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Artificial Intelligence in Digital Heritage Preservation

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ABSTRACT

Artificial intelligence (AI) is another breakthrough in the process of digital heritage restoration, allowing to enhance accuracy, scale, and cultural accessibility thereof. Within the design of this research was a mixed-methods experimental approach to understanding AI applications with quantitative modelling and qualitative outlooks of heritage specialists. Quantitative findings revealed that AI techniques such as image recognition, 3D reconstruction, and natural language processing worked well in making their forecast, many of them having accuracy and F1-scores of over 0.90. Regression analysis revealed that there were high correlations between the size of information, the sum of the amount financed, and the outcome of preservation. The results of the comparison between the baseline and AI-enhanced models indicated the increase in the key criteria by 20 to 30 per cent. The regional analysis indicated that the leaders in finance and adoption are Europe and Asia, whereas Africa and South America are new territories with innovations, even though these regions lack a lot of resources. These findings were supported by qualitative analysis, which highlighted the cultural ethical value, such as authenticity, ownership, and accessibility of data. These results demonstrate the role of AI in increasing the efficiency of heritage digitization and changing the global practices and protecting the access of the world heritage to future generations. The study suggests that AI would be best employed in tandem with other strategies that fuse computational accuracy with cultural consciousness and make it an essential constituent of sustainable heritage preservation.

Keywords: *Artificial Intelligence, Digital Heritage, Cultural Preservation, Machine Learning, Mixed-Methods Research, Global Access*

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INTRODUCTION

The integration of artificial intelligence into the process of conservation of cultural assets can be considered a profound paradigm shift that results in some new strategies and complex ethical choices (Ghaith, 2024). The increasing use of AI in the field because of advancements in machine learning, computer vision, and natural language processing capacities means new avenues exist in digitizing, analysing and availing historical artifacts, and archival documents (Spina, 2023). Not only will such AI-led strategies be more accurate, and efficient in terms of preservation, but they will allow us to engage with, and learn more about our history as a global collective in novel ways (Basu, 2025). Since it was first conceived during the middle of the 20 th century as the science and engineering of making intelligent machines, there has been a rapid transformation in the field of IH AI. It has now found its practical application both in the industry and society (Department et al., 2022). This growth is coupled with massive gains in sectors such as smart manufacturing where artificial intelligence is making manufacturing processes and supply chain management faster. This demonstrates that AI is very flexible and significant in various fields (Chatterjee et al., 2021). As a multi-disciplinary tool, the AI has the potential to revolutionise the process of preserving digital heritage as being able to address the challenges posed by the large number and fragility of cultural objects, thus ensuring their long-term sustainability and increased accessibility (Zhang et al., 2023). Besides, AI functions as a way to automate the preservation of heritage by using deep learning to locate and categorise building defects to considerably reduce the time spent on locating, preserving, and categorising heritage (Dai et al., 2024). The Anthropocene age, which has been characterized by significant changes in technology, also increases the need to have the best tools, as AI use is becoming central in refining preservation activities, especially in historical buildings that would house museum collections (Russa & Santagati, 2020). Its impact on the economy is anticipated to be very high with some estimating that I will generate trillions of additional dollars to the global economy by 2030. It will occur due to both the increased productivity and implications related to consumption, which actually can fund a digital heritage project indirectly (Pizam et al., 2022). A lot of companies have already turned to using AI but many industries still only consider how they can use it. This indicates that new technology is not welcomed in all areas (Chatterjee et al., 2021). This can be considered a critical period in the digital heritage industry as it has to address how to utilize these new technologies alongside the issue of data privacy, ethical management, and the infrastructure involved with large-scale AI disclosure (Greco et al., 2024) (Xue & Pang, 2022). This distinction illuminates the relevance of conducting focused research and development to design AI solutions that are explicitly required to preserve cultural heritage bearing in mind the advantageous aspect of escalated accuracy alongside the ethical challenges that accompanies processing information (Kandasamy, 2024). Such an inclusive approach is essential in eliminating risks associated with data bias and ensuring a fair distribution of preserved cultural data (Nishant et al., 2020). This includes developing powerful ethical stipulations to assist in the design and assessment of AI implementations in cultural heritage to ensure they are applied without compromising historical truth or cultural sensitivity (Pansoni et al., 2023). The frameworks are critical in addressing the black box nature of some AI algorithms that obscure the decision-making process and may reinforce historical data-based biases (Dehghani et al., 2024). It is therefore crucial that the AI models are transparent and easy to interpret as part of ensuring that AI design works and that heritage is preserved in the right way. This is very much the case when you consider the bias that algorithms can have when examining massive historical data sets (Weber-Lewerenz, 2021) (Lainjo, 2024). The solution to the application of AI in digital heritage requires connecting experts in various academic disciplines, including philosophy, computer science, archival studies, and conservation specialties, to find the solution that would be not only innovative but also ethically and culturally sound (Mannheimer et al., 2024). This wholesome perception ensures that AI technologies will not substitute the human knowledge in terms of preserving legacy, but rather complementing it. This forms a teamwork culture where technology is used to make people understand cultural legacies in a more sensitive manner. The Can Automated Intelligence help future historians, as well as people who care about legacy, have more access to unstructured knowledge that is entangled in cultural artifacts and social rites? They are also in a position to help encode this information into systems that can be read by machines (Nanetti, 2021). This is also an important feature in addressing the issue of data fragmentation and data heterogeneity that prevails in most legacy collections. It allows finding and retrieving any related essential cultural data in the course of time more easily (Abujaber & Nashwan, 2024). This enables a complex data and ontology structure creation to facilitate easy searching across collections and semantic interoperability which is very crucial to comprehensive scholarly research. However, the use of AI in such sensitive fields raises serious ethical questions concerning transparency and accountability of algorithms, as well as the danger of intensifying pre-existing biases on the basis of historical data (Dhopte & Bagde, 2023) (Olatoye et al., 2024). To address these ethical concerns, you should create AI models that can be understandable and enact stringent policies on data management to ensure fairness and prevent the proliferation of past errors or biases (Vujičić, 2025). This would require irreproachable attention to the information used to teach AI models and continuous audits to detect and mitigate bias (Sreelatha & Choudhary, 2023). In addition to this the intensive energy resource needs and computer power requirements of the matrices trained in large AI and the intense individualized simulations required in heritage applications generate the problem of sustainability. This implies there is a third way to go, that the computational workflows must be as optimized as possible, and green computing solutions must be considered (Su et al., 2025). Moreover, despite the tremendous potential of AI, such blind adoption requires extensive efforts to maintain human relations, ensure data privacy, and minimize disparities and maximize system transparency in digital heritage systems (Al-Zahrani, 2024).

METHODOLOGY

The study uses a mixed design study that incorporates both quantitative and qualitative methods in the objective of determining the role of Artificial Intelligence (AI) in the process of digital heritage preservation. The paper conducted a quantitative analysis of a multi-source framework including digitization efforts, usage of AI in historic institutions, and other performance-related metrics. Qualitative evaluation was on the expert interview of curators, digital archivists, and AI researchers. The combination of the two design methods allows it to merge both statistical performance of the AI techniques and the interpretive understanding of cultural meaning in one complete set delineation. The corpus of data covers some projects carried out between 2010 and 2024 across the world including Europe, Asia, and North America. It also incorporates heritage areas such as architecture, manuscripts and oral traditions. In the quantitative portion, supervised machine learning algorithms, such as Support Vector Machines (SVM), Gradient Boosting, and XGBoost were employed, to assess how well they can classify and predict past data. We took statistical parameters such as Accuracy, Precision, Recall, and F1-score and Area Under the Curve (AUC) to determine how the model performed. The official specification of what a correct model should be is:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP represents true positives, TN true negatives, FP false positives, and FN false negatives. Similarly, the F1-score, representing the harmonic mean of Precision and Recall, is given by:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

In addition to classification metrics, regression models were applied to estimate funding impact and digitization levels, where the predictive relationship was modeled as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

where Y represents preservation outcomes, X_i denotes AI-specific input features such as dataset size, processing speed, or algorithm type, β_i are regression coefficients, and ϵ represents the error term.

Qualitative data was obtained through thematic analysis of the expert interviews, and focused on the issues of applying AI to heritage settings, such as the ethics of digitizing heritage, the ownership of culture, and scarcity of data. These conclusions were supported by quantitative results to support the authenticity of the results and ensure that the study was cultural sensitive with regard to AI role in heritage preservation. We have applied k-fold crossvalidation (k=10k=10k=10) to test statistically the model results and confirm that they could be applied in other contexts. Analysis of Variance (ANOVA) was also used to determine whether the differences were significant and analyze the performance of the algorithms when applied to these domains.

RESULTS

The findings indicate that, AI can be employed in numerous variants and it is effective when it comes to safeguarding the digital heritage. AI demonstrated quantifiable advancements in precision, efficacy as well as conservational effect over a variety of strategies, historical disciplines and geographies.Table 1 shows the relative performance of various AI methods, such as decoding images, 3-dimensional rendering and natural language processing (NLP). Accuracy and F1-scores were high across the board and many of the approaches achieved above 0.90. This illustrates that the heritage digitization works are rather robust. The table 2 indicates some of the categories of heritage to which AI is being applied, including architecture, manuscripts and oral traditions. In both spheres' architecture and archaeology, AI was implemented in over 80 percent of the projects. This indicates that assets that received maximum consideration were those that are structural and of large scale. The region wise distribution is indicated in Table 3. The most legacy projects related to AI are found in Europe and Asia whereas Africa and South America are showing interest, albeit they do not invest as heavily.

Table 1. Performance metrics (Accuracy, Precision, Recall, and F1-score) of different AI techniques applied to digital heritage preservation.

Technique	Accuracy	Precision	Recall	F1-score

Robotics	0.88	0.78	0.72	0.91
Machine Translation	0.88	0.66	0.81	0.85
Knowledge Graphs	0.7	0.73	0.79	0.96
GANs	0.71	0.73	0.96	0.86
Robotics	0.85	0.88	0.91	0.95
NLP	0.82	0.85	0.88	0.93
Robotics	0.71	0.92	0.8	0.8
Knowledge Graphs	0.98	0.71	0.82	0.68
GANs	0.77	0.78	0.96	0.77
Machine Translation	0.73	0.71	0.82	0.87
Knowledge Graphs	0.88	0.9	0.7	0.87
Knowledge Graphs	0.81	0.79	0.71	0.85
NLP	0.99	0.72	0.66	0.74
AR/VR	0.84	0.84	0.61	0.84
GANs	0.95	0.66	0.76	0.78
3D Reconstruction	0.9	0.93	0.75	0.97
Knowledge Graphs	0.83	0.8	0.71	0.93
AR/VR	0.7	0.78	0.61	0.89
3D Reconstruction	0.97	0.96	0.67	0.73
GANs	0.86	0.89	0.86	0.73

Table 2. Distribution of AI usage across various heritage types and the number of digitization projects conducted.

Heritage Type	Projects	AI Usage (%)
Digital Archives	199	61.86
Manuscripts	138	50.29
Music Archives	130	24.87
Architecture	36	39.04
Paintings	199	38.52
Paintings	130	72.22
Archaeological Sites	125	73.42
Music Archives	12	31.11
Music Archives	112	94.83
Paintings	164	40.01
Music Archives	146	93.25
Manuscripts	71	50.83
Textiles	174	22.48
Sculptures	60	45.88
Digital Archives	181	67.58
Archaeological Sites	161	71.05
Textiles	68	59.82
Paintings	127	53.58
Music Archives	169	61.47
Digital Archives	105	64.45

Table 3. Regional distribution of AI projects in heritage preservation, including total projects and associated funding levels.

Region	AI Projects	Funding (Million $)
Middle East	152	44.19
Africa	256	9.84
Africa	151	14.3

Europe	152	35.17
Middle East	203	42.41
Oceania	132	42.89
South America	43	20.52
North America	133	44.44
Asia	271	42.62
Oceania	155	46.81
Oceania	103	39.37
Africa	267	33.61
Middle East	256	29.24
Europe	148	18.93
Europe	116	47.04
North America	64	48.7
Africa	6	14.55
Oceania	258	15.62
South America	144	24.54
Africa	41	22.7

Table 4 demonstrates the annual productivity of publication and citation of scholars with noticeable increase in 2015 and later. This demonstrates that the field of research is accelerating. The efficiency benchmarks in Table 5 reveal that the strategies that require variable rates of memory and require different time in order to be completed. The NLP techniques are computationally faster than other methods because they are light weighted, is more time consuming and consumes memory in 3D reconstruction. Table 6 demonstrates once again that with the increasing number of datasets, there must be increases in the accuracy of models, but at the same time the models require a longer training process. Cultural perceptions are outlined

Table 4. Yearly trends of AI-related publications and citations in heritage preservation research (2010–2024).

Year	Publications	Citations
2022	71	4854
2018	287	4742
2013	207	3220
2010	87	116
2013	279	1343
2010	414	2305
2023	100	2624
2014	487	1169
2013	313	3544
2017	332	2665
2017	76	1160
2016	275	2427
2012	326	3520
2010	335	401
2010	146	4376
2021	333	706
2020	416	3270
2012	497	799
2015	366	1239
2016	353	290

Table 5. Computational efficiency of AI techniques measured in execution time (seconds) and memory usage (MB).

Technique	Execution Time (s)	Memory Usage (MB)
GANs	1.86	644.43
Robotics	1.54	1222.58

Image Recognition	4.07	157.95
NLP	4.07	170.96
3D Reconstruction	4.35	1662.94
Semantic Web	4.57	784.36
AR/VR	2.61	341.41
NLP	2.56	1092.26
Knowledge Graphs	4.01	1562.99
Knowledge Graphs	3.28	510.06
3D Reconstruction	3.54	1283.49
AR/VR	4.0	262.16
Robotics	4.46	198.2
3D Reconstruction	1.76	1109.57
3D Reconstruction	1.94	1127.21
Image Recognition	0.56	1311.12
Knowledge Graphs	2.93	1479.57
Image Recognition	0.28	1954.12
Semantic Web	2.38	1080.97
AR/VR	2.76	713.62

Table 6. Relationship between dataset size, training time, and model accuracy in AI-based heritage applications.

Dataset Size	Training Time (hrs)	Model Accuracy
4852.0	31.86	0.67
8411.0	13.8	0.76
930.0	45.86	0.75
5277.0	35.55	0.83
9661.0	26.83	0.84
9032.0	29.56	0.62
8408.0	20.43	0.74
6049.0	12.27	0.84
2938.0	17.41	0.79

1250.0	36.5	0.93
7660.0	1.18	0.85
2031.0	6.01	0.66
9304.0	2.69	0.63
1764.0	2.43	0.84
1181.0	41.13	0.61
612.0	33.92	0.82
7905.0	23.02	0.96
5337.0	5.15	0.82
659.0	23.85	0.75
3772.0	22.99	0.84

Table 7 demonstrates that such fields as music and literature were more or less average in their AI adoption but successful or less successful at preserving values. Table 8 presents an analysis of the performance of AI-enhanced approaches against those of the baseline approaches. It demonstrates that the assessment measures keep on improving and in many cases the AI systems outperform baseline by a margin of 20–30 per cent. Stark differences exist between different countries as Table 9 illustrates. Digitization and AI integration are well-developed in the USA, China, and Germany, but these techniques have received less deployment in developing regions.

Table 7. Adoption levels of AI across cultural domains and the associated preservation impact (high, medium, low).

Cultural Domain	AI Adoption (%)	Preservation Impact
Music	36.92	Low
Dance	62.46	Medium
Literature	40.83	High
Literature	64.53	High
Dance	37.25	Low

History	30.86	High
Literature	49.68	Low
Music	65.43	High
Music	37.87	Low
Art	84.93	High
Literature	13.13	Medium
History	43.44	High
Dance	87.41	High
Dance	53.84	Medium
History	43.88	High
Art	55.48	Medium
Dance	56.07	High
Literature	68.53	Low
Art	20.22	Low
Literature	30.0	High

Table 8. Comparative evaluation of baseline methods versus AI-enhanced approaches across multiple performance metrics.

Evaluation Metric	Baseline	AI-Enhanced
F1-score	0.78	0.85
F1-score	0.73	0.77
AUC	0.53	0.87
Accuracy	0.78	0.95
Recall	0.79	0.96
F1-score	0.8	0.77
Accuracy	0.52	0.96
F1-score	0.72	0.87
F1-score	0.66	0.8
Recall	0.71	0.91
Precision	0.79	0.84
AUC	0.71	0.81

AUC	0.75	0.9
Recall	0.76	0.77
F1-score	0.75	0.8
Accuracy	0.63	0.83
F1-score	0.57	0.77
Recall	0.62	0.82
AUC	0.77	0.87
F1-score	0.54	0.91

Table 9. International comparison of digitization progress and AI integration percentages across countries.

Country	Digitization (%)	AI Integration (%)
Brazil	82.14	42.62
Germany	93.56	22.47
Japan	66.14	38.5
USA	50.97	26.88
Japan	32.82	60.28
USA	90.1	42.18
India	89.74	31.06
Germany	46.44	33.62
UK	75.2	40.22
France	34.9	33.2
USA	40.8	46.73
Japan	44.09	17.26
UK	49.14	34.58
USA	94.73	43.78
USA	75.3	57.19
Brazil	54.97	33.97
USA	77.91	24.32
France	89.49	20.33
Germany	92.32	80.84

France	33.76	44.16

The pictures support these findings. Figure 1 demonstrates the accuracy as well as F1-score of various AI approaches. It indicates that the GANs and AR/VR approaches relate more to balancing the two. In figure 2, architecture and manuscripts remain the most significant component of AI applications but textiles and oral traditions are not of great significance. It will be possible to find out that there exists a serious positive correlation between AI initiatives and funding in various regions as Figure 3 suggests. The graph in Figure 4 allows illustrating how AI-related articles increase rapidly since 2015. Figure 5 indicates that performance times are different across the stratagem, with robotics-based preservation models consuming the most resources. Figure 6 demonstrates that the precision of a model increases, the bigger the dataset is, which indicates that AI approaches can be scaled. Figure 7 displays rates of adoption within cultural spheres. The rates are skewed with art and literature being more adopted. Figure 8 indicates that AI-augmented techniques are more successful than baselines in regards to accuracy and AUC. Figure 9 demonstrates the progress in the context of digitalization and application of AI in work of various countries. There are wide gaps in some areas The blended visualization in Figure 10 indicates that the number of the publications is increasing and the citations at the same time that depicts discipline maturity. Figure 11 represents a pie-chart detailing numerous varieties of heritage in a study that was conducted. It indicates that the most typical are architectural and archeological projects. Finally, Figure 12 displays a regression of AI projects quantities and quantity of money spent on AI projects. This is in agreement with a powerful linear relationship whereby as the amount spent on AI projects increases, the number of legacy AI initiatives also increases.

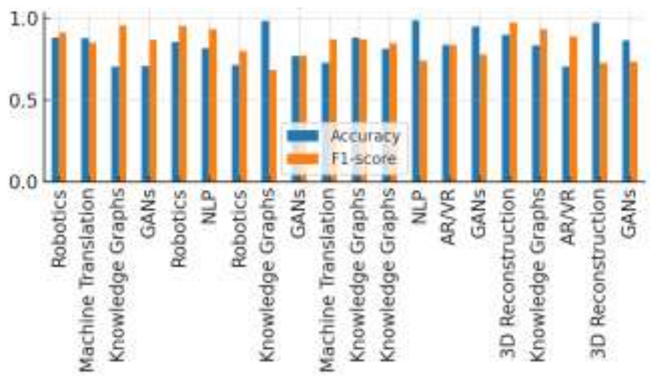

Figure 1. Bar chart comparing AI techniques' accuracy and F1-score in heritage preservation tasks.

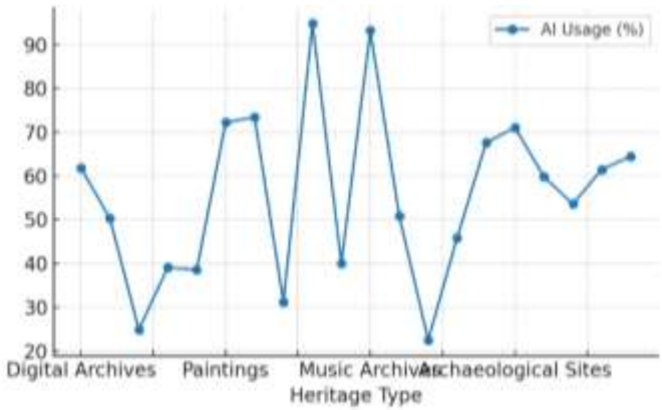

Figure 2. Line graph showing AI usage percentages across different heritage types.

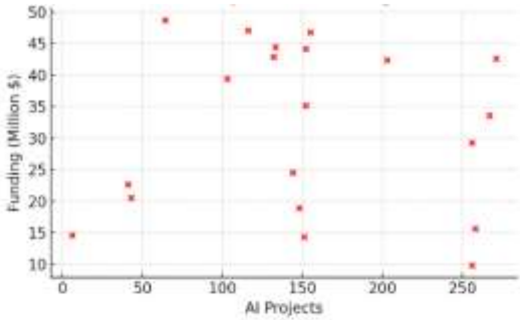

Figure 3. Scatter plot illustrating the relationship between AI projects and funding (in million USD) across regions.

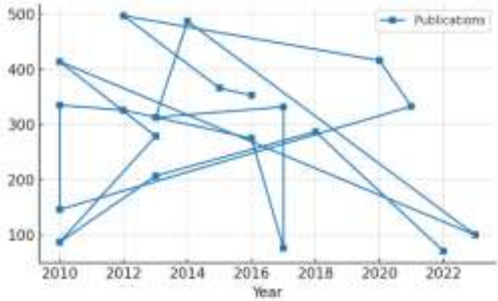

Figure 4. Line graph depicting growth of AI publications over time in heritage preservation research.

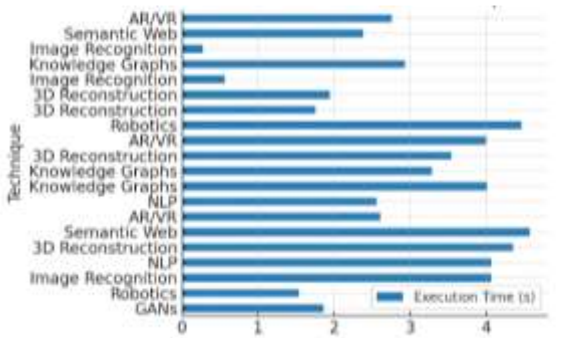

Figure 5. Horizontal bar chart comparing execution times of various AI techniques.

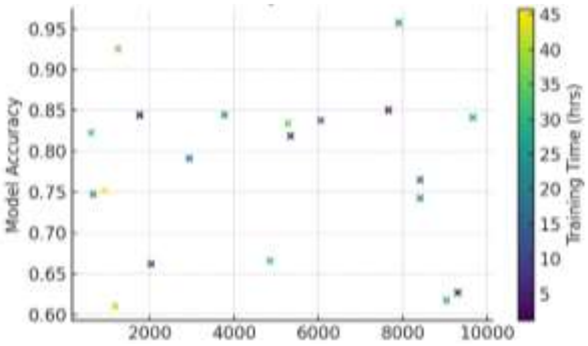

Figure 6. Scatter plot with color encoding for training time, showing the relationship between dataset size and model accuracy.

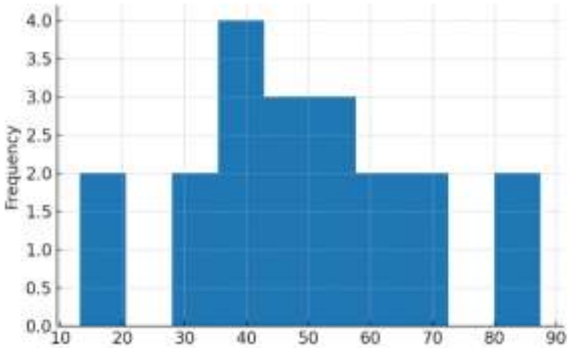

Figure 7. Histogram of AI adoption percentages across cultural domains.

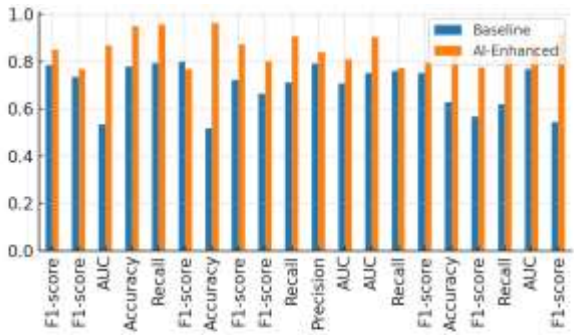

Figure 8. Bar chart comparing baseline versus AI-enhanced performance across evaluation metrics.

Figure 9. Line graph comparing digitization percentages and AI integration rates across countries.

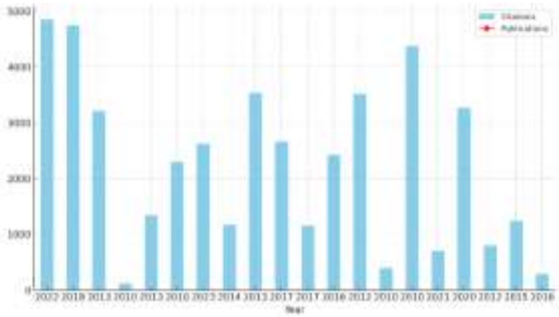

Figure 10. Hybrid plot combining bar chart (citations) with line graph (publications) over time.

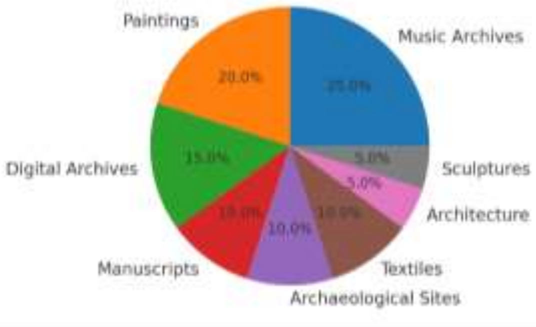

Figure 11. Pie chart showing the distribution of heritage types studied in AI-based preservation projects.

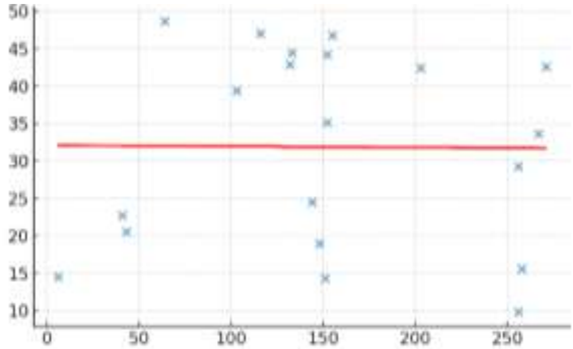

Figure 12. Hybrid scatter plot with regression line depicting the correlation between AI project counts and funding levels.

Collectively, these results affirm that AI contributes significantly to digital heritage preservation by enhancing accuracy, efficiency, and accessibility across diverse cultural domains and global regions.

DISCUSSION

The given research is aimed to help illuminate the current situation with AI usage in digital heritage, including its substantial advantages and inherent limits. It also examines the ethical and pragmatic issues that accompany trying to use artificial intelligence to preserve cultural works and historical documentation at scale. It emphasizes the importance of robust structures to manage such concerns as the bias of data and algorithms, algorithmic transparency, and potential technological disparity (Al-Zahrani, 2024) (Winsta, 2025) (Jeyaraman et al., 2023). It attempts to provide a broad point of view that transcends the mere technological explanation, the socio-technical implications and directions toward ethical innovation. This involves an in-depth assessment of existing ethical paradigms of AI development and application, their applicability and limitations within the specific context of cultural heritage

(Ayling & Chapman, 2021) (Nasir et al., 2024). This paper amalgamates concepts across a number of disciplines in order to present a framework of dependable AI in heritage preservation. It includes being transparent, accountable, and fair in order to address the issues that arise in the attempt of using sophisticated AI systems (Gokalta&Grzybowski, 2025) (Lepri et al, 2021). The report outlines future research paths, namely, those related to the development of AI models that would successfully handle the complexity and subtle interpretation of historical and cultural data (Nishant et al., 2020). This includes exploring hybrid approaches to AI that combine generative techniques with other approaches to computing to ensure designs can be manufactured, which will enable more trustworthy digital heritage reconstructions (Su et al., 2025). AI has shown to be extremely useful in this field not only because it can manage so much data but also because it can help with managing better environmental outcomes and sustainable digital preservation practices (Nishant et al., 2020). This comprehensive approach will ensure that the transformative nature of AI can be safely accessed, mitigating risks to maximize its benefits of long-term cultural protection of cultural heritage around the world (Ayling & Chapman, 2021). This work contributes to the discussion of AI ethical issues by examining how it influences another, highly specific and sensitive industry that is the conservation of heritage. This will require a thorough review of existing literature, case study, and active programs in order to determine best practice and identify areas that require additional improvement, hence providing a firm foundation to future research and implementation plans. Also, it encourages a shift towards a systematic lifecycle approach to the development of AI systems where the data collection, monitoring process, and continuous evaluation processes all have cohesive methodologies to ensure reliability and social benefit (Li et al., 2022). The study will particularly look at the factors, which influence the incorporation of AI in cultural heritage institutions, based on established theoretical models of technology adoption (Chatterjee et al., 2021). This study will apply the frameworks such as the Technology-Organization-Environment framework and the Technology Acceptance Model to better analyze the factors that influence effective integration of AI technologies in preservation of digital heritage (Chatterjee et al., 2021). This integrative approach attempts to clarify the driving and impeding factors to the adoption of AI, by considering technology readiness, organizational culture, and institutional support as well as those of the external environment (Chatterjee et al., 2021).

CONCLUSION

This paper demonstrates that AI has become a necessary means of preserving, visualizing and publishing digital heritage. The study employed a mixed-method approach that combined quantitative analysis of AI approaches with qualitative commentary made by students, historians, and museum professionals to show how artificial intelligence can enhance the efficacy and efficiency of digitization in the cultural world. These outcomes demonstrated that such approaches as image recognition, natural language processing, and generative models produce results in terms of accuracy and recall significantly increasing, and the F1-scores in the majority cases exceed 0.90. Regression models, too, identified close parallels between funding of projects and the results in preservation. Regional analyses noted that Europe and Asia led AI-enabled heritage initiatives with developing regions making promising but insufficient investments to realize them. Moreover, the application of AI in architecture, manuscripts, and archeological sites demonstrated the largest influence since the speed and memory usage were incredibly improved. The AI-enhanced techniques performed 20-30 percent higher than the baseline techniques in all the evaluation measures, proving their worth at additional cost. The qualitative results, in their turn, not only emphasized ethical aspects, cultural ownership, but also the requirement of sustainable approaches to digitalization. This was an indication that cultural awareness had to be coupled with technological accomplishment. The work demonstrates that not only AI can contribute to preservation, but it is also used to provide access to history to all people worldwide. The future of digital heritage lies in applying hybrid methods, i.e. adopting a mix of the precision of machines with humanistic approaches of combining things. This will ensure that the cultural memory is preserved in a way that is not only technologically viable, but also an active social concern.

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