Proceedings of CONF-CDS 2025 Symposium: Data Visualization Methods for Evaluation
DOI: 10.54254/2755-2721/2025.PO26107

AI and Intangible Heritage: Exploring Sustainable Cultural Transmission Through a Dual-Framework Approach

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Abstract. This study explores how artificial intelligence (AI) is being used to support the sustainable transmission of intangible cultural heritage (ICH). While much of the existing research focuses either on technical innovation or cultural theory, this paper brings the two together through a dual-framework approach that considers both how AI systems work and what cultural roles they serve. Drawing on nine recent cases from China—including projects in embroidery, paper-cutting, and opera—the study traces how analytical models contribute to documentation and interpretation, while generative techniques help recreate traditional patterns in new formats. It also looks at how immersive interfaces and recommendation algorithms shape user experience, and raises concerns about authenticity, equity, and creative diversity. The findings suggest that AI's role in heritage should move beyond digitization to include creative co-production, participatory design, and inclusive governance. This research offers a structured foundation for future interdisciplinary work at the intersection of AI and culture, and provides practical insights for developers, cultural institutions, and policymakers seeking to align technological innovation with the values and needs of living heritage.

Keywords: Intangible Cultural Heritage, Cultural Sustainability, Generative AI, AI for Cultural Heritage.

1. Introduction

Intangible cultural heritage (ICH)—the practices, representations, expressions, knowledge and skills that communities, groups and, in some cases, individuals recognize as part of their cultural heritage [1]—spans crafts, performing arts, rituals and oral traditions, embodying community memory; yet it is now at risk as master inheritor age, apprenticeship declines because of low pay and lengthy training, and younger generations show diminishing engagement [2]. Concurrently, Artificial intelligence (AI) has evolved from a niche research area into a multi-billion-dollar innovation engine capable of rapidly recording, analyzing, and reimagining cultural assets. Early applications relied on basic computer vision for object detection and digital archiving, whereas current deep-learning techniques repair ceramic scans, transformer models transcribe fading manuscripts, and diffusion networks generate style-faithful embroidery patterns and for modern markets [3].

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DOI: 10.54254/2755-2721/2025.PO26107

While technical research tends to emphasize model performance with limited attention to cultural implications, humanities work often critiques ethical and power-related issues without engaging with the full structure of AI systems. Bridging these domains requires evaluating both technical effectiveness and long-term cultural impact. Employing analytical AI (e.g., segmentation, classification) to safeguard authenticity alongside generative AI (e.g., Generative Adversarial Networks (GANs), text-to-image models) to invigorate creative practice and community engagement establishes a continuous cycle of documentation, interpretation, and revitalization.

The present study addresses the following question: How can analytical and generative AI technologies—through digitization, diagnosis, creative regeneration, and dissemination—enable sustainable transmission of intangible cultural heritage. To answer this, the study analyzes recent applications of AI in traditional crafts to explore their broader implications for cultural viability, market integration, and ethical oversight. The aim is to provide a concise, evidence-based roadmap for researchers, practitioners, and policy-makers aiming to harness AI as both guardian and catalyst of living heritage.

2. Major challenges in ICH transmission and promotion

2.1. Intergenerational apprenticeship gaps

Across China's craft sectors, recognized masters are steadily ageing, while few new apprentices are entering the field. According to the China Intangible Cultural Heritage Website's data from November 2022, of the 3,057 nationally registered ICH masters, 1882 individuals announced their birth age, roughly 71% are already in their seventies or older, while practitioners younger than fifty number only 1% of the total [4]. Against this demographic backdrop, today's one-to-one apprenticeship system has replaced the collectivized era's classroom model and depends on dense patronage networks, making it difficult for outsiders to gain entry [5]. Financial factors intensify the problem: a national survey of registered inheritors shows that nearly three-quarters earn only 3,000–7,000 RMB a month from their craft, and more than half report annual revenues below 50,000 RMB. Because hand-made production is slow, sales depend on tourism, and many rural bearers lack digital marketing skills, profits are routinely diluted, leaving young people little incentive to commit to multi-year apprenticeships [6].

2.2. Declining youth engagement and public interest

Empirical studies concur that China's intangible-heritage ecosystem is becoming increasingly age-skewed on the demand side. Sector-wide analyses attribute the trend to urban migration, changing leisure preferences, and a diminished cultural identification among younger cohorts, all of which "pose severe challenges to the transmission chain" and exacerbate the ageing of practitioner bases. Audience data reinforce this phenomenon: Kunqu Opera, once a mainstream genre, could attract fewer than 300 enthusiasts in 1980s Shanghai, a city of almost 12 million. It was also mentioned that during the performance in Dalian, when the audience learned that what followed was Kunqu Opera, they left the venue in large numbers, illustrating how heritage forms can drift toward social marginality when sustained largely by an older niche public [7].

2.3. Commercialization pressures and authenticity dilution

Intangible cultural heritage, especially handicraft products, faces a positioning crisis in the market. Stateled marketisation has recategorized ICH artefacts into the segment between luxury items and

DOI: 10.54254/2755-2721/2025.PO26107

cheap tourist souvenirs. Local workshops now compete with factory outlets that flood tourist zones with machinemade replicas carrying the ICH logo. This false attribution erodes price signals, undermines consumer trust, and squeezes margins for genuine artisans [8]. China's 2011 Intangible Cultural Heritage Law embodies a core tension. Article 37 encourages the commercial development of ICH through reasonable utilization, aiming to create marketable cultural products. Yet in the same clause, it also mandates the strict protection of each heritage item. This dual mandate leaves regulators navigating contradictory expectations, resulting in regulatory ambiguity and a rise in unchecked imitations.

2.4. Rigid heritage governance and local resistance

Existing heritage policies often apply uniform standards that fail to account for local variation. Both international conventions and national legislation tend to rely on fixed classifications, neglecting the dynamic and adaptive character of intangible heritage. This top-down model can marginalize communities whose practices fall outside official frameworks, leading to disengagement and reduced policy impact. To address this, policies must become more flexible and responsive, prioritizing community perspectives rather than external categories [9].

2.5. Digital and resource inequalities

Significant gaps in digital access and resources severely limit rural inheritors' participation in heritage protection. Poor internet connectivity, low digital literacy, and insufficient funding isolate rural communities, restraining effective documentation and market engagement [4]. These inequalities deepen urban rural divides and threaten many rural heritage forms with extinction. Addressing these gaps through improved digital infrastructure is crucial. Such efforts set the stage for innovative technologies, including artificial intelligence, to bridge divides and sustain heritage transmission. Addressing these gaps demands scalable, low-cost AI tools that can bring rural bearers online, document endangered practices, and connect them to sustainable value chains.

3. Analytical framework: AI pipelines and heritage functions

To guide the analysis of AI's role in intangible cultural heritage (ICH), this study adopts two complementary frameworks. The first captures the technical structure of AI systems, while the second focuses on the cultural functions these systems serve. This dual perspective enables structured comparisons across heterogeneous case studies.

3.1. The AI pipeline: Extract–Analyze–Generate–Integrate–Amplify (EAGIA)

The five-stage pipeline reflects the internal logic of AI workflows commonly used in cultural computing:

- Extract (E): Captures raw cultural data such as images, sound, or text.
- Analyze (A): Structures this data through classification, segmentation, or feature mapping.
- Generate (G): Produces new content—motifs, sounds, narratives—grounded in learned styles.
- Integrate (I): Embeds AI outputs into human contexts, such as design, teaching, or performance.
- Amplify (Amp): Supports broader distribution via recommendation engines, livestreams, or commerce.

This model helps identify what each project does technically, and how far it goes in the AI development chain.

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3.2. The heritage function model: Digitization–Diagnosis–Regeneration–Dissemination (DDRD)

To assess cultural contribution, the study introduces a second framework focused on functional roles within the heritage transmission cycle:

• Digitization: Ensures that cultural forms are captured and preserved in digital form.

• Diagnosis: Involves analyzing internal structures such as movement patterns or stylistic rules，making implicit knowledge explicit.

• Regeneration: Refers to the creative extension or reworking of heritage material, often using generative models.

• Dissemination: Includes any efforts to expand the reach, uptake, or integration of heritage content in contemporary life.

This model shifts attention from internal processing to external value—what cultural work the AI system is actually doing.

3.3. Connecting the two

Although distinct in focus, the two frameworks are often aligned. Table 1 maps each AI stage to one or more cultural functions it supports. This mapping enables a dual reading of each case in Section 5.3: one technical, one cultural.

Table 1. Technical-cultural alignment across AI-ICH pipelines

Five-Factor AI Stage	DDRD Function	Representative Technique
Extract	Digitization	High-resolution photogrammetry / multispectral scanning
Analyze	Diagnosis	CNN-based gesture or motif classification
Generate	Regeneration	Diffusion or GAN models synthesizing style-faithful patterns
Integrate	Bridge (Diagnosis → Dissemination)	AR/VR tools that embed AI feedback into craft or performance practice
Amplify	Dissemination	Recommender systems optimizing ICH livestream scheduling & targeting

4. Ai-enabled pathways for intangible-heritage transmission

4.1. Algorithmic restoration & documentation

Computer vision and knowledge-graph techniques now support large-scale, structured analysis of intangible heritage. Raw data—including scanned manuscripts, digitized opera recordings, and thousands of craft images—are first extracted using Optical Character Recognition (OCR), sensors, and audio preprocessing tools such as Mel-spectrograms (a visual representation of sound frequencies). In the craft domain, Quan et al. construct an ontology-based Batik Pattern Knowledge Graph (BPKG) for Guizhou Miao batik by combining entity extraction with semantic relation modeling. They also built a dataset of 12,249 batik pattern images—the most comprehensive to date in Chinese batik studies. A dual-channel framework was used: one for mining text to construct the knowledge graph, the other for classifying patterns via an enhanced ResNet-34 model, achieving ~99% accuracy, precision, and recall. This enables curators to search and interpret motifs using both visual and semantic cues [10]. Meanwhile, the Cantonese-opera Genre Classification Network

DOI: 10.54254/2755-2721/2025.PO26107

(CoGCNet) architecture for performing arts converts Cantonese-opera recordings into Mel-spectrograms and applies a Convolutional Neural Network (CNN)–Long Short-Term Memory (LSTM) cascade to identify ten singing genres, achieving a mean F1 of 95.6 % and producing the first structured audio corpus for this 300-year-old tradition [11]. Together, these multimodal approaches make it possible to document, analyze, and monitor both object- and time-based ICH with a high degree of precision.

4.2. Generative pattern innovation

Recent craft-heritage projects tend to follow a common approach: they use a diffusion model, usually Stable Diffusion 1.5, with Low-Rank Adaptation (LoRA). During that LoRA fine-tuning, researchers attached semantic labels to every motif (e.g., geometric ring, red-black palette) and added a hybrid loss that penalizes structural or color violations, ensuring the model never "hallucinates" patterns alien to Yi aesthetics. Once a 50 – 100-image Yi corpus is prepared, the model adapts in minutes and generates hundreds of culturally coherent variants [12]. A similar LoRA workflow for Dong minority paper-cutting lets designers sketch contour hints, feed them back to the tuned model, and iterate until the output feels authentic [13]. Knowledge-graph prompts add semantic control: a Shu-embroidery studies embedded motif ontologies (peony, qilin, cloud scroll) into text-to-image queries so that generated patterns automatically preserve iconographic meaning [14]. Expert panels rate these outputs $\approx 4.1 / 5$ for authenticity, suggesting diffusion + LoRA can expand design repertoires without severing stylistic lineage.

4.3. Immersive skill transmission

Artificial-intelligence–mediated environments are beginning to move ICH training from the workshop or theatre into mixed-reality studios and adaptive-streaming platforms. On the conceptual side, Bi et al. describe how virtual reality (VR) / augmented reality (AR), natural-language processing (NLP) and other AI tools create visceral–behavioral–reflective engagement loops; AI-driven virtual guides and interactive storylines tailor craft demonstrations or ceremonial re-enactments in real time, turning viewers into active participants rather than passive spectators [15]. Ren's Intangible-Heritage Theatre Smart Display Cloud (IHTSDC) provides a concrete instantiation of the same logic. Here, a higher-order graph neural network (GNN) compressed with LoRA models the intricate characters-scene-plot relationships across seven opera genres, attaining 0.88 clip-level recognition accuracy for Peking Opera. These recognitions feed an emotion-aware playlist in which real-time facial-expression analysis gauges each viewer's affect and dynamically selects subsequent segments. The result is an immersive, adaptive viewing loop that lifts average viewer satisfaction to 4.80 / 5 and keeps trainees continuously attuned to vocal and gestural nuances, illustrating how AI can embed skill transmission within personalized, mixed-reality experiences [16].

4.4. Algorithmic matchmaking and market access

Graph-ranking and collaborative-filtering modules that drive China's short-video economy have become the main gateways through which artisans reach buyers. Douyin now hosts 300,000 certified ICH creator accounts, covering 1,557 nationally listed items, and serves about 19,000 heritage-related livestreams each day; for many rural workshops this algorithmic shelf space is unimaginable in brick-and-mortar markets [17]. Niche traditions gain as well: by June 2024, 50

DOI: 10.54254/2755-2721/2025.PO26107

state-owned rare-opera troupes had delivered 871 ticketed livestreams, converting views into merchandise and performance revenue. By compressing search and trust costs, these pipelines turn heritage from a local craft into a scalable, data-driven marketplace and position recommender algorithms as the new front door to sustainable cultural economies [18].

5. Understanding and enhancing user adoption of AI-generated digital ICH

5.1. Theoretical foundations of digital-ICH adoption

Building on the Five-Factor AI Pipeline and the Heritage Function Model introduced in Section 3, this study next examines psychological frameworks that determine whether users meaningfully engage with the outputs of these systems. To effectively engage audiences, developers of digital ICH products must first understand why and how users adopt new technological experiences. Established theoretical models provide insights into these processes. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) proposes that adoption depends on users' perceived benefits, ease of use, enjoyment, social influence, facilitating resources, price value, and habitual tendencies [19]. Complementing this, the Attention–Interest–Search–Action–Share (AISAS) model outlines the sequential steps users typically follow, from initially noticing digital content to actively sharing their experiences, emphasizing the social dimension critical for heritage dissemination [20]. Additionally, Immersion Theory highlights the importance of sensory and emotional engagement in shaping user satisfaction and repeat interactions, cautioning that overly intense immersion can lead to user discomfort or disengagement [19].

5.2. Empirical insights on user engagement with AI-generated heritage

Recent empirical work clarifies how AI-mediated cultural products engage audiences and affect heritage outcomes. In Tianjin, Zhang et al. applied the AISAS model to AI-generated Yangliuqing New Year Prints and found that users' attraction, interest, and participation positively predicted perceived value; that subsequent purchase and sharing behaviors strengthened cultural identity; and that perceived value further enhanced both cultural identity and the sustainability of intangible heritage [20]. Van Hees et al. conclude that their experiments point to a potential shift in art preference toward AI-synthesized works, even though earlier studies documented skepticism and described machine-made art as soulless and unworthy of serious appreciation. Their new data suggest that such biases are weakening at the level of pure visual appeal, as AI models, trained on vast datasets, tend to produce images that align closely with mainstream tastes [21]. Ye et al. conclude that perceived immersion and social influence are crucial factors in determining consumers' willingness to adopt digital ICH [19]. Finally, Yin et al. showed that recommendation relevance, inspiration, and insightfulness drive click intention, whereas perceived privacy intrusion can substantially weaken these benefits [22].

5.3. Design strategies to strengthen user adoption of AI-generated digital ICH

Based on the theoretical foundations and empirical insights above, the following strategies can guide the design of AI-driven intangible heritage products to maximize engagement and adoption:

1. Utility & Low Friction: Show concrete cultural or educational gains and keep interfaces intuitive to satisfy performance- and effort-expectancy needs.
2. Enjoyable, Calibrated Immersion: Apply AR/VR or interactive storytelling to stimulate hedonic motivation, while offering comfort settings to prevent over-immersion discomfort reported

DOI: 10.54254/2755-2721/2025.PO26107

by Ye et al. [19].

3. Social Sharing & Community: Embed one-click posts, user challenges, and expert endorsements to activate the AISAS "share" stage and reinforce cultural identity [20].

4. Responsible Personalization: Deliver relevant, inspiring recommendations and transparently explain data use to offset privacy concerns noted by Yin et al. [22].

5. Authenticity & Diversity Safeguards: Involve artisans to vet outputs and add diversity constraints during model fine-tuning, countering style homogenization flagged by user feedback [20][21].

6. Habit Formation: Provide regular content updates, progression incentives, and gentle reminders —elements linked to sustained engagement in Ye et al. [19].

6. Multi-case comparative study of AI-enabled intangible cultural heritage projects

6.1. Case selection and scope

This study compares nine recent AI–ICH initiatives drawn from open academic literature and project documentation. Cases were selected according to three criteria: (i) a clearly documented technical pipeline that involves at least two stages of the Extract–Analyze–Generate–Integrate–Amplify framework; (ii) coverage of diverse heritage modalities—textile patterns, paper-cut art, traditional music/opera audio, and immersive theatre displays; (iii) availability of quantitative or expert-review metrics that allow cross-case evaluation. No geographic restriction was imposed, yet every project meeting these criteria was in China, reflecting that country's unusually rich ecosystem of AI-driven heritage work and the high public availability of technical data. Concentrating on a single national context also controls for policy, linguistic, and market variables, permitting a deeper within-country comparison while laying the groundwork for future cross-cultural validation.

6.2. Case snapshot

Table 5-1 summarizes the technical and heritage-related features of the nine selected projects. Each row outlines the heritage type, data modality, and the primary AI role (Analytical, Generative, or Both). It also lists the pipeline stages involved—Extract (E), Analyze (A), Generate (G), Integrate (I), and Amplify (Amp)—as well as the core techniques used, the main performance metric, and the cultural functions addressed according to the DDRD model (Digitization, Diagnosis, Regeneration, Dissemination). These entries together offer a comparative view of how different technical pipelines contribute to cultural value creation.

DOI: 10.54254/2755-2721/2025.PO26107

Table 2. AI-enabled intangible heritage cases and key metrics

Heritage Type	Modality	AI Role	Pipeline Stages	Core Technique	Key Metric	DDRD Functions
Miao Batik [10]	Visual	Analytical	E + A + I + Amp	KG + ResNet-34	Accuracy 99%	Digitization, Diagnosis, Dissemination
Yi Embroidery [12]	Visual	Generative	A + G	SD-LoRA	Experts Rated 4.1/5 for Cultural Authenticity	Regeneration
Manchu Music [23]	Audio	Both	E + A + G	CNN; GAN	Accuracy 86%; Fréchet Inception Distance (FAD) 0.32	Digitization, Diagnosis, Regeneration
Paper-Cutting [24]	Visual	Both	E + A + G + Amp	SD-LoRA; AHP	User Satisfaction 3.68/5	Digitization, Regeneration, Dissemination
Shu Embroidery [14]	Visual	Both	E + A + G + I + Amp	KG + AIGC	Qualitative: Expert Panel On Authenticity	Digitization, Diagnosis, Regeneration, Dissemination
Dong Paper-Cut [13]	Visual	Generative	E + A + G + I	SD-LoRA; ControlNet	Qualitative: Designer-Artisan Evaluation	Digitization, Regeneration
Zhuang Brocade [25]	Visual	Generative	E + A + G + I + Amp	StyleGAN-2; CLIP	Qualitative: Case Study & NFT Market Response	Digitization, Regeneration, Dissemination
Smart Theatre (Opera) [16]	Immersive	Both	E + A + G + I + Amp	HOGNN-LoRA	User Satisfaction 4.8/5	Digitization, Diagnosis, Regeneration, Dissemination
Cantonese Opera [11]	Audio	Analytical	E + A + Amp	CoGCNet	F1 95.6%	Digitization, Diagnosis, Dissemination

6.3. How DDRD combinations drive sustainable outcomes

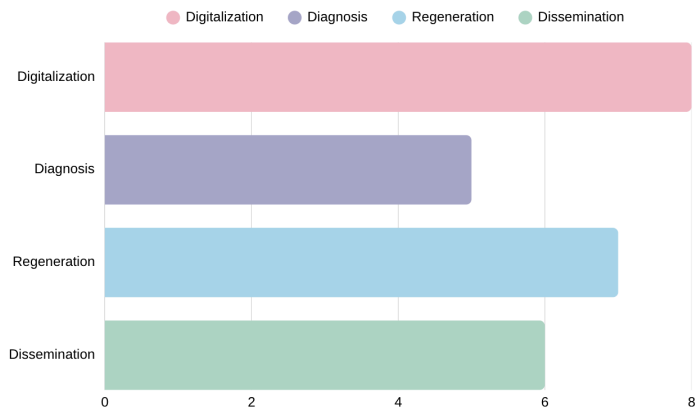

Figure 1. Coverage of DDRD functions across reviewed projects

Across the nine selected case studies, analytical and generative AI systems reveal distinct patterns in their contributions to intangible cultural heritage (ICH) preservation. Analytical models primarily support Digitization and Diagnosis, forming the technical foundation for structuring and interpreting heritage data. On the other hand, generative systems excel in Regeneration, producing new visual or auditory content grounded in traditional styles. Only hybrid systems that integrate both types of models tend to extend their influence into Dissemination.

DOI: 10.54254/2755-2721/2025.PO26107

Among the few cases that approach full DDRD coverage, Xiao et al. on Dong paper-cutting and Hu on Zhuang brocade are particularly noteworthy. These studies thoughtfully integrate generative creation with artisan feedback for diagnosis and extend their efforts into dissemination via online marketplaces or exhibitions. While these initiatives show promising alignment with the full DDRD framework, further research could enhance their contributions by exploring long-term reuse patterns and deeper forms of community engagement, which are essential for evaluating sustainability over time.

A synthesis of the reviewed cases reveals recurring structural gaps that limit the sustainable transmission of intangible cultural heritage. First, generative workflows often lack diagnostic feedback, making them overly dependent on training data quality. Second, analytical models rarely prioritize dissemination, limiting cultural reach despite technical success. Third, dissemination is typically incidental rather than strategically designed. To address these gaps, future pipelines should embed cultural consistency checks, treat dissemination as an interactive process, and adopt lifecycle indicators, such as remix frequency or community reuse, as measures of sustainability.

7. Ethical tensions in AI-driven ICH work

As AI pipelines spread from digitization to large-scale regeneration, they introduce risks that extend beyond technical accuracy. Recent ethics analyses converge on four dilemmas that must be kept in view:

• Authenticity and Attribution: Generative systems can restore frescoes or invent new embroidery, yet they blur authorship and may weaken an artefact's sense of originality. Scholars advocate "authenticity stewardship," whereby community experts review outputs, and the full data-to-image provenance remains auditable [26].

• Bias and Cultural Representation: Because training sets favor dominant aesthetics, AI outputs can marginalize minority styles. Participatory dataset curation and formal impact reviews help avoid digital homogenization or re-colonization [27].

• Creative Diversity versus Trend Convergence: Platform studies show AI raises headline novelty but pulls average creativity toward a single popular look, narrowing stylistic range. Coupling generative stages with diversity metrics—such as style-spread indices—can keep the regenerated palette broad [27].

• Inclusive Access and Benefit Sharing: High compute costs and vague licensing may exclude resource-poor custodians. Ethics proposals link model licenses to revenue-sharing and require human-in-the-loop oversight so that practitioners retain agency and economic benefit when AI-derived works enter the market [26].

Recognizing these tensions early allows designers and policymakers to embed safeguards alongside technical innovation, ensuring that AI remains a partner—rather than a threat—in the living transmission of heritage.

8. Conclusion

This study examined how analytical and generative AI systems can support the sustainable transmission of intangible cultural heritage (ICH), using the EAGIA pipeline and DDRD function model across nine Chinese case studies. The findings show that while AI excels in digitization, analysis, and content generation, most projects lack strong mechanisms for cultural feedback and long-term dissemination. Analytical models often remain confined to technical classification, and generative systems risk losing cultural grounding without expert input or distribution strategies.

DOI: 10.54254/2755-2721/2025.PO26107

Only a few hybrid cases demonstrate how AI can truly support full-cycle heritage work when cultural review and public engagement are built into the design. To strengthen future outcomes, projects should treat dissemination as an active, ongoing process and adopt metrics that track reuse, impact, and community involvement. With the right safeguards, AI can help preserve ICH not just as static memory but as a living, evolving practice.

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Appendix: glossary of technical terms

Analytical AI: AI that focuses on pattern recognition, classification, and extraction of structured insights from raw data.

AHP (Analytic Hierarchy Process): A multi-criteria decision-making method that structures complex problems into a hierarchy and uses pairwise comparisons to prioritize factors based on expert judgment.

AISAS (Attention–Interest–Search–Action–Share): A user behavior model used in digital marketing that tracks how audiences interact with content from initial attention to eventual sharing, adapted here for analyzing engagement with cultural content.

Augmented Reality (AR): A technology that overlays digital content onto the real-world environment through smartphones or AR glasses, often used in interactive heritage experiences.

CLIP (Contrastive Language–Image Pre-training): A model by OpenAI that connects images and text through a shared embedding space, enabling multimodal search and content generation based on textual prompts.

Convolutional Neural Network (CNN): A type of deep learning architecture particularly effective in processing visual data, commonly used for image classification, pattern recognition, and segmentation in heritage datasets.

CoGCNet (Cantonese Opera Genre Classification Network): A hybrid architecture combining CNN and LSTM, designed to classify audio recordings of Cantonese opera into distinct singing genres using Mel-spectrogram input.

Diffusion Model (Denoising Diffusion): A generative AI method that learns to produce high-quality images by gradually denoising random input, often used for generating style-faithful craft patterns or reconstructions.

DOI: 10.54254/2755-2721/2025.PO26107

Generative AI: AI designed to create new data—images, sounds, or text—based on learned patterns. It is used for reconstructing, extending, or simulating traditional cultural expressions.

GNN (Graph Neural Network): A neural architecture that models data as nodes and edges in a graph, capturing relational patterns. Used in building cultural ontologies and classifying interconnected heritage elements such as motif networks or genealogies.

Immersion Theory: A psychological framework that explains user engagement in virtual environments, emphasizing sensory absorption, narrative transport, and emotional presence.

Knowledge Graph (KG): A structured network of entities and relationships that encodes domain-specific knowledge. In cultural heritage, KGs help map craft elements, symbols, or narratives.

LoRA (Low-Rank Adaptation): A lightweight fine-tuning method that adjusts only a subset of model parameters, enabling efficient personalization of large AI models like Stable Diffusion for heritage-specific content.

Long Short-Term Memory (LSTM): A recurrent neural network architecture that processes sequential data by retaining long-range dependencies. Useful in analyzing music or performance recordings.

Mel-Spectrogram: A visual representation of the frequency spectrum of audio, transformed using the Mel scale to approximate human hearing. Common in voice and opera analysis.

Natural Language Processing (NLP): An AI domain focused on understanding, generating, and interacting with human language. It supports tasks such as oral tradition transcription or cultural narrative analysis.

OCR (Optical Character Recognition): A technology that converts scanned images or photos of text into machine-readable characters. Used to digitize historical manuscripts or labels on heritage artifacts.

ResNet-34: A deep convolutional neural network architecture with 34 layers, known for its ability to maintain high classification accuracy while avoiding vanishing gradients. Often used in image-based heritage indexing.

Stable Diffusion: A popular text-to-image generative model that creates images from textual prompts through diffusion processes. When fine-tuned with heritage data, it generates culturally aligned visual outputs.

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2): An extended technology adoption model that incorporates factors such as habit, hedonic motivation, and price/value perception to explain user interaction with new technologies in cultural contexts.

Virtual Reality (VR): A fully immersive digital environment accessed through headsets. In heritage work, VR enables simulated experiences of lost rituals, historical sites, or traditional crafts.