased, metadata are poor, or uncertainty is hidden, AI may confer unwarranted scientific legitimacy on partial interpretations. Critical AI scholarship shows that algorithmic systems can reproduce racial, colonial, gendered and economic hierarchies when social assumptions are embedded into data and models (Benjamin, 2019; Birhane, 2021; Crawford, 2021; Noble, 2018). Heritage institutions must therefore treat AI as a governed sociotechnical system, not merely as software.

### *2.3. Digital Cultural Heritage and Preservation Infrastructures*

Digital cultural heritage includes digitised heritage, born-digital heritage, computational documentation and digitally mediated interpretation. Its preservation requires durable formats, metadata, storage redundancy, access policies, rights management and institutional continuity. The Open Archival Information System (OAIS) reference model, the Digital Preservation Handbook and UNESCO/PERSIST guidance remain foundational because they emphasise long-term stewardship rather than short-term digitisation projects (Consultative Committee for Space Data Systems, 2012; Digital Preservation Coalition, 2015; UNESCO/PERSIST, 2016). Recent AI applications can support automatic annotation, image recognition, reconstruction and monitoring (Belhi, 2023; Fiorucci et al., 2020; Jankovic, 2020; Li et al., 2026). Yet these tools cannot compensate for weak preservation policy. AI depends on data quality, documentation context, provenance and controlled uncertainty. The FAIR principles-findability, accessibility, interoperability and reusability-help define technical data quality, while the CARE principlescollective benefit, authority to control, responsibility and ethics-address indigenous and community data governance (Carroll et al., 2020; Wilkinson et al., 2016). Sustainable AI-enabled preservation requires both: data must be technically usable and socially legitimate.

### *2.4. Sustainable Heritage Governance and Social Impact*

Sustainable heritage governance connects preservation to environmental, social, cultural and economic objectives. UNESCO conventions and policy instruments emphasise cultural diversity, intangible heritage, documentary heritage and sustainable development (UNESCO, 1972, 2003, 2015a, 2015b, 2019, 2022). ICOMOS (2020), ICCROM (2021) and ICOM

(2022) further situate heritage within public value, community participation and institutional responsibility. These frameworks imply that heritage governance should be evaluated not only by the survival of objects, but by the quality of participation, interpretation, education, accessibility and intergenerational transmission. Social impact is not a rhetorical add-on. It concerns whether preservation practices improve cultural rights, public learning, inclusion, institutional trust and policy capacity (Bornmann, 2013; Spaapen & van Drooge, 2011). In AI-enabled heritage, impact assessment should therefore examine who benefits, who is represented, who can contest automated outputs and whether decisions improve community well-being. This is especially important in Latin America, where indigenous, Afro-descendant, migrant and rural communities have frequently been marginalised in state-centred cultural narratives (Escobar, 2018; Ricaurte, 2019; Smith, 2006).

### *2.5. Interdisciplinary Research and Latin American Institutional Contexts*

The problem cannot be addressed by computer science, conservation or cultural policy alone. It requires an interdisciplinary configuration involving heritage studies, information science, museum studies, archival science, data ethics, public policy, environmental management, anthropology and science communication. Convergence research and responsible innovation both suggest that complex public problems require integrated expertise and social learning rather than disciplinary aggregation (National Academies of Sciences, Engineering, and Medicine, 2014; Owen et al., 2012; Stilgoe et al., 2013). Latin America intensifies the need for such integration. Regional policy reports show progress in digital transformation but also persistent gaps in connectivity, skills, institutional capacity and data governance (ECLAC, 2022; OECD et al., 2020, 2023; World Bank, 2024). Digital heritage policy must therefore be realistic about capacity. Theoretical debates on data colonialism and digital worlds from the South also caution against importing models that ignore local epistemologies, languages and infrastructures (Couldry & Mejias, 2019; Milan & Treré, 2019; Risam, 2018; Ricaurte, 2019). The framework proposed below treats AI adoption as a public cultural governance question rather than as a technological upgrade.

## 3. MATERIALS AND METHODS

### *3.1. Research Design*

The study uses a qualitative, interdisciplinary and documentary research design. It is not an empirical survey and does not report new field data. The design combines critical literature review, institutional policy analysis and conceptual modelling. This approach is appropriate because the research problem involves technological capabilities, cultural values, public institutions and social impact, none of which can be adequately examined through a single disciplinary method.

### *3.2. Epistemological Positioning*

The article adopts a critical realist and pragmatist position. It assumes that heritage risks, digital infrastructures and institutional inequalities are real, but that their interpretation is socially mediated. It also assumes that research should generate usable knowledge for public decision-making while remaining critical of power relations embedded in data, algorithms and cultural classifications. This position supports an evidence-based but non-technocratic understanding of AI governance.

### *3.3. Methodological Approach*

The methodological approach consisted of three linked procedures. First, the literature was mapped across five domains: AI and society, digital cultural heritage, preservation infrastructures, scientific culture and Latin American digital policy. Secondly, institutional documents were analysed to identify governance requirements relevant to heritage policy. Thirdly, the findings were synthesised into an analytical framework and a policy evaluation matrix. The process follows the logic of integrative review and conceptual synthesis rather than statistical meta-analysis.

### *3.4. Data Sources*

The source base included peer-reviewed journal articles, academic books, international standards and institutional reports. Academic sources covered machine learning for heritage, AI ethics, data justice, public engagement, digital preservation, heritage theory and research impact (Belhi, 2023; Birhane, 2021; Fiorucci et al., 2020; Jobin et al., 2019; Li et al., 2026; Poulopoulos & Wallace, 2022). Institutional sources included UNESCO conventions and recommendations, ICOMOS and ICCROM policy guidance, ICOM's museum definition, the European Union Artificial Intelligence Act, the NIST AI Risk Management Framework, OECD AI principles and Latin American digital development reports (European Parliament & Council, 2024; ICCROM, 2021; ICOM, 2022; ICOMOS, 2020; NIST, 2023; OECD, 2019; UNESCO, 2015a, 2021a, 2021b, 2022).

### *3.5. Inclusion and Exclusion Criteria*

Sources were included when they met at least one of the following criteria: direct relevance to AI or machine learning in heritage; relevance to scientific culture, responsible innovation or public engagement; relevance to digital preservation, data governance or archival stewardship; relevance to Latin American digital policy or institutional capacity; or recognised international authority in heritage governance. Sources were excluded if they were promotional, unverifiable, not attributable to a credible author or institution, or concerned purely technical optimisation without relevance to governance, interpretation, preservation or public impact.

### *3.6. Analytical Procedure*

The analysis used thematic coding across seven categories: preservation function, data condition, institutional actor, community participation, ethical risk, policy mechanism and social impact. Each source was reviewed for its contribution to one or more categories. Findings were then compared to identify convergences and tensions. The final framework was built by linking technical AI functions to governance conditions and social outcomes. The results are presented as documentary and conceptual findings, not as statistical findings.

### *3.7. Validity and Reliability Strategy*

Validity was strengthened through source triangulation across academic literature, international standards and policy documents. Conceptual validity was supported by distinguishing technical functions from governance outcomes. Reliability was supported through explicit inclusion criteria, transparent analytical categories and avoidance of unverifiable references. A final citation audit checked that every cited source appears in the reference list and that every reference is cited in the manuscript.

### *3.8. Ethical Considerations*

No human participants were involved. Ethical analysis focused on the societal implications of AI in heritage governance. The key ethical issues are data provenance, indigenous data sovereignty, intellectual property, representational harm, algorithmic bias, environmental cost, public accountability and community consent (Carroll et al., 2020; Christen, 2012; D'Ignazio & Klein, 2020; UNESCO, 2021a). The article therefore treats ethics as a design condition rather than as an external compliance requirement.

### *3.9. Limitations of the Method*

The method is limited by its documentary nature. It does not measure actual AI adoption across Latin American heritage institutions and cannot estimate causal effects. It also depends on published literature and available institutional documents, which may underrepresent community-led initiatives, indigenous knowledge infrastructures and local archival practices. These limitations are addressed by presenting the results as a conceptual and policy framework for future empirical validation.

## 4. RESULTS

The results are organised as four documentary and conceptual findings derived from the analytical procedure. They should not be interpreted as new empirical measurements.

### *4.1. Result 1: AI Contributes to Heritage Governance Through Four Distinct Functions*

The literature shows that AI can contribute to heritage governance through documentation, interpretation, risk anticipation and policy learning. Documentation includes metadata enrichment, image classification, handwriting recognition and three-dimensional reconstruction (Belhi, 2023; Fiorucci et al., 2020; Jankovic, 2020). Interpretation includes multilingual access, semantic linking and support for public engagement. Risk anticipation includes structural monitoring, environmental risk detection and predictive maintenance (Li et al., 2026). Policy learning includes the use of evidence dashboards and evaluation systems to connect preservation decisions to social outcomes. The key finding is that these functions should not be collapsed into a single claim that AI improves heritage governance. Each function carries different risks, data requirements and ethical obligations. For example, automatic classification can improve access while reinforcing inherited categories; predictive risk tools can support preventive conservation while obscuring uncertainty; and public-facing generative systems can widen engagement while producing inaccurate or culturally insensitive narratives. Governance must therefore be function-specific.

### 4.2. Result 2: Scientific Culture Is the Mediating Condition Between Technology and Public Value

AI supports public value only when scientific culture mediates between technical output and social interpretation. Scientific culture requires explainability, contestability and public reasoning. In heritage contexts, this means that institutions should explain how AI outputs were produced, what data were used, what uncertainty remains and how communities can challenge or enrich interpretations. This finding is consistent with responsible innovation and public engagement research, which emphasises anticipation, inclusion, reflexivity and responsiveness (Owen et al., 2012; Stilgoe et al., 2013). Table 1 summarises the analytical dimensions identified in the review.

**Table 1: Analytical dimensions for AI-enabled heritage governance.**

| Dimension | Documentary finding | Governance implication |
|---|---|---|
| Preservation function | AI is most useful for annotation, classification, reconstruction, monitoring and evidence synthesis. | Institutions should specify the precise preservation task before procuring or developing AI systems. |
| Data condition | Model quality depends on provenance, metadata, interoperability, community authority and long-term preservation. | FAIR and CARE principles should be jointly applied to heritage data. |
| Institutional capacity | AI requires technical skills, policy rules, infrastructure and continuity of funding. | Regional capacity-building is as important as software acquisition. |
| Public interpretation | AI-generated outputs can influence cultural narratives and public memory. | Explainability, contestability and community review should be built into public interfaces. |
| Ethical risk | Bias, extraction, misclassification and platform dependence can undermine public trust. | Independent audit, human oversight and procurement transparency are required. |
| Social impact | Heritage AI has value when it improves access, education, inclusion, risk preparedness and policy learning. | Evaluation should measure public benefit, not only technical accuracy. |

***Note. The table reports conceptual findings from the documentary synthesis; it does not present statistical data. Source. Prepared by the author from the literature and institutional sources reviewed in this article.***

### 4.3. Result 3: Latin American Adoption Requires Public-Interest Infrastructure

The Latin American evidence base indicates that AI-enabled heritage governance cannot depend exclusively on project-based digitisation or private platform access. Regional digital transformation reports identify gaps in connectivity, skills, institutional capacity and data governance (ECLAC, 2022; OECD et al., 2020, 2023; World Bank, 2024). In heritage, these constraints may produce fragmented repositories, weak interoperability, precarious storage and dependence on external vendors. The result is a governance paradox: AI is promoted as a tool for preservation, yet its benefits depend on long-term public infrastructures that many institutions lack. The documentary analysis therefore supports a public-interest infrastructure model. Such a model includes interoperable repositories, public procurement standards, preservation budgets, community data agreements, multilingual metadata, audit procedures and training programmes. It also requires attention to environmental sustainability, because high-resolution digitisation, model training and storage consume energy and hardware. Sustainable governance should evaluate digital preservation not only by access metrics but also by durability, reuse, equity and ecological cost.

### 4.4. Result 4: A Framework Linking Technical Capacity, Scientific Culture and Policy Feedback

The proposed framework in Figure 1 synthesises the results. It positions AI as one component within a broader governance cycle. Technical functions generate preservation evidence; scientific culture translates evidence into public reasoning; participatory governance evaluates legitimacy; and policy feedback adjusts standards, resources and institutional practice.

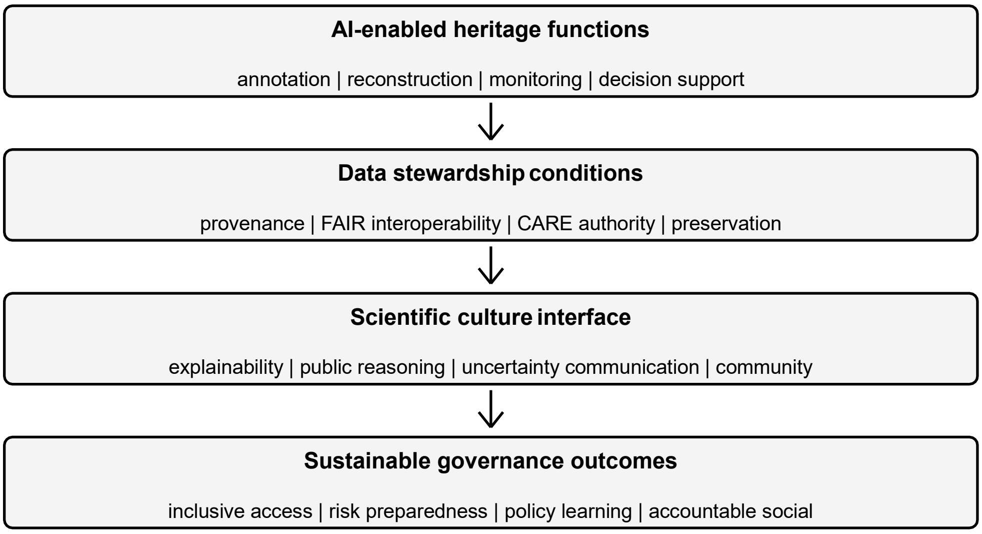


***Figure 1: Interdisciplinary framework for AI, scientific culture and heritage governance.***

***Note. This original conceptual figure is prepared as an original conceptual figure for the revised manuscript. Source. Prepared by the author from the documentary synthesis.***

## *4.5. Operationalisation of the Proposed Framework*

The proposed framework can be operationalised through a staged governance cycle that moves from diagnosis to institutional implementation and policy feedback. First, heritage institutions should identify the specific preservation problem to be addressed, such as metadata enrichment, risk monitoring, reconstruction, multilingual access or evidence synthesis. Secondly, they should evaluate the quality, provenance, rights status and community sensitivity of the data before selecting any AI tool. Thirdly, they should establish human oversight procedures, including expert review, community consultation, audit logs and mechanisms for contesting automated classifications or interpretations. Fourthly, they should connect system outputs to policy decisions, budgets, preservation priorities and public learning activities. Finally, they should evaluate social impact through indicators of access, inclusion, cultural legitimacy, preservation durability and institutional trust.

Operationalisation should therefore be understood as a public governance process rather than as a technical deployment plan. In practical terms, ministries of culture, museums, archives, universities and community organisations can use the framework as a checklist for procurement, project design, risk assessment and evaluation. The framework is especially relevant for Latin America because it explicitly considers asymmetries in infrastructure, skills, funding and data sovereignty.

***Table 2: Summary of the conceptual framework and operational dimensions.***

| **Framework dimension** | **Operational purpose** | **Main actors** | **Policy or management instruments** | **Suggested evidence** |
|---|---|---|---|---|
| AI-enabled heritage functions | Define the exact task for which AI will be used in heritage governance. | Heritage agencies, museums, archives, universities, technical teams. | Use-case definition, procurement criteria, model documentation, human review protocols. | Task description, model cards, validation records, implementation reports. |
| Data stewardship conditions | Ensure that heritage data are technically usable, ethically governed and culturally legitimate. | Archivists, data stewards, indigenous and community representatives, legal offices. | FAIR and CARE principles, metadata standards, consent protocols, rights management. | Metadata audits, provenance records, data-sharing agreements, repository policies. |
| Scientific culture interface | Translate technical outputs into explainable, contestable and publicly meaningful evidence. | Curators, educators, researchers, communities, public engagement officers. | Explainability notes, public communication plans, community review boards, uncertainty statements. | Interpretation records, participation logs, public feedback, educational materials. |
| Participatory governance | Guarantee that affected communities can participate in decisions and challenge automated | Local communities, civil society organisations, cultural authorities, ethics committees. | Consultation procedures, grievance mechanisms, participatory evaluation, advisory councils. | Meeting minutes, consent records, revision logs, community validation reports. |

| | | | | |
|---|---|---|---|---|
| | interpretations. | | | |
| Policy feedback and social impact | Connect preservation evidence to decisions, budgets, accountability and long-term public value. | Policymakers, funders, institutional directors, evaluators, regional organisations. | Impact indicators, budget alignment, risk registers, independent audits, open reporting. | Evaluation reports, budget decisions, risk assessments, impact dashboards. |

***Note. The table translates the proposed conceptual framework into practical dimensions for institutional implementation and policy evaluation. Source. Prepared by the authors from the revised documentary synthesis.***

The framework does not present AI as a replacement for curators, conservators, archivists, communities or policymakers. Instead, it defines AI as a technical layer whose public value depends on governance. This is the central result of the article: AI can strengthen heritage governance only when it is attached to scientific culture and accountable public institutions.

### *4.5. Result 5: Evaluation Must Combine Technical, Cultural and Social Indicators*

A policy-relevant evaluation system should avoid reducing success to accuracy, speed or number of digitised objects. Table 2 proposes a compact set of indicators aligned with the framework.

***Table 3: Policy evaluation matrix for AI-enabled heritage initiatives.***

| Evaluation domain | Indicative questions | Evidence source |
|---|---|---|
| Technical reliability | Are model performance, uncertainty and error rates documented for the specific heritage task? | Validation reports, model cards, audit logs. |
| Preservation quality | Are metadata, formats, storage and rights managed for long-term access? | Repository records, OAIS-aligned policies, preservation plans. |
| Cultural legitimacy | Were affected communities consulted and can they contest classifications or narratives? | Consent records, community review minutes, participation logs. |
| Equity and access | Does the system improve access for underserved groups and languages? | Usage data, accessibility audits, multilingual interface review. |
| Policy learning | Do AI outputs inform decisions, budgets and risk planning? | Policy documents, budget allocations, risk registers. |
| Environmental responsibility | Are energy use, hardware lifecycle and storage expansion considered? | Sustainability reports, procurement criteria, infrastructure assessments. |

***Note. The matrix is a conceptual policy tool; indicators require contextual adaptation before empirical use. Source. Prepared by the author.***

### *4.6. Discussion*

The findings support a cautious but constructive interpretation of AI in cultural heritage. AI can assist preservation and public policy, but only if institutions move beyond technological solutionism. This interpretation aligns with AI ethics literature, which stresses accountability and human oversight (European Parliament & Council, 2024; Floridi & Cowls, 2019; NIST, 2023; UNESCO, 2021a), and with heritage scholarship, which emphasises values, interpretation and cultural rights (Avrami et al., 2019; Harrison et al., 2020; Smith, 2006). The article's original contribution is to connect AI-enabled preservation to scientific culture. Existing technical reviews show that machine learning can classify, reconstruct and monitor heritage objects (Fiorucci et al., 2020; Li et al., 2026). This article adds that such functions become socially meaningful only through institutions capable of explaining evidence, recognising uncertainty and enabling public contestation. Scientific culture is thus not a dissemination layer added after technical work; it is a governance condition that determines whether technical evidence becomes legitimate public knowledge. The theoretical implications are threefold. First, the article extends digital heritage theory by treating AI as a sociotechnical system embedded in institutional and cultural contexts. Secondly, it contributes to responsible innovation by specifying how anticipation, inclusion, reflexivity and responsiveness apply to heritage AI. Thirdly, it advances social-impact thinking by proposing indicators that connect preservation quality to public value rather than to digitisation volume alone. The methodological implications concern evaluation. AI systems in heritage should not be assessed solely through machine-learning metrics. Accuracy, precision or recall may be necessary, but they are insufficient for public cultural governance.

Evaluation must also consider data provenance, interpretive legitimacy, participation, interoperability, preservation durability and policy uptake. This suggests the need for mixed-methods assessment combining technical validation, documentary audit, stakeholder interviews, community review and policy analysis. The policy implications are substantial for Latin America. Governments and heritage agencies should avoid fragmented procurement of proprietary AI tools without preservation strategy. Priority should be given to interoperable public repositories, open standards, multilingual metadata, community data agreements, public-sector skills and independent audit capacity. Regional cooperation is also important because many institutions cannot individually sustain AI infrastructure, long-term storage or specialised expertise. Public universities, memory institutions and regional organisations could form shared laboratories for ethical AI and heritage preservation. The social impact of the proposed framework lies in its emphasis on cultural rights, participation and public trust. AI can widen access to collections, support education, identify risks and improve evidence-based policy. It can also harm communities if it misclassifies cultural materials, extracts knowledge without consent or presents probabilistic outputs as authoritative truth. Social impact therefore depends on procedural justice: who participates, who benefits, who can challenge outputs and who controls data reuse. The study has limitations. It is conceptual and documentary, not empirical. It does not compare actual AI systems across Latin American coun-

tries, nor does it measure social impact outcomes. The framework is intentionally general and must be adapted to different institutional scales, from national heritage agencies to community archives. Future research should conduct comparative case studies, develop validated indicators, analyse procurement practices, evaluate community-led AI governance and examine the environmental cost of large-scale digital preservation. Studies should also investigate indigenous data governance, Afro-descendant heritage, endangered languages and climate-risk monitoring as priority areas.

## 5. CONCLUSIONS

This article has answered the general objective by developing an interdisciplinary framework explaining how AI can support scientific culture, sustainable cultural heritage governance, digital preservation and social impact in Latin America. The evidence reviewed indicates that AI is most relevant to heritage governance when it supports documentation, interpretation, risk anticipation and policy learning. These functions answer RQ1, but they also show that technical utility is task-specific and cannot justify uncritical adoption. RQ2 concerned ethical and institutional conditions. The article concludes that trustworthy AI in heritage requires provenance, FAIR interoperability, CARE-based community authority, explainability, human oversight, auditability and long-term preservation policy. RQ3 concerned social impact. The findings indicate that social impact emerges when AI improves access, education, cultural rights, risk preparedness and policy capacity, while enabling communities to contest and enrich interpretation. RQ4 concerned policy architecture. The proposed framework links AI functions, data stewardship, scientific culture and governance outcomes through a feedback cycle suitable for evidence-based policy. The scientific contribution is the integration of AI ethics, digital preservation, heritage theory, scientific culture and Latin American policy analysis into a single governance framework. Its novelty lies in treating scientific culture as the mediating condition between algorithmic output and public value. Its innovation lies in translating that argument into analytical dimensions and evaluation criteria. The interdisciplinary relevance is clear: sustainable heritage governance requires computer science, conservation, archival studies, policy analysis, social science, ethics and community knowledge. The prudent conclusion is that AI can strengthen heritage governance in Latin America, but only when it is institutionally accountable, socially participatory and scientifically transparent.

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