

Article

AI–Human Collaborative Interpretation (AHCI)—A Methodological Framework for Human–Machine Collaboration in the Visualisation and Aesthetic Evaluation of Complex Cultural Heritage

Liwen Zhang, Yiqi Liu, Jingya Li and Yuexi Dong * 

School of Architecture and Art, Beijing Jiaotong University, Beijing 100044, China

* Correspondence: 9888@bjtu.edu.cn

Abstract

This paper proposes the AI–Human Collaborative Interpretation (AHCI) human–machine collaboration methodological framework, offering a new research pathway for the digital interpretation of complex cultural heritage. The framework integrates multi-source data processing, formalised feature modelling, interpretable analysis and human–machine feedback mechanisms, translating the complex information of cultural heritage into an analysable and interactive structure. Building upon this, the *Tianlai.China* project serves as a case study for the multimodal data integration, aesthetic feature modelling and interactive visualisation of the *Illustrated Catalogue of Famous Porcelains Through the Ages*. The effectiveness of the collaborative mechanism is validated through expert–public–AI comparative experiments and human–AI feedback loop experiments. The main contributions of this paper include: proposing a methodological framework for human–machine collaboration in cultural heritage value assessment; constructing an interpretable formalised model of cultural features and a corresponding visualisation system; analysing the impact of AI explanations on expert cognition through empirical research; and exploring the transferability of this framework across different types of cultural heritage. Against this backdrop, the human–machine collaboration system developed by AHCI—comprising ‘data semantics–feature modelling–visual output–cognitive feedback’—possesses cross-domain applicability.

Keywords: human–machine collaboration; cultural heritage visualisation; explainable artificial intelligence; cultural computing; digital humanities; methodological framework



Academic Editor: Francesco Fontanella

Received: 27 April 2026

Revised: 2 July 2026

Accepted: 7 July 2026

Published: 11 July 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The interpretation of cultural heritage has long relied on expert experience and historical documents [1]; however, in situations where ‘there are images but no physical objects’ and where sources are incomplete, research faces significant challenges: aesthetic judgements are highly subjective, evaluation criteria are difficult to standardise, and the aesthetic logic implicit in the texts is hard to express and verify systematically. Taking the *Illustrated Catalogue of Famous Porcelains Through the Ages* (hereinafter referred to as the *Catalogue*) by the Ming Dynasty Chinese collector Xiang Yuanbian as an example [2], the *Catalogue* consists primarily of two-dimensional line drawings and subjective commentary; it lacks corroboration from physical artefacts and contains a large number of aesthetic judgements that are difficult to quantify. The interpretation of such cultural heritage is often constrained

by factors such as incomplete data, obscure terminology, excessive subjectivity, and an incomplete contextual framework. In this context, how to conduct a structured, comparable and interpretable analysis of complex cultural characteristics remains an issue that digital humanities research has yet to fully resolve [2–5].

In recent years, artificial intelligence has been widely applied to tasks such as image processing, text analysis and 3D reconstruction in the field of cultural heritage, demonstrating significant advantages in multi-source data processing and feature extraction [6]. However, current research remains primarily focused on the computation of visible features or semantic retrieval tasks, with insufficient attention paid to the in-depth understanding and visual interpretation of aesthetic and cultural significance [7,8]. At the same time, AI is often viewed merely as a tool within the cultural heritage sector; its analytical results lack interpretability and struggle to interact effectively with expert knowledge. Particularly in scenarios involving value judgements, AI outputs often lack interpretability regarding subjective aesthetic judgements and struggle to form interactive models that facilitate expert reflection. While AI can encode explicit cultural knowledge from training data, the tacit, context-dependent nature of aesthetic experience remains difficult to formalise [6]. External knowledge bases may partially address this, but they do not eliminate the need for human–AI dialogue in value-laden assessments.

With the development of explainable artificial intelligence (XAI) and human-in-the-loop approaches, the role of AI is shifting from that of a mere computational tool to a collaborative analytical mechanism [9]. By providing traceable explanatory information, AI can participate in the cognitive process of cultural heritage, transforming implicit aesthetic experiences into observable, comparable structures, and translating intuitive judgements scattered across texts and experiences into computable multidimensional features. This provides new points of reference for expert judgement and constructs a verifiable, interpretable and transferable process for assessing cultural value [1,10]. This human–machine collaborative model offers the potential to bridge the gap between ‘data presentation’ and ‘interpretation of meaning’.

This research focuses on how human–computer collaboration, utilising AI tools, can facilitate the visualisation and transformation of cultural heritage within complex contexts, thereby establishing a collaborative mechanism in cultural heritage research that bridges subjective aesthetic experience and computational models. This study primarily explores three core questions: Firstly, how can human aesthetic experience be formalised by AI into structured representations to support the quantitative analysis of complex cultural characteristics? Secondly, can interpretable AI collaboration enhance public understanding and research efficiency, whilst prompting experts to engage in ‘secondary cognition’ (AI-triggered reflection) upon viewing model outputs, thereby fostering cognitive reflection and re-evaluation? Thirdly, how can a transferable human–AI collaboration methodology be developed for the interpretation, analysis and evaluation of different types of cultural heritage?

In response to the above issues, this paper proposes the AI–Human Collaborative Interpretation (hereinafter referred to as AHCI) methodological framework, which treats AI as a collaborative partner in the process of interpreting cultural heritage. Guided by this methodology, and using the ‘Tianlai.China’ project as a practical case study, this paper conducts multimodal data integration, aesthetic feature modelling and interactive visualisation of the *Illustrated Catalogue of Famous Porcelains Through the Ages*. The effectiveness of the collaborative mechanism is then validated through expert–public–AI comparison experiments and human–machine feedback loop experiments.

The main contributions of this paper are as follows:

1. Proposing the AHCI framework for the valuation of cultural heritage, which integrates multi-source data processing, visualisation system design, interpretable analysis and human–computer feedback mechanisms to translate complex cultural heritage data and information into a visual, analysable and interactive structure.
2. Design and implement comparative experiments and human–machine feedback loop experiments involving three groups—AI, experts and the public—to validate the effectiveness of AHCI in terms of knowledge explicitisation, judgement consistency and cognitive inspiration.
3. Using the ‘Tianlai.China’ project as a case study, we have constructed an AI-driven formalised model system for cultural characteristics. This system encompasses text-based extraction of aesthetic preferences, quantification of uniqueness based on visual features, and a logical completion mechanism for 3D generative models, whilst incorporating explainable artificial intelligence (XAI) to design multiple types of interpretative outputs. Building on this foundation, we demonstrate the operationalisation of the AHCI framework in the digitisation of cultural heritage and explore the framework’s transferability across different types of cultural heritage.

2. Related Research

2.1. *The Digitisation of Cultural Heritage and the Application of AI*

2.1.1. Visualisation of Cultural Heritage and Cultural Computing

One of the core objectives of research into the digitisation of cultural heritage is to achieve high-fidelity reproduction and interpretable representation of cultural content. In this context, visualisation serves not only as a means of presenting data, but also as a vital medium for connecting cultural information with cognitive understanding. As Belhi et al. point out, a key component of digital preservation in cultural heritage lies in the visual representation of content, the aim of which is to reproduce it in a form as close as possible to the original object, thereby supporting alternative viewing experiences and the construction of digital twins [11]. This perspective highlights the dual nature of visualisation in cultural heritage research: on the one hand, it serves as a representation of physical information and form; on the other, it acts as a mechanism for conveying and disseminating cultural meaning.

Building on this, ‘cultural computing’ has gradually emerged as a key research direction within the digital humanities. Rauterberg points out that cultural computing must not only focus on the functionality of technology, but also emphasise its role in cultural transmission and identity construction [12]; subsequent research has further emphasised that computational systems should delve into the core layers of user culture, stimulating users’ experiences of and reflections on cultural archetypes through interactive narratives [1]. In terms of visualisation, relevant research not only focuses on the form of data presentation but is also dedicated to embedding cultural contexts, aesthetic characteristics and historical logic within visual expressions, thereby achieving a shift from ‘data display’ to ‘cultural interpretation’ [5]. However, existing research largely concentrates on the levels of information presentation and interactive experience; systematic methods for translating complex aesthetic judgements into computable structures, and for further supporting interpretative analysis, remain lacking [1,12].

2.1.2. Current Applications of AI in Cultural Heritage

In recent years, the application of artificial intelligence (AI) technology in the field of cultural heritage has seen rapid development, demonstrating significant advantages in areas such as data processing, conservation, analysis and dissemination. Through a systematic analysis of relevant research, Gîrbacia notes that AI has been widely applied to

tasks such as damage detection, object recognition, data analysis and 3D reconstruction, with its performance already surpassing that of traditional methods in many scenarios [13]. Deep learning technology can identify patterns and correlations within vast datasets of cultural artefacts, texts and historical records, making it suitable for the digital representation of complex cultural heritage [13]. For example, easy DL is an open platform for identifying and classifying historical artefacts, utilising deep learning to protect cultural heritage. Deep learning technology can also automatically generate information models of heritage buildings [14]. Haznedar et al. (2023) demonstrated how deep learning can generate 3D visualisations of heritage buildings, thereby facilitating their conservation efforts [14–16].

In the field of 3D model reconstruction, artificial intelligence technology is capable of efficiently generating three-dimensional objects from two-dimensional images and supports the generation of visual objects based on text-based instructions. Vazquez de Ágredos Pascual et al. (2022) utilised artificial intelligence technology to develop a ‘3D virtual museum’ to visualise Rome’s cultural heritage, enabling the study and archiving of cultural heritage within a museum framework; this initiative represents an interdisciplinary integration of physical, cultural and 3D technologies with artificial intelligence [14,17].

In the field of text processing, natural language processing (NLP) technologies have significantly enhanced the accessibility and analysability of historical documents [13]. For example, the Transkribus platform utilises machine learning-based neural networks for automatic transcription and keyword recognition, demonstrating the practical application of artificial intelligence in the extraction and identification of historical documents. These methods can improve the accuracy of text segmentation, author identification, document restoration and transcription, thereby transforming historical document data—which were previously difficult to access and utilise—into structured information resources [13]. Artificial intelligence language models can translate cultural heritage metadata to facilitate cross-linguistic sharing of cultural heritage, and can also transcribe handwritten texts, enabling researchers to access and understand historical documents and conduct automated analysis [18].

The application of artificial intelligence in the field of cultural heritage has given rise to five main research clusters: conservation assessment, exhibitions and visualisation, software solutions, virtual exhibitions, and metadata and databases [14]. These five areas correspond respectively to the needs of cultural heritage conservation in terms of ‘assessment’, ‘display’, ‘tool support’, ‘immersive experiences’ and ‘data management’. The four-layer architecture of the AHCI framework proposed in this study—comprising the data layer, model layer, interaction layer and analysis layer—systematically integrates the core requirements of the five aforementioned areas [14]. The data layer implements data management and tool support functions; the model layer provides a quantitative foundation for ‘preservation assessment’; the interaction layer supports ‘exhibitions and visualisation’ as well as ‘virtual exhibitions’; whilst the analysis layer conducts systematic validation and iterative feedback on assessment results and interaction outcomes [14]. Consequently, the AHCI framework elevates AI from a single-task tool to a collaborative partner that permeates the entire process. Nevertheless, existing research remains largely focused on the identification and reconstruction of ‘visible features’, such as morphological, structural and stylistic classifications, whilst paying insufficient attention to deeper interpretative issues involving aesthetic judgements and cultural significance [13]. At the same time, in most applications, AI is still utilised as a ‘black-box tool’, with its decision-making processes lacking transparency and interpretability. Consequently, how to transform AI from a ‘computational tool’ into a collaborative agent capable of participating in the interpretative process has become a significant shift in current research.

2.2. Explainable Artificial Intelligence (XAI) and Human–Machine Collaboration

The evolution from early ‘tool-based AI’, which primarily focused on automated classification, restoration and 3D reconstruction, to ‘cognitive partner AI’ capable of forming collaborative relationships with experts stems not only from technological advancements but also reflects the academic community’s renewed understanding of human–machine collaboration and knowledge co-creation models. Relevant research indicates that advancements in interactive AI, natural language interfaces and multimodal perception technologies are fostering closer collaborative relationships between humans and machines, transforming AI from a mere auxiliary tool into a collaborative participant in complex tasks [19]. Generally speaking, human–machine collaboration is understood as a process in which multiple agents share tasks, engage in continuous interaction and complement each other’s capabilities towards a common goal; its core lies in integrating human intuitive judgement with AI’s computational power [20]. Within this framework, AI is no longer merely a tool, but rather a collaborative agent participating in the cognitive process.

2.2.1. Dual-Process Theory and Distributed Cognition

Building upon the cognitive foundations of human–machine collaboration, the Dual-Process Theory provides a crucial explanatory framework. This theory posits that human cognition comprises ‘System 1’, driven by intuition, and ‘System 2’, driven by analysis. In the interpretation of cultural heritage, experts’ aesthetic judgements often rely on experience and intuition, whilst AI excels at systematic analysis and pattern recognition [21,22]. Consequently, integrating AI into cognitive processes essentially externalises the capabilities of ‘System 2’, thereby supporting the rational analysis of complex cultural features. From the perspective of distributed cognition theory, which emphasises that cognition is not confined to the individual but is distributed across people, tools and the environment, AI can be regarded as part of the cognitive system. Its output is not merely a computational result but also serves as a mediator in knowledge construction; this theory provides a crucial foundation for understanding the process of ‘human–machine co-construction of knowledge’.

Aesthetic judgements in cultural heritage research are often highly tacit in nature and difficult to express through explicit rules. The concept of ‘tacit knowledge’ proposed by Polanyi (1966) in his work *The Tacit Dimension*—namely, that humans ‘know more than they can express’—is particularly prominent in art appreciation and cultural evaluation [23]. Consequently, how to transform tacit knowledge into analysable structures has become a key issue in cultural computing. Against this backdrop, ‘knowledge formalisation’ emerges as a key pathway: utilising computational methods to transform textual descriptions, visual features and expert experience into structured data, thereby enabling comparable and interpretable analysis [1,14]. This process is not merely a matter of data processing, but involves a cognitive transformation from sensory experience to formalised expression.

2.2.2. Explainable AI (XAI) and Human–Machine Collaboration

Explainable artificial intelligence (XAI) provides crucial support for human–machine collaboration. Research by El-Hajj et al. indicates that its introduction within a historical research framework requires the establishment of a transparent workflow and the formulation of training set principles capable of covering all layers of explanation and their specific aspects [6]. XAI enables machine learning models to provide transparency regarding the specific features underlying classification decisions; consequently, the ‘black box’ is at least partially opened. On the one hand, this implies that classification results are not merely accepted at face value. Rather, they are intended to be examined, scrutinised and ques-

tioned [6]. AI can be regarded as a ‘cognitive collaborator’, whose value lies in revealing data correlations that experts might overlook and in triggering new cognitive processes.

To this end, researchers have further proposed the concept of ‘historian-centred XAI’, emphasising that explainability should serve scholars’ need for ‘interpretative validity’. XAI explanations must satisfy two principles: they must be faithful and comprehensive, whilst also being comprehensible to humans [6,24]. This principle is particularly important in cultural heritage research, as explanations not only affect the credibility of findings but also directly relate to the construction of cultural meaning.

In summary, whilst existing research has made significant progress in the digitisation of cultural heritage, the application of artificial intelligence, and theories of human–machine collaboration, there remain shortcomings. At the technical level, current research largely focuses on tasks such as image recognition, text processing and 3D reconstruction, whilst lacking systematic modelling methods for aesthetic judgement and cultural value assessment. At the methodological level, although explainable artificial intelligence and human–machine collaboration theories have been widely discussed, their integration within the context of cultural heritage remains limited, with a particular lack of a unified framework centred on ‘knowledge translation’. At the empirical level, research on whether AI explanations can influence expert cognition, promote reflection and enhance judgement consistency remains scarce. Consequently, there is an urgent need for a methodological framework capable of integrating multi-source data processing, explainable modelling and human–machine collaboration mechanisms to support the systematic interpretation of complex cultural heritage.

3. The AHCI Human–AI Collaborative Methodology Framework

3.1. Overview of the Framework

The AHCI (AI–Human Collaborative Interpretation) methodology framework aims to provide a systematic collaborative paradigm for the intelligent interpretation of cultural heritage. The core objective of this framework is not to pursue autonomous AI understanding of cultural meaning, but rather to construct a cognitive enhancement environment characterised by mutual interpretation between humans and AI. The AHCI framework is structured around a closed-loop system comprising the four interdependent elements of ‘data, model, interaction and analysis’. Each layer of this four-tier architecture serves as a node for collaboration between ‘humans’ and ‘AI’, with cognition progressively deepening through this iterative cycle. This design aligns with the human–AI collaboration design space proposed by Holter and El-Assady, which consists of three high-level categories: agency, interaction and adaptation [25]. Within the AHCI framework, agency manifests as a dynamic balance between human experts’ authority to define cultural heritage and AI’s computational execution; interaction lies in the flow of information between data layers and the modes of interaction between humans and the design system; and adaptation is characterised by experts adjusting and enriching their self-understanding in response to AI interpretations, whilst computational models undergo iterative optimisation based on feedback from human experts. Specifically, the functional positioning and design logic of each layer are as follows (Figure 1); Sections 3.1.1–3.1.4 elaborate on the specific composition and operational mechanisms of each layer:

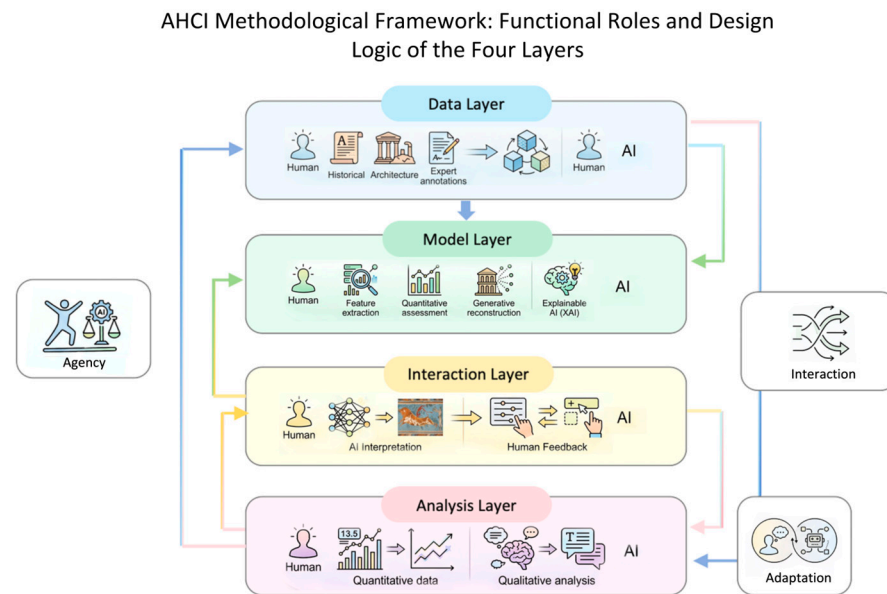


Figure 1. Functional architecture and design logic of the four layers of the AHCI methodological framework. The framework consists of a closed loop of data layer, model layer, interaction layer, and analysis layer. The data layer integrates multi-source heterogeneous cultural heritage data; the model layer constructs explainable AI cultural cognition models; the interaction layer enables bidirectional “AI explanation → human feedback” interaction; and the analysis layer evaluates collaboration effectiveness and feeds results back to preceding layers for iterative optimisation.

The design principles of human–machine collaboration systems include transparency, trust, user-centred design and effective communication (Mamidala et al., 2024) [19,26]. Within the AHCI framework, transparency is achieved through XAI mechanisms at the model layer and visual explanations at the interaction layer; trust is established through quantitative verification and qualitative reflection on AI reliability at the analysis layer; user-centred design is reflected in the retention of interfaces for expert intervention and user feedback across all layers; and effective communication relies on a bidirectional explanation paradigm at the interaction layer [19].

Blessing argues that effective human–AI collaboration depends on well-considered system design that ensures AI is understandable, trustworthy and aligned with human needs [19]. Explainable artificial intelligence aims to provide human users with an understanding of the principles underlying AI outputs and any potential errors through clear visualisations, interpretable models and explanations of underlying reasoning [27]. Such transparency in collaboration can, to a certain extent, ensure that human collaborators critically evaluate AI recommendations, intervene when necessary, and make informed decisions. For example, Lee et al. developed a feature selection system that provides quantitative analysis of patient conditions to enhance rehabilitation assessment practices [20]. This analysis is presented via a graphical user interface, allowing experts to provide feedback to adjust features, thereby better meeting patient needs and enabling personalised rehabilitation. The four-tier division of labour within the AHCI framework embodies this complementary logic: collaboration between humans and AI enables the scalability of complex tasks. AI can simultaneously process vast amounts of data, monitor multiple task processes and perform repetitive computations, undertaking highly repetitive, computationally intensive tasks such as data cleaning, feature extraction, pattern recognition and quantitative calculations. In this process, humans can focus their attention on higher-level or creative tasks, such as defining concepts within cultural dimensions, interpreting historical contexts, and assigning ultimate meaning, thereby transforming AI from a passive

tool into an intelligent partner capable of working side-by-side with humans across a wide range of tasks and domains [19,20].

3.1.1. Data Layer: Integration of Multi-Source Heterogeneous Data

The application of digital humanities technologies in the field of cultural heritage has evolved from simple digital archiving to complex knowledge reconstruction and intelligent analysis [28,29]. Researchers are increasingly adopting data quantification methods to analyse and calculate the ‘cultural genes’ of various cultural heritage indicators, thereby abstracting the patterns or principles underlying culture [1,5,30]. Data sources in cultural heritage research are typically multi-source and heterogeneous, encompassing unstructured text represented by ancient texts and manuscripts, two-dimensional images such as maps, rubbing prints and photographs, as well as structured attribute records found in archaeological reports. These data vary significantly in format, granularity and semantic density; feeding them directly into the model layer would result in information loss and semantic fragmentation [1].

The data layer processing workflow consists of collection, cleaning, structuring and linking. Text structuring will be assisted by large language models, whilst computer vision-driven image feature extraction will be employed for remaining two-dimensional images (such as line drawings, old photographs and rubbing prints). Key tasks include using edge detection algorithms to obtain the outer contours of artefacts, quantifying colours within images, and identifying and separating decorative patterns on the surface of artefacts for pattern segmentation and organisation. The process of extracting visual features can be performed automatically by AI, but the accuracy of feature extraction (such as the threshold setting for edge detection) can be adjusted based on expert feedback; this human-machine collaboration ensures a high degree of accuracy in the data layer. Furthermore, the value of cultural heritage lies not only in the physical attributes of individual artefacts but is also reflected in the network of relationships between them. By constructing a knowledge graph, the data layer links isolated structured data into a semantic network. Consequently, the core function of the data layer is to transform raw cultural heritage data into computable, interlinked structured data, thereby laying the foundation for feature extraction and quantitative analysis in the model layer.

3.1.2. Model Layer: An Interpretable AI Cultural Cognition Model

The model layer constitutes the computational core of the AHCI framework, undertaking the key function of transforming the structured information produced by the data layer into quantifiable and interpretable cultural cognition outcomes. The model layer of the AHCI framework emphasises the dual objectives of interpretability and intervenability; every score or generated result produced by the model must be accompanied by an explanation that is comprehensible to humans [31]. Furthermore, the model’s internal parameters and computational logic should permit human experts to calibrate and intervene based on their domain knowledge. As cultural heritage is a multidimensional and complex concept that is difficult to measure using a single indicator, the AHCI framework employs a human-machine collaborative strategy—where dimensions are defined by humans and objectively weighted by AI—to construct quantitative models [1], such as the uniqueness quantification model illustrated in this paper using the ‘Tianlai.China’ project as an example. Secondly, a vast amount of value-related information regarding cultural heritage exists in historical documents in the form of subjective commentary. The model layer utilises natural language processing (NLP) technology to convert these subjective annotations into quantifiable sentiment polarity and semantic structures [32]. For cultural heritage where ‘images exist but physical objects do not’ (such as porcelain for which only two-dimensional line drawings

remain), generative AI (using Tripo3D as an example) is introduced to perform logical completion based on limited information, generating a reconstructive model and realising a collaborative model of AI generation and expert verification [33].

3.1.3. Interaction Layer: A Two-Way Explanation Interaction Paradigm

Blessing argues that the effectiveness of human–AI collaborative systems depends not only on the computational capabilities of AI, but also on the technologies used to facilitate meaningful interaction, mutual learning and shared decision-making [19]. The interaction layer serves as the ‘interface’ for human–AI collaboration within the AHCI framework, undertaking the key function of transforming the computational results from the model layer and XAI explanations into an interactive experience that is perceptible, explorable and responsive to human feedback. In traditional AI applications, interaction is often simplified to a unidirectional channel of “input query–output result”, whereas the design of the interaction layer in the AHCI framework adheres to the core principle of bidirectional explanation: AI explains its reasoning to humans, and humans provide feedback to AI regarding corrections. Puerta-Beldarrain et al. point out that effective collaboration requires bidirectional communication to establish mutual understanding, enabling participants to perceive one another through natural, fluid interaction [20]. Fragiadakis et al. identified three modes of human–AI collaboration: AI-centric, human-centric, and symbiotic. The symbiotic mode represents a balanced partnership in which humans and AI systems work closely together to mutually enhance each other’s capabilities, characterised by bidirectional interaction, shared decision-making, and continuous feedback exchange [19,20,34].

3.1.4. Analysis Layer: Evaluation of the Collaboration Process and Iterative Optimisation

The analysis layer constitutes the reflection and calibration stage in the closed-loop AHCI framework. It requires the use of systematic experimental design and mixed-methods evaluation to validate the effectiveness of the models and interactive systems developed under the framework’s guidance. Furthermore, based on the evaluation results, it identifies areas for optimisation in human–machine collaboration to generate feedback, thereby enabling iterative optimisation across the data layer, model layer and interaction layer. Evaluating the effectiveness of human–AI collaborative systems requires a multidimensional approach, capturing not only task performance but also human–AI factors and interaction quality. Key evaluation metrics include how AI collaboration enhances outcomes, accuracy and efficiency, as well as user-centred satisfaction and trust, user cognition and usability [19]. Consequently, the analysis layer of the AHCI framework focuses not only on ‘whether the AI is accurate’, but also on ‘whether the AI’s explanations alter human cognitive pathways’ and ‘whether humans have established an appropriate level of trust in the AI’. The specific evaluation methods—including quantitative measures (such as consistency scores and correlation coefficients) and qualitative methods (such as thematic analysis of interviews)—will be illustrated in the experimental design of the case study (see Section 5).

3.2. The Four-Stage Collaborative Process of AHCI

The four-stage collaborative process of AHCI is as follows: human input context–AI formalisation and quantification–AI interpretation and feedback–human reflection and collaborative conclusion (Figure 2). This process abstracts the dynamic operation of the four-layer architecture into a collaborative workflow along the temporal dimension; the AHCI framework can be summarised as four sequential stages that permit backtracking and iteration.

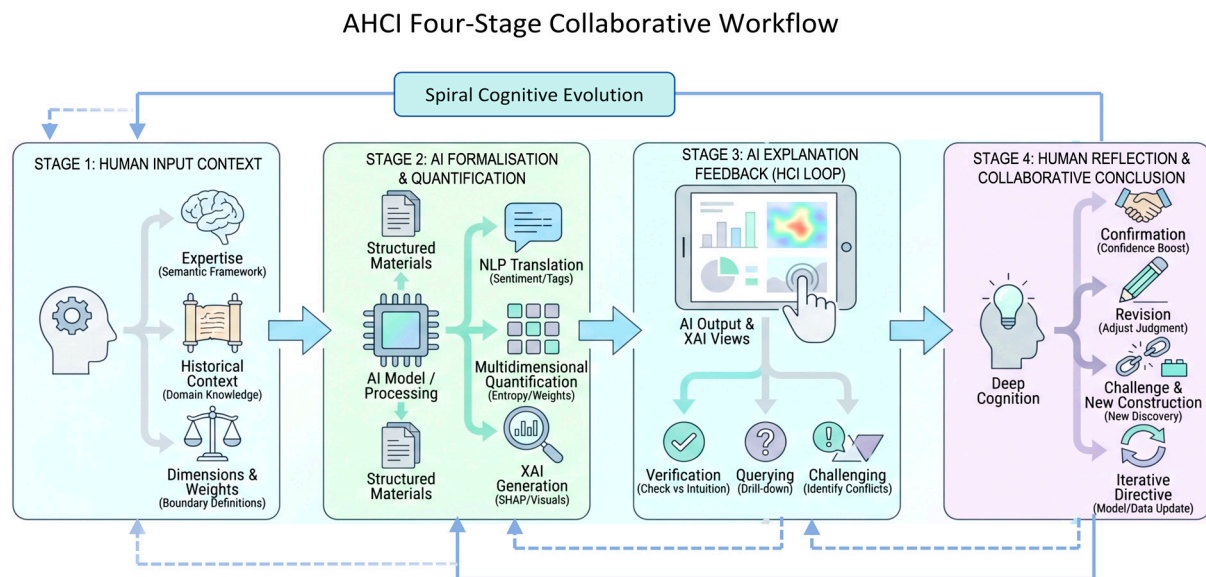


Figure 2. AHCI four-stage collaborative workflow: human input background–AI formalisation & quantification–AI explanation feedback–human reflection & collaborative conclusion.

The four-stage process is not a strictly linear, one-way path; conclusions drawn in Stage 4 may trigger a new round of Stage 1 (redefining cultural dimensions) or Stage 2 (re-training the model), resulting in a spiralling evolution of understanding. ‘Spiral cognitive evolution’ is a cycle of cognitive deepening that allows for backtracking and iteration; the conclusions reached in Stage 4 can trigger a new round of Stage 1 (redefining cultural dimensions) or Stage 2 (retraining the model), enabling human cognition and AI models to deepen continuously through iteration. The cyclical mechanism of ‘execution → reflection → backtracking → re-execution’ forms a spiralling process of cognitive evolution.

Human–machine collaboration transforms AI from a passive tool into an active partner capable of adapting to evolving tasks within human intentions and dynamic environments, and the four-stage process serves as the temporal framework for this dynamic adaptability.

4. Case Study: The ‘Tianlai.China’ Project

4.1. Project Background

The *Illustrated Catalogue of Famous Porcelains Through the Ages* (hereinafter referred to as the *Catalogue*), compiled by the renowned Ming Dynasty collector Xiang Yuanbian, is one of the earliest Chinese catalogues to systematically compile porcelain from famous kilns across the ages. The *Catalogue* features 83 pieces of porcelain, recording their forms, glaze colours and colophons and annotations in the form of text and illustrations, totalling approximately 42,000 characters. It profoundly embodies and presents Xiang Yuanbian’s own connoisseurship and aesthetic system, holding significant value for the study of connoisseurship practices and aesthetic discourse since the Ming and Qing dynasties [2].

However, the physical artefacts depicted in the *Catalogue* have all been lost. This unique characteristic—where ‘there are images but no physical objects’—makes the *Catalogue* an ideal case study for testing AI’s ability to assist in the interpretation of cultural heritage. If the porcelain itself still exists, researchers can directly examine the body, glaze and traces of craftsmanship, comparing and calibrating the AI’s inferences against the physical object. In such cases, the AI functions more as an auxiliary measurement tool, with the physical object serving to directly verify the accuracy of the data; consequently, the focus of human–machine collaboration lies in enhancing efficiency. However, as none of the porcelain pieces recorded in the *Catalogue* survive in physical form, it is impossible to obtain reference standards through physical examination; inferences must rely solely

on the literature and expert experience. This is precisely the core challenge that the AHCI framework seeks to address: how AI can collaborate with experts to complete logical inferences and aesthetic judgements in the absence of standard answers. Rather than the recognition of ‘existing answers’, this study focuses on how AI can participate in the structured analysis and collaborative interpretation of complex cultural heritage under conditions of incomplete information and high uncertainty.

Its data composition encompasses the typical modal combinations found in cultural heritage digitisation (images, text, and attributes). The challenge posed by the absence of physical artefacts highlights the research value of exploring AI’s ability to logically fill in gaps, whilst the rich aesthetic judgements contained in Xiang Yuanbian’s annotations provide a high-quality data foundation and research significance for exploring the formalisation of human tacit knowledge (Figure 3).



Figure 3. Visual effects of website visualisation design (some parts).

4.2. Application and Practice of the AHCI Framework

In accordance with the four-layer architecture of the AHCI framework outlined in Section 3—namely, the ‘data layer, model layer, interaction layer and analysis layer’—this section details, layer by layer, the specific implementation process of the ‘Tianlai.China’ project, as well as the specific division of labour and methods of collaboration between ‘humans’ and ‘AI’.

4.2.1. Data Layer: Fusion of Multi-Source Data for 83 Pieces of Porcelain

The project’s data sources comprise three tiers: image data, text data, and structured attribute data, including name, date, kiln site, dimensions, glaze type, craftsmanship description, and provenance records. The core task of the data layer is to transform raw data from multiple sources into computable, interrelatable structured data; this process involves image vectorisation and 3D reconstruction, text data cleansing and structuring, and the construction of a parameter database (Figure 4).

The project employs a human–machine collaborative workflow combining AI-assisted preliminary processing with manual proofreading to ensure both the efficiency of the structured process and semantic fidelity. Through AI-assisted extraction, the large language model DeepSeek-V3 is utilised to perform structured recognition of the classical Chinese original text and English translations in the Catalogue, extracting the corresponding porcelain name, kiln origin, date, glaze colour description, form description, craftsmanship features and comments by the Xiang family for each artefact. For highly specialised vocabulary in classical Chinese (such as the names of ancient ritual vessels like ‘dou’), AI tools are used to perform bilingual translation and comparison for linguistic verification, in order to identify subtle semantic differences. Subsequently, the AI-generated structured data undergo comprehensive manual proofreading.

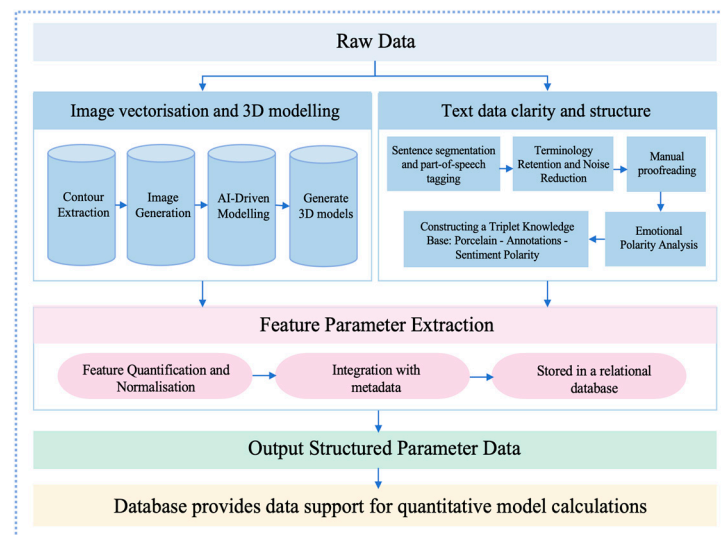


Figure 4. Data preprocessing flowchart.

The data layer utilises computer vision technology to extract line drawings of 83 porcelain pieces, capturing their outer contours and calculating shape parameters such as height-to-width ratios, curvature integrals and symmetry deviations. It also extracts the dominant colour tones from the line drawings and cross-references them with glaze colour descriptions found in ancient texts. To assist the general public in intuitively understanding the proportions and spatial structure of porcelain in the absence of physical artefacts, and to bridge the cognitive gap between two-dimensional drawings and three-dimensional objects, this study utilised the AI-driven Tripo3D to generate 3D models from 2D sketches [21–23]. However, this reconstruction involves uncertainties; for instance, when line drawings provide only a front view, the curvature of the rear inferred by the AI may deviate from that of the historical artefact. Consequently, experts must review the generated 3D models to serve as a basis for subsequent fine-tuning.

As a result, the data layer no longer outputs a single data table, but rather a structured data network that integrates porcelain attributes, visual characteristics, aesthetic semantics and historical context.

4.2.2. Model Layer: Quantitative Model for the Uniqueness of Porcelain

The uniqueness and value of cultural heritage constitute a multidimensional and complex concept that is difficult to measure using a single indicator. The AHCI framework employs a human–machine collaborative strategy, combining human-defined dimensions with AI-generated objective weightings to construct a quantitative model. Taking the ‘Tianlai.China’ project as an example: first, porcelain research experts define five dimensions for assessing uniqueness—form, decoration, glaze colour, craftsmanship and historical background—based on disciplinary consensus; second, computable quantitative indicators are designed for each dimension (such as the height-to-width ratio, curvature integral and symmetry deviation for the form dimension); subsequently, AI (using the entropy weighting method) automatically calculates weight allocations based on the dispersion of data across each indicator, resulting in 38% for form, 22% for decoration, 25% for glaze colour, 12% for craftsmanship, and 3% for historical context; finally, Z-score standardisation is applied to weight and synthesise the scores from each dimension into a comprehensive uniqueness score (Table 1) [35–37]. The form dimension carries the highest weight, indicating that, within the *Catalogue* dataset, differences in geometric shape are the most pronounced and constitute the core element of its visual and functional distinctiveness. This aligns with the consensus in artefact studies that the description and analysis of an object’s shape form the

foundation of research [38,39]. It is particularly noteworthy that the historical background dimension carries a relatively low weight; this is primarily because the *Catalogue* consists largely of items from the Xiang family's private collection, which exhibits a high degree of homogeneity. This implies that, when 'distinguishing the uniqueness of two porcelain pieces', the historical background dimension provides far less effective information than the complex and variable characteristics of form and glaze colour. This does not negate the importance of historical background, but rather illustrates that, within the current quantitative framework centred on the *Catalogue* text, historical narratives are relatively concentrated and stable, whilst physical and visual characteristics are the core variables determining the individual differentiation of artefacts.

Table 1. The quantification model for porcelain uniqueness: definition, calculation method, and data source for each dimensional metric.

Parameter	Definitions and Calculation Methods	Source of Data
Shape parameters	Z-score mean based on aspect ratio, curvature integral, and symmetry deviation of line graphs	ImageJ (version 1.54r) extracts the outline of the Atlas line drawing and computes geometric features
Parameters of ornamentation	Pattern complexity (line density 1–5 points) + innovation (0–3 points), standardised and summed up	Manual coding and classification cross-referencing in the Dictionary of Chinese Ornamentation
Glaze colour parameters	Glaze rarity (1–5 points, with reference to 'Chinese ceramics glaze colour examination and interpretation') standardisation	Literature assignment and kiln glaze database matching
Process parameters	Process complexity (thin = 1, kiln-formed = 2, stripped = 3) standardised	Technical classification of the Jingdezhen Pottery Catalogue
Historical parameters	Number of mentions in the item Bianbian's commentary (+1 point per mention, max. 3 points) + frequency of documentation (+0.5 points per document) standardised	Textual analysis of the Atlas and Search of Ming History, Drinking Liuzhai on Porcelain

The core value of this human–machine collaboration model lies in the fact that human experts are responsible for assigning cultural semantics to dimensions (answering the question 'What constitutes uniqueness?'), whilst AI is responsible for capturing the statistical structures within the data (answering the question 'Which dimensions show the greatest variation across samples?'). By combining these two approaches, we avoid both the arbitrariness of purely subjective weighting and the semantic deviations that may arise from a purely data-driven approach. For example, whilst the historical dimension might be assigned an extremely low weight due to sparse information in the *Catalogue*, its cultural significance remains undeniable.

4.2.3. Interaction Layer: Construction of a Four-Dimensional Visualisation System

The interaction layer transforms the computational results from the model layer and XAI explanations into an interactive experience that is perceptible, explorable and responsive to user feedback. ‘Tianlai.China’ has developed a four-dimensional visualisation system (publicly accessible at: <https://www.tianlai.art> (accessed on 20 April 2026); please use Google Chrome to access the site). The framework follows a four-stage progressive visualisation narrative path of “Traceability–Appreciation–Exploration–Rhyme Tasting” (Figure 5a), systematically integrating contextual reconstruction, data deconstruction, model interpretation and subjective–objective dialogue.



Figure 5. (a): Overview of visual effects in the four-dimensional visualisation module; (b): “Traceability”: interactive curated collection game interface.

Tracing Origins: Immersive Historical Context Reconstruction. The ‘Tracing Origins’ section aims to address the ‘lack of context’ often encountered in the study of historical texts. By constructing knowledge graphs and virtual scenarios, it places users within Xiang Yuanbian’s network of collectors and physical spaces, with the aim of establishing a foundational historical understanding and empathy before delving into the artefacts themselves. Utilising historical documents verified by human experts, AI-assisted generation is employed to digitally reconstruct Tianlai Pavilion, thereby concretising the abstract concept of ‘collection’. This renders implicit social capital visible, helping users understand why a particular piece of porcelain was collected and the social motivations behind its likely transmission pathways (Figure 6b).

Appreciation Section: Presentation of Basic Attributes of Multidimensional Data. The Appreciation Section uses data visualisation techniques to present the basic attribute information of 83 porcelain pieces. Firstly, the visualisation process transforms the original illustrated catalogue into a digital archive of these 83 pieces (Figure 6a). This replaces the linear and inefficient traditional method of leafing through books to locate specific information; the digital archive enables rapid, intuitive multidimensional filtering, knowledge graph associations and logical navigation. In addition, the core visualisation components include the porcelain–kiln–period Sankey diagram (Figure 6b), which employs nested spatial–temporal and decorative evolution trees for porcelain to illustrate the hierarchical structure and quantitative distribution of the classification system, guiding users to identify micro-categories worthy of further exploration from macro-level distributions. A radar chart utilising the physical characteristics of vessel forms compares the contour differences between various forms across physical dimensions such as the height-to-width ratio, curvature and symmetry (Figure 7). By extracting the dominant hues from the line drawings of porcelain in the Catalogue and combining them with descriptions of glaze colours found

in ancient texts, a visual colour spectrum library comprising 83 pieces of porcelain was created, forming a circular colour distribution chart.



Figure 6. (a): Digital archive of 83 porcelains and digital archive interactive details: including commentary transcripts and uniqueness analysis information; (b): porcelain–kiln–age flow Sankey diagram and porcelain evolutionary tree: chronology, provenance, and ornamentation.

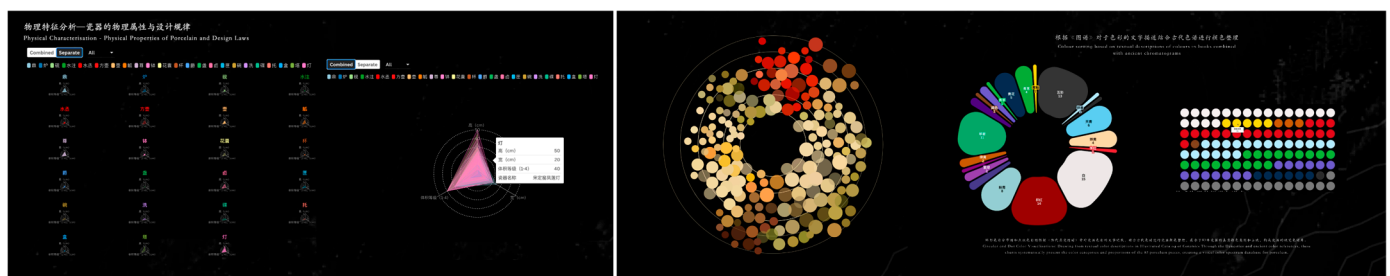


Figure 7. Radar chart of porcelain shape physical characteristics: individual shape mode and overall analysis mode; a circular chromatic distribution map: a computational analysis and data curation workflow for automatically extracting dominant colours from porcelain sketches, integrated with textual and historical data from the "Chromatographic Atlas".

Exploration Section: Visual Interpretation of the Uniqueness Quantification Model. The Exploration Section is an interactive visual representation of the uniqueness quantification model within the model layer. Its core objective is to make the AI's computational logic transparent and interpretable, transforming the abstract concept of 'uniqueness' into concrete, comparable visual forms and numerical values. The key interactive components of the 'Exploration Section' include a five-dimensional uniqueness radar chart, which overlays the standardised scores for each piece of porcelain across five dimensions using polygonal outlines, providing an intuitive understanding of the strengths and weaknesses in each dimension. Furthermore, 3D models generated by the AI from two-dimensional sketches are rendered as dynamic particle systems, transforming abstract parameters of shape complexity into a dynamic visual experience with a sense of spatial depth (Figure 8).



Figure 8. Visual metaphor in a dynamic particle system.

Rhyme Tasting Section: Semantic Visualisation of the Dialogue Between Subjective and Objective Perspectives. The Rhyme Tasting Section presents the analytical results of the aesthetic preference model in the form of an interactive semantic network, transforming Xiang Yuanbian's subjective annotations into a computable, visual structure, and exploring the correlations between these and objective quantitative models. The emotional polarity distribution chart of Xiang's commentary utilises NLP sentiment analysis to quantify the implicit emotions within the classical Chinese commentary as sentiment scores, visualising the text's emotional tone and categorising it as 'Extremely High', 'High' or 'Medium'. The emotional intensity levels are displayed using a nested ring layout, and clicking on each level allows users to expand it to view the original commentary text. The co-occurrence network diagram of aesthetic preference keywords reveals the evolutionary patterns of Xiang Yuanbian's aesthetic design from a visual perspective. The resulting diagram reveals clusters of concepts that define Xiang Yuanbian's aesthetic philosophy. For instance, users can observe whether 'exquisite craftsmanship' is frequently linked to 'painting-like quality', or whether 'archaic simplicity' clusters with 'Song Dynasty porcelain', thereby uncovering the cultural sedimentation underlying the design language (Figure 9).



Figure 9. Interaction flow for the sentiment polarity distribution of Xiang's commentary; network diagram of semantic and ornamental features.

The four sections mentioned above do not constitute a collection of isolated perspectives, but are linked by a unified navigation structure to form a progressive cognitive pathway: users begin by exploring the historical context, gain an understanding of the fundamental attributes, delve into quantitative analysis, and ultimately arrive at a dialogue between the objective and the subjective.

4.2.4. Analysis Layer: AI-Collaborative Experiments and Evaluation

The analysis layer validates the effectiveness of the AHCI framework through systematic experiments. This study designed a comprehensive experiment integrating multi-group evaluation, objective–subjective comparison and system usability testing, and designed and conducted three sets of comparative experiments: the AI group (using the DeepSeek-V3 model as the automated evaluation baseline and employing a 'Role-Play' strategy), the

expert group ($n = 20$) and the public group ($n = 50$), to evaluate the performance of the quantitative model and the visualisation system in terms of knowledge explicitisation, judgement consistency and cognitive inspiration.

The experiment required evaluators from all three groups to rate the ‘overall distinctiveness’ of 83 porcelain pieces (on a scale of 1–10). The expert group and the public group completed the System Usability Scale (SUS) questionnaire and participated in semi-structured interviews. The specific experimental procedure is as follows (Figure 10):

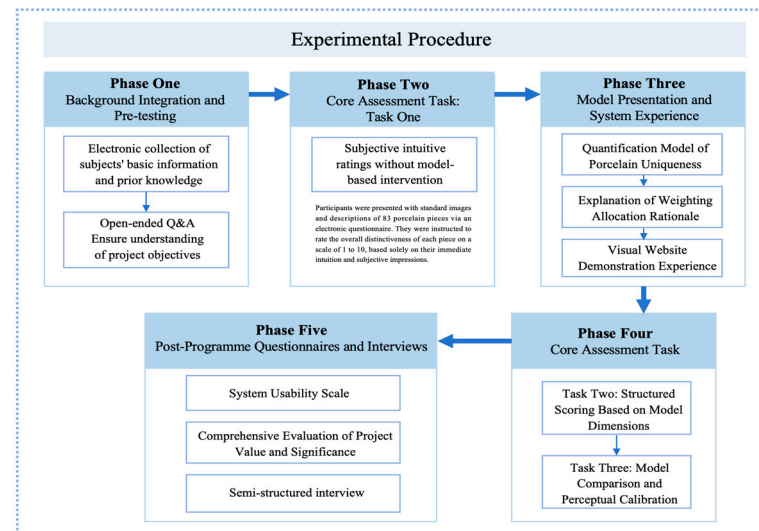


Figure 10. Specific experimental procedure.

Regarding the validation of the model’s validity, the results showed a highly significant positive correlation between the model scores and the expert scores: Pearson correlation coefficient $r = 0.81$ [95% CI: 0.72, 0.88] ($p < 0.001$); Spearman’s rank correlation coefficient $\rho = 0.78$ [95% CI: 0.68, 0.85] ($p < 0.001$); and the AI model DeepSeek also showed a moderate correlation with the expert scores ($r = 0.65$ [95% CI: 0.51, 0.76], $p < 0.01$).

Regarding cognitive differences between groups, there was a significant difference between the expert group ($M = 7.35$, $SD = 1.28$, 95% CI [6.79, 7.91]) and the general group ($M = 6.02$, $SD = 1.59$, 95% CI [5.58, 6.46]) ($F(2, 67) = 15.38$, $p < 0.001$, $\eta^2 = 0.24$); this reflects the influence of accumulated professional knowledge on appreciation ability and corroborates the model’s professional validity.

Regarding the analysis of subjective and objective dialogue, we conducted NLP sentiment analysis on Xiang Yuanbian’s annotations. The sentiment polarity analysis of Xiang Yuanbian’s annotations revealed that 73% of the porcelain pieces rated as ‘extremely high’ by him overlapped with the model’s high-scoring samples ($MS > 0.8$). This indicates that the model demonstrates a high degree of consistency in capturing historical aesthetic preferences.

Regarding system usability and user experience evaluation, the results showed an average score of 79.6 ($SD = 7.1$, 95% CI [77.9, 81.3]), falling within the “good” range, indicating that the system as a whole possesses high usability and user experience.

The findings from the analysis phase not only validate the effectiveness of the technical outputs guided by the AHCI framework but also provide evidence-based grounds for further optimisation of the framework. For instance, the issue of low weighting for the historical dimension suggests that a mechanism for expert knowledge calibration needs to be introduced in the future.

4.3. AI-Driven Collaborative Innovation in the Project

This section examines the innovative role of AI in the ‘Tianlai.Chinal’ project from a collaborative perspective, focusing on the division of labour and mutual reinforcement mechanisms between AI and human experts in specific tasks. Human–machine collaboration can enhance creativity, whilst AI systems can provide novel perspectives, generate alternative solutions or simulate hypothetical scenarios, thereby inspiring human users to explore new possibilities [19].

4.3.1. A Multidimensional Value Assessment Model Developed Through Human–Machine Collaboration

The quantitative assessment of porcelain’s uniqueness involves both subjective value judgements and the measurement of objective characteristics. The innovation of the ‘Tianlai.China’ project lies in the structured division of labour between the two: human experts, drawing on professional knowledge and cultural logic, design five assessment dimensions—form, decoration, glaze colour, craftsmanship and historical context—whilst AI, utilising the entropy weighting method, objectively calculates weights based on the dispersion of data across each dimension and synthesises a comprehensive score through weighted aggregation. Humans define the semantic framework, whilst AI performs the objective calculations; their collaboration forms an evaluation system that possesses both cultural interpretative power and data-driven robustness. Human experts need not worry that personal preferences will interfere with the weightings, as these are objectively determined by the data. Nor need they fear that the AI’s calculations might lack cultural significance, as the dimensions are collectively determined by human experts. Consequently, the model possesses both the objective stability of data-driven analysis and the semantic depth of cultural interpretation.

4.3.2. AI-Driven Visualisation of Cultural Context: Immersive Scenarios

The interpretation of cultural heritage’s value can never be divorced from its original historical context; the significance of a piece of porcelain lies not only in its form and glaze colour, but is also closely linked to the spatial and social knowledge networks within which it was collected, admired and appraised. In the vast body of the literature, the information regarding Xiang Yuanbian’s art collection activities at Tianlai Pavilion and the layout of Ming Dynasty literati study rooms is largely fragmented; it is difficult for the general public to construct a concrete historical space or scene of art appreciation. Therefore, from this collaborative perspective, the role of AI is defined as driving the visualisation of cultural contexts. The project team has organised the historical textual information gathered from the literature—including records of Xiang Yuanbian’s collecting activities and descriptions of Ming Dynasty literati gatherings for calligraphy and painting—into structured text prompts, which are then fed to the AI to generate virtual scenes of the Tianlai Pavilion. The AI can produce initial visual materials for screening and modification within a very short timeframe, a process far more efficient than traditional manual modelling and texturing workflows. However, the output of generative AI has fundamental limitations and may produce visual elements that do not align with the historical reality of the Ming Dynasty. In this phase, human experts are responsible for verifying the historical accuracy of the scene and making corrections. This collaborative model transforms abstract historical contexts into spatial experiences that humans can perceive and explore, whilst the expert review mechanism effectively mitigates potential errors in the visual elements generated by generative AI.

4.3.3. Xiang Yuanbian's 'Aesthetic Agent': The Knowledge Translation of Historical Texts

Xiang Yuanbian's aesthetic judgements are recorded in the illustrated catalogue in the form of 42,000-character annotations; however, the intuitive, fragmented and unstructured nature of these texts makes it difficult for contemporary researchers to gain a clear understanding of the overall patterns of Xiang Yuanbian's aesthetic preferences. Consequently, within this collaborative framework, the AI is positioned as a knowledge translator; its task is not to understand Xiang Yuanbian, but to render his implicit, fragmented, and intuitive descriptions into an intuitive and formalised format. For instance, through natural language processing, it extracts high-frequency aesthetic keywords such as 'moist and lustrous', 'rustic', and 'unparalleled', and constructs a co-occurrence network of keywords to reveal conceptual clusters—such as the association between 'rustic' and 'Song porcelain'.

The value of this translation lies in providing contemporary experts with an intuitive perspective on which ceramics received the highest emotional evaluations and which aesthetic concepts are interrelated within his discourse of appreciation. This does not involve AI replacing experts in interpreting Xiang Yuanbian, but rather offers a new, data-driven perspective to support their interpretative activities; the final attribution of aesthetic significance and historical value remains in the hands of human experts. This is precisely the core practical manifestation of the AHCI framework's philosophy that "AI serves as a cognitive partner rather than a bearer of meaning".

5. Experiment: Verification and Evaluation

In order to comprehensively capture the multidimensional effects of the AHCI human-machine collaboration framework, the experimental evaluation employed a mixed-methods approach combining quantitative and qualitative methods. The quantitative analysis focuses on Δ Score (a measure of the degree of change) to assess the extent to which human evaluators modify their initial scores after being presented with AI explanations. The correlation coefficients (Pearson r /Spearman ρ) between the scores of each group and the expert consensus scores are calculated to assess consistency with the expert benchmark. Through interaction log analysis, the system records users' dwell time, click depth and the sequence of functional modules accessed to evaluate the cognitive guidance effectiveness of the interaction design. Qualitative analysis is dedicated to revealing the cognitive processes underlying the quantitative metrics. This can be achieved through reflective notes and interview transcripts, where reflective texts and interview content are subjected to open coding and axial coding to extract core cognitive themes. The analysis layer feeds the quantitative and qualitative outputs back into each layer for iterative optimisation, endowing the AHCI framework with the adaptive capacity for continuous evolution.

Evaluating human-AI collaboration in cultural heritage assessment requires capturing both objective performance and subjective cognitive processes. Quantitative metrics alone (e.g., consistency with expert benchmarks, modification rates) can reveal whether AI explanations influence judgements, but they cannot explain why or how such influence occurs. Conversely, qualitative analysis of interviews and reflective questionnaires can uncover cognitive mechanisms—such as AI-triggered reflection or the discovery of previously overlooked features—but lacks statistical generalisability. A mixed-methods approach is therefore essential: quantitative measures provide evidence of effect magnitude and reliability, while qualitative analysis supplies the interpretive depth needed to understand expert cognition. Neither component alone would suffice. An exclusively quantitative evaluation might suggest that AI explanations improve consistency without revealing whether experts genuinely reflect on their criteria or merely acquiesce to algorithmic suggestions; an exclusively qualitative evaluation might generate rich insights but could not demonstrate statistical robustness or transferability. The AHCI framework therefore mandates a mixed-

methods design to fully capture the complexity of human–AI interaction in value-laden cultural interpretation.

5.1. Experimental Design

A total of 20 participants were recruited for the experiment and divided into two groups:

- (1) Expert group ($n = 5$): Comprising PhD students specialising in art history, museum researchers and experienced ceramic collectors, with an average of 8.5 years' relevant professional experience.
- (2) General public group ($n = 15$): Individuals with an interest in culture and the arts but without specialist knowledge of ceramic authentication.

A stratified sample of 20 ceramics was drawn from the 83 pieces featured in the *Illustrated Catalogue of Famous Ceramics Through the Ages* based on their uniqueness scores (model score), covering high, medium and low tiers. For each ceramic, a two-dimensional illustration from the *Catalogue* and basic attribute information (name, period) were provided; all materials were made available to participants via an electronic questionnaire.

Each participant (from both the expert and general groups) sequentially completed three assessment conditions, as shown in Table 2:

Table 2. Evaluation conditions.

Condition	Task Mode	AI Intervention Content
C1 (Human Independent)	No AI intervention; rely solely on personal knowledge and intuition	None
C2 (AI Tool Mode)	Display only the AI-assigned score for the porcelain, without any visual explanation	Display only: AI Score: 9.0
C3 (AHCI Collaborative Mode)	Present AI score, explainable visualisations, and allow further questioning	Score, various visual charts, and the ability to use AI to continue questioning for explanation

To control for order effects and material repetition effects, the 20 porcelain pieces were randomly divided into three groups (6–7 pieces per group), with one group being evaluated under each experimental condition (C1, C2, C3). This ensured that the porcelain pieces assessed by each participant under each condition did not overlap, and that the number of times each piece was assessed was balanced across all conditions.

Under condition C3, participants could use the AI to ask follow-up questions for further explanation. The AI (DeepSeek-V3) generated natural language responses based on model-level XAI outputs and a historical commentary database. For example, participants could input customised questions such as ‘Why is the glaze colour given a higher weighting?’ or ‘In what ways is the shape of this porcelain piece unique?’. The experimental system recorded all follow-up questions and AI responses for subsequent analysis of interactive behaviour.

The evaluation utilised a large language model (DeepSeek-V3) as an independent evaluator, following the emerging ‘LLM-as-a-judge’ paradigm [40]. In this approach, the LLM is prompted to assume the role of a domain expert (‘expert in the authentication of ancient Chinese ceramics’) and provides dimensional scores, an overall uniqueness

score, and human-like explanatory answers. This method has been shown to exhibit high agreement with human expert judgements in structured evaluation tasks; however, it must be acknowledged that potential biases exist in LLM evaluations. Consequently, we employ the triangulation of AI scores with those of human experts and the general public to mitigate such biases.

This evaluation benchmark is derived from expert ratings collected during the early stages of the project. It is based on the assessments of 20 experts, including art historians, museum researchers, seasoned ceramic collectors and cultural relics authentication specialists, with an average of 12.5 years' professional experience. These experts rated the individual distinctiveness of all 83 porcelain pieces in the *Catalogue* (on a scale of 1–10), and the mean score for each piece was taken as the 'expert consensus benchmark'. The collection of this benchmark data was conducted independently of the experimental process, ensuring the external validity of the reference framework.

5.2. Experimental Procedure

The experiment is divided into three stages: background introduction, three rounds of assessment, and a comprehensive interview and questionnaire. The entire experiment is expected to take 30–45 min and is conducted by a single experimenter. The specific procedure is as follows:

Stage One: Background Questionnaire and Training

- Complete the prior knowledge questionnaire, self-assessing familiarity with porcelain authentication on a scale of 1–5.
- Familiarise participants with the rating scale (1–10 points, operational definition of 'uniqueness') and platform operation methods.

Stage Two: Three Rounds of Assessment

Each round corresponds to a specific experimental condition (C1/C2/C3), with 6–7 pieces of porcelain assessed in each round. The assessment procedure for a single piece of porcelain is as follows (Table 3):

Table 3. Experimental conditions.

Step	C1 (Human Independent)	C2 (AI Tool Mode)	C3 (AHCI Collaborative)
S1 Initial Judgement	Rate uniqueness (1–10) and briefly record reasoning	Same as C1	Same as C1
S2 AI Information Intervention	None	Display AI score (numerical value only)	Display AI score, explainable views (radar chart, highlight, word cloud), and query function
S3 Final Judgement	After reviewing all evaluated porcelain items, may return to revise any rating	May retain or revise the rating, and record the reason for revision	Same as C2
S4 Reflection Record	What factors influenced your final judgement?	Answer: "Did the AI score influence your judgment? If so, how?"	Answer: "Did the AI explanation influence your judgment? Which part was most convincing or confusing?"

Stage Three: Comprehensive Interviews and Questionnaires

- Complete the System Usability Study (SUS) and the Confidence Scale questionnaire.

- Participate in semi-structured interviews: Experts will focus on whether ‘AI explanations prompt a re-evaluation of cognition’ and ‘knowledge discovery within the human–machine feedback loop’; members of the general public will focus on whether ‘AI explanations helped them understand technical terminology’ and ‘whether they enhanced confidence and efficiency in decision-making’.

5.3. Experimental Results and Analysis

This section validates the effectiveness of the AHCI (Human–Machine Collaborative Interaction) framework in the evaluation of the uniqueness of porcelain by comparing the scoring performance of the expert group and the general public group across three experimental conditions (C1, C2, C3). The summary statistics of the experimental results are shown in Table 4.

Table 4. Summary statistics of experimental results.

Metric	Group	C1 (Human Independent)	C2 (AI Tool Mode)	C3 (AHCI Collaborative)
Consistency with Benchmark (r)	Expert	0.61 ± 0.05	0.63 ± 0.06	0.85 ± 0.04
	Public	0.52 ± 0.09	0.55 ± 0.08	0.78 ± 0.06
Mean Absolute Δ Score	Expert	—	0.11	0.64
	Public	—	0.21	0.86
Modification Rate ($ \Delta \geq 0.5$)	Expert	—	11.4%	45.7%
	Public	—	17.1%	67.6%

Expert validation: Under C3 conditions, experts’ agreement with the benchmark rose from 0.63 to 0.85, and a 45.7% trigger rate for modifications indicates that AI explanations did indeed prompt experts to actively adjust their cognitive assessments (Figure 11a). In interviews, experts noted that the AI’s dimensional decomposition helped them to systematically examine judgements that had previously relied on intuition; some experts revised their evaluations of specific porcelain pieces based on information regarding glaze colour rarity revealed by the AI—precisely the ‘secondary cognition’ sought by the AHCI framework.

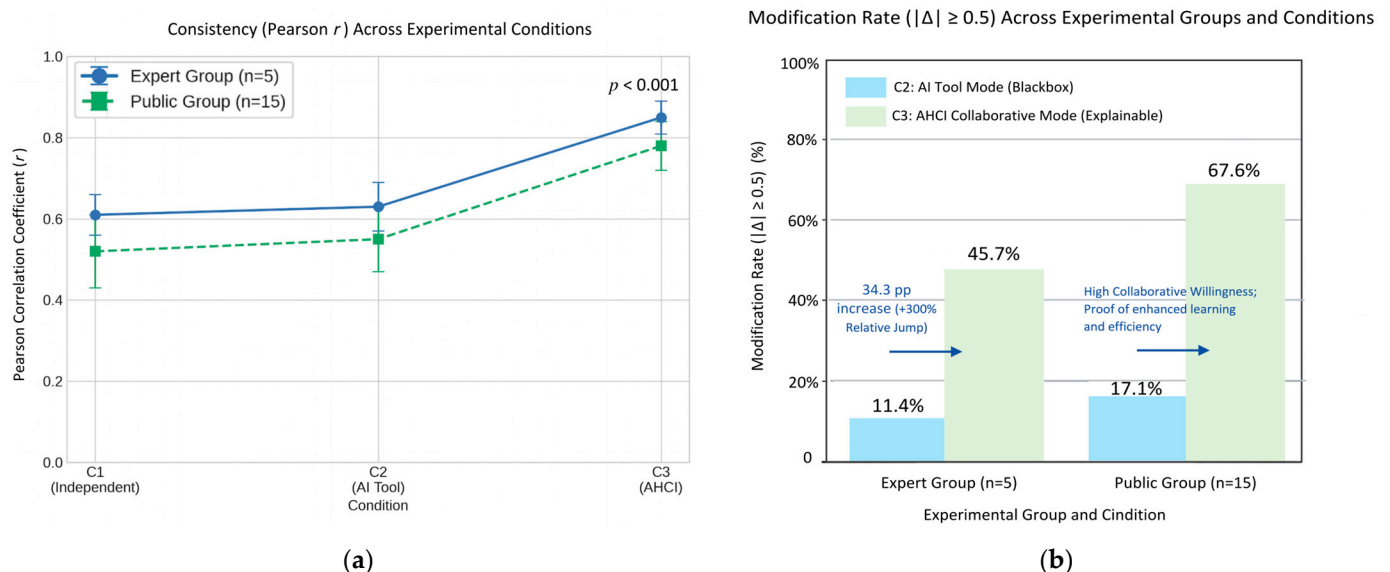


Figure 11. (a): Trend of consistency across experimental conditions; (b): modification rate ($|\Delta| \geq 0.5$) across experimental groups and conditions.

Public empowerment validation: Under Condition C3, the public's consistency with the benchmark rose from 0.55 to 0.78—an increase of 0.23—which is significantly higher than the 0.03 increase observed under Condition C2 (Figure 11b). This indicates that the AHCI model can effectively bridge the public's knowledge gap, bringing their judgements closer to the consensus level of domain experts. The public frequently mentioned in their reflective texts that “I didn't realise glaze colours could also have a degree of rarity”, indicating that the framework successfully externalised implicit appreciation knowledge into assessment criteria that the public could understand and apply.

Mechanism validation: For both experts and the public, the increase in consistency under Condition C2 (where only AI scores were provided) was negligible. This strongly demonstrates that interpretability and interactive feedback are essential conditions for human–machine collaboration to generate value. Isolated AI scores cannot be converted into effective cognitive resources for either experts or the public.

To comprehensively evaluate the collaborative effectiveness of the AHCI framework, semi-structured interviews and reflective questionnaires were conducted with experts and the public following the experiment. One expert remarked: ‘In the past, I could only say “the glaze colour of this porcelain piece”; now I can see that “the glaze colour accounts for 42% of the score”, which allows me to reflect more clearly on my own judgement.’ Another expert noted: “I questioned the AI's low score for the antique-style tripod, and upon further inquiry, the AI displayed a comparison of curvature, which led me to revise my initial intuition.” It is evident that explainable outputs helped experts shift their perception of the AI from a mere auxiliary tool to a collaborative partner, thereby enhancing trust and consistency in judgement. The public, meanwhile, reported that the visual interface lowered the barrier to understanding. Regarding the human–machine feedback loop, respondents acknowledged that the ‘observation–understanding–feedback–reanalysis’ cycle enables the AI to make dynamic adjustments. At the same time, some experts noted that the AI's explanations for highly context-dependent aesthetic judgements remain somewhat superficial. Overall, the AHCI framework achieves an effective balance between professional expertise, interpretability and user experience.

6. Discussion

6.1. Portability and Applicability Boundaries of the AHCI Framework

The AHCI framework proposed in this paper is fundamentally a mechanism for cultural heritage research centred on interpretable AI–human collaboration. Its key strength lies not in reliance on specific data types, but in the ability to transform complex cultural heritage materials into quantifiable data and computable features, and to complete the cognitive feedback loop through interpretable mechanisms, thereby achieving the visualisation and digitisation of cultural heritage. In the practical implementation of the ‘Tianlai.China’ project, AI is not utilised as a single tool in a highly localised manner, but rather permeates multiple critical stages—including data processing, model construction, 3D generation and experimental evaluation—forming a complete chain of human–machine collaboration. The core significance of this process lies not in automation, but in establishing a mapping relationship between the language of human experience and machine-processable features, thereby bringing aesthetic knowledge—which is inherently difficult to quantify—into an analysable domain.

The core value of the AHCI framework lies not only in its effective support for the single case study of ‘Tianlai.China’ presented in this paper, but also in its versatility as a methodological template and its capacity for cross-disciplinary application. Even when removed from the specific context of porcelain research, the four-tier architecture of ‘data–model–interaction–analysis’ and the four-stage collaborative process remain adaptable to

a wide range of cultural heritage types, including calligraphy and painting, ancient texts, architecture, and intangible cultural heritage. Specifically, the framework stipulates that the data layer involves the integration and transformation of multi-source, heterogeneous data into structured data; the model layer establishes a human–machine co-creation model comprising human-defined dimensions, AI-driven objective computation, and XAI-based explanations; the interaction layer constitutes a bidirectional interaction paradigm between AI explanations and human feedback; and the analysis layer formulates a hybrid evaluation logic combining quantitative and qualitative approaches.

The following section illustrates the content adaptation logic of the AHCI framework using three typical categories of cultural heritage as examples (Table 5):

Table 5. Content adaptation logic of the AHCI framework across cultural heritage types.

Cultural Heritage Type	Data Layer Adaptation	Model Layer Adaptation	Interaction Layer Adaptation	Analysis Layer Adaptation
Painting and Calligraphy	Images, brushwork and ink characteristics, colophon texts, and seals	Brushwork quantification model (brushstroke, composition, coloration)	AI-annotated compositional principles with expert correction	Mixed quantitative and qualitative evaluation
Ancient Texts	Multi-version images, annotated texts, and textual genealogy	Textual style analysis and variant text detection	Human–AI collaborative collation interface	Collation consistency evaluation
Architecture	Survey drawings, historical documents, and spatial point clouds	Spatial feature quantification (scale, proportion, symmetry)	AR/VR immersive co-exploration	Spatial cognition experiment
Historical Photographic Archives	Scanned images, capture metadata, and contextual documents	Image content recognition, damage detection, and dating inference	Timeline-based browsing, AI-assisted annotation with expert correction	Retrieval efficiency and annotation consistency evaluation
Music/Audio Archives	Audio files, spectrograms, metadata (composer, period, instrument)	Melodic/rhythmic pattern extraction, style classification, source separation	Spectrogram highlighting, comparative listening, expert style validation	Classification accuracy, expert–AI agreement on stylistic attribution
Archaeological Sites	Remote sensing data, LiDAR point clouds, excavation reports, GIS layers	Terrain feature extraction, anomaly detection (e.g., potential buried structures)	3D terrain visualisation, AI-highlighted anomalies, expert ground-truthing	Detection accuracy, expert–AI agreement on site interpretation

Consequently, the transferability of the AHCI framework should be understood as ‘reuse at the process level’, rather than a simple porting of tools. Its core lies in transforming the tacit knowledge within cultural heritage into analysable objects, and reintroducing the computational results into human cognitive processes through interpretable mechanisms, thereby establishing a stable relationship of harmony between humans and machines. Within this relationship, humans remain responsible for the interpretation of meaning

and value judgements, whilst artificial intelligence provides support in terms of reconstructing and comparing perspectives. However, its applicability remains limited. Firstly, the framework relies on formalisable knowledge structures; for cultural objects that depend on context, symbols and narratives, it requires the collection of vast amounts of multidimensional data and the establishment of standards. Secondly, the varying demands for ‘interpretation’ across different fields necessitate highly designed interpretation mechanisms; otherwise, it is difficult to effectively trigger expert cognitive feedback loops.

6.2. *AI Subjectivity and Aesthetic Boundaries: Balancing Roles in Collaboration*

The core of the AHCI framework does not rely on enhancing AI performance, but rather on restructuring the human–machine relationship. Existing research generally holds that the central objective of human–machine collaboration is to achieve synergistic effects that transcend the cognitive capabilities of any single agent through the complementarity of strengths [20]. Molina et al. (2024) further note that whilst artificial intelligence excels at processing semantic and data-driven problems, humans remain irreplaceable in intuitive judgement, fuzzy reasoning and meaning generation [19,32]. Consequently, in the field of AI research—which relies heavily on interpretation and value judgements—humans must retain a central role in ‘meaning-making’. AI cannot comprehend culture, but it can assist humans in formalising implicit aesthetic experiences [33]. In research on explainable artificial intelligence (XAI), El-Hajj et al. (2023) note that the value of XAI evidence lies not in providing ‘correct answers’, but in offering ‘clues for questioning and forward-looking interpretation’ [6]. Consequently, in AHCI, AI-generated explanations should not be regarded as conclusions, but rather understood as a cognitive trigger mechanism.

In light of the experimental findings of this study, it is evident that AI explanations can indeed trigger secondary cognition; however, their effectiveness depends on the quality of the explanations, which must satisfy two conditions: fidelity and comprehensibility [6]. This reconstructs the pathways of cultural understanding and establishes a harmonious relationship of human–machine collaboration that is comprehensible, trustworthy and aligned with human needs [19].

6.3. *Ethics and Limitations: Critical Reflection*

Although the AHCI framework has demonstrated potential in the field of cultural heritage digital visualisation, its application still faces a series of ethical and epistemological challenges that cannot be ignored.

Firstly, AI models rely heavily on training data, and their outputs are directly influenced by the selection of those data. Biases within the data may lead to systematic judgements; particularly in the realms of culture, history and value judgements, such biases may be amplified into ‘erroneous cultural narratives’ [20]. Although artificial intelligence is capable of extracting complex features, its understanding of cultural context remains limited. Particularly when symbolic meaning, historical context and aesthetic experience are involved, artificial intelligence is prone to producing results that are ‘formally correct but devoid of meaning’. Consequently, cultural expression often involves multimodal and implicit imagery; modelling it requires not only data but also profound cultural knowledge and interdisciplinary engagement [14]. Simultaneously, a core risk of human–machine collaboration systems lies in ‘automation bias’. Humans may place excessive trust in AI outputs, leading to diminished judgement or a suspension of critical thinking. In the context of this study, experts may be inclined to accept AI scores; if the explanation mechanism is poorly designed, it may reinforce bias [20]. Consequently, AHCI must impose constraints by encouraging multi-pathway comparative analysis and designing ‘reflective interfaces’ [14,41]. Furthermore, from a methodological perspective,

AHCI still faces certain limitations: firstly, when data are extremely sparse (such as in the case of a single surviving artefact), AI struggles to establish a reliable statistical foundation, necessitating a shift to a lightweight model where experts take the lead and AI provides only visual assistance [42]. Secondly, highly abstract intangible cultural heritage (such as ritual performances) presents challenges in fully representing its core value through visual or textual features alone, necessitating the incorporation of multimodal data and more complex semantic modelling [43].

The diversity and uniqueness of human interpretations of shared cultures and aesthetics are qualities that AI cannot replicate or homogenise. Two equally experienced porcelain experts may hold differing views on the same artefact; such differences stem from their respective knowledge frameworks, aesthetic preferences and even personal experiences, and constitute the very vitality of humanities research. AI's tendency to produce a 'single correct score' is fundamentally at odds with this diversity. The value of the AHCI framework does not lie in replacing experts' diverse judgements with standardised AI assessments, but rather in transforming this diversity into a structure that is visual, comparable and open to dialogue, thereby encouraging experts to articulate the basis of their judgements more clearly, rather than pursuing a single correct answer.

7. Conclusions

This paper addresses the central question of 'how to achieve a visual integration between subjective aesthetic experience and computational models' within complex cultural contexts. It proposes the Artificial Intelligence–Human Collaborative Interpretation (AHCI) methodological framework and, using the digital interpretation of the Illustrated Catalogue of Famous Porcelains Through the Ages as a practical case study, systematically explores the application pathways of human–computer collaboration in cultural analysis, visualisation and value assessment. In response to the three research questions raised in the introduction, this paper presents corresponding discussions and practical implementations across three dimensions: methodological construction, system implementation and experimental validation.

Firstly, with regard to the visualisation of aesthetic expression, this paper utilises multimodal data integration to transform textual descriptions, image features and three-dimensional structures into a computable feature system. This facilitates the translation of experiential aesthetic judgements into formalised expressions of experience, thereby enhancing the comparability and analysability of complex cultural features and providing a foundation for quantitative assessment and visualisation. Secondly, regarding the impact of AI explanations on expert cognition, by introducing explainable artificial intelligence (XAI) and human–machine feedback loop experiments, this paper verifies that AI outputs can stimulate experts' 'secondary cognition'. The results indicate that AI, acting as a cognitive trigger mechanism, guides experts to revise and interpret their subjective judgements through feature visualisation and explanation pathways, thereby enhancing consistency and the depth of interpretation. Regarding the transferability of the methodology, this paper constructs the AHCI framework comprising data, model, interaction and analysis layers, establishing a practical research pathway for human–AI collaboration. This framework has not only been validated in porcelain research but also holds potential for extension to fields such as painting, calligraphy and ancient architecture. Finally, this paper emphasises that the role of artificial intelligence in cultural heritage research should shift from that of a 'tool' to that of a 'collaborative partner'. In this process, artificial intelligence undertakes data processing and feature analysis tasks, whilst humans take the lead in making judgements regarding meaning and value. Through an interpretable collaborative relationship, the two complement one another, thereby transforming cultural interpretation from a unidirectional

judgement into a dynamic and constructive process. This enhances its interpretability and verifiability, providing a new research pathway for the digital visualisation of complex cultural heritage.

This study still has certain limitations. On the one hand, the effectiveness of the method depends on data quality and the extent of expert involvement, and it continues to face challenges in situations where data are scarce or the context is complex; on the other hand, artificial intelligence's understanding of cultural meaning remains at a formal level, and its interpretative capabilities require further improvement. Future research could be further developed in three directions. Firstly, in terms of interpretation optimisation, efforts could be made to deepen multimodal modelling and cross-modal association capabilities, thereby enhancing the AI's accuracy in expressing and interpreting complex cultural experimental contexts, whilst optimising interpretable mechanisms to ensure more stable and verifiable interpretation results [44,45]. Longitudinal tracking experiments could be conducted to examine the long-term impact of sustained collaboration between experts and AI on cognitive habits, judgement criteria and professional practice, thereby further validating the robustness and adaptability of the framework [46]. Secondly, regarding method transfer, the scale and types of data could be expanded by incorporating more categories of cultural heritage and cross-cultural samples to further validate the generalisation capabilities and scope of application of the AHCI framework. Finally, at the interaction level, we can explore more granular human–machine feedback loops and expert participation models, introducing XR and VR technologies to enhance immersive interaction experiences and strengthen dynamic feedback capabilities during the collaborative process, thereby improving the efficiency and reliability of human–machine collaboration in complex cultural interpretation [47].

Author Contributions: Conceptualization, L.Z. and Y.L.; Methodology, L.Z. and Y.L.; Software, L.Z. and Y.L.; Validation, J.L. and Y.D.; Formal analysis, L.Z. and Y.L.; Investigation, L.Z. and Y.L.; Resources, L.Z. and Y.L.; Data curation, L.Z. and Y.L.; Writing—original draft, L.Z. and Y.L.; Writing—review & editing, L.Z., Y.L., J.L. and Y.D.; Visualization, L.Z., Y.L. and Y.D.; Supervision, J.L. and Y.D.; Project administration, J.L. and Y.D.; Funding acquisition, J.L. and Y.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China under Grant No. KAA0824005533.

Institutional Review Board Statement: In the absence of a standalone ethics committee at Beijing Jiaotong University, this study underwent formal review and received approval from the Academic Committee of the School of Architecture and Art Design, Beijing Jiaotong University on 1 January 2025.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: This research and creative work, user research and experiments, and the writing of this paper have benefited from support and assistance from many quarters. We would like to express our gratitude to the creative team, comprising Zheng Wang, Jingya Li, Liwen Zhang, Yiqi Liu, Mingyang Liu and Yifei Wang. Furthermore, the ‘Tianlai.China’ project case study discussed in this paper was previously published as a conference paper (Digital Preservation and Cultural Computing Practice: The Visualisation System and Multidimensional Quantitative Model for the *Illustrated Catalogue of Famous Porcelains Through the Ages*) at the IEEE Pacific Visualization Symposium (PacificVis) 2026. Building upon the original work, this paper focuses on proposing the AHCI human–machine collaboration methodological framework, incorporating new theoretical constructs, experimental validation and cross-domain transfer analysis, thereby forming a more comprehensive

academic contribution. During the writing of this paper, the author utilised generative artificial intelligence tools (ChatGPT-4.1 and DeepSeek-V4) to refine the language, correct grammar and optimise academic English expression, thereby enhancing the writing style. Specifically, these tools were employed to improve the text's readability, fluency and consistency of expression, with the aim of enhancing the quality of the English. The author confirms that artificial intelligence was not used to fabricate the content of the paper, nor did it alter the original research findings, conclusions or data. All core content and key conclusions were produced independently by the author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Li, M.; Wang, Y.; Xu, Y.Q. Computing for Chinese cultural heritage. *Vis. Inform.* **2022**, *6*, 1–13. [CrossRef]
2. Bushell, S.W. *Chinese Porcelain: Sixteenth Century Coloured Illustrations with Chinese Manuscript Text by Hsiang Yuan Pien*; Oxford University Press: Oxford, UK, 1908.
3. Thomas, H.A. The Origin and Development of Porcelain in China: A Study Based on Dated Vessels. Ph.D. Thesis, The University of Chicago, Chicago, IL, USA, 1943.
4. Hippisley, A.E. *A Catalogue of the Hippisley Collection of Chinese Porcelains: With a Sketch of the History of Ceramic Art in China*; US National Museum: Washington, DC, USA, 1890.
5. Zhao, H.; He, J. AI-based digital acquisition and innovation framework for Liao Dynasty porcelain. *Int. J. High Speed Electron. Syst.* **2025**, 2540893. [CrossRef]
6. El-Hajj, H.; Eberle, O.; Merklein, A.; Siebold, A.; Shlomi, N.; Büttner, J.; Valleriani, M. Explainability and transparency in the realm of digital humanities: Toward a historian XAI. *Int. J. Digit. Humanit.* **2023**, *5*, 299–331. [CrossRef]
7. Chen, Y.; Peng, Y.; Tan, Y.; Luo, G.; Wang, M. Achieving cultural heritage sustainability through digital technology: Public aesthetic perception of digital Dunhuang murals. *Sustainability* **2025**, *17*, 7887. [CrossRef]
8. Windhager, F.; Federico, P.; Schreder, G.; Glinka, K.; Dörk, M.; Miksch, S.; Mayr, E. Visualization of cultural heritage collection data: State of the art and future challenges. *IEEE Trans. Vis. Comput. Graph.* **2018**, *25*, 2311–2330. [CrossRef] [PubMed]
9. Kumar, S.; Datta, S.; Singh, V.; Datta, D.; Singh, S.K.; Sharma, R. Applications, challenges, and future directions of human-in-the-loop learning. *IEEE Access* **2024**, *12*, 75735–75760. [CrossRef]
10. Mazzanti, M. Cultural heritage as multi-dimensional, multi-value and multi-attribute economic good: Toward a new framework for economic analysis and valuation. *J. Socio-Econ.* **2002**, *31*, 529–558. [CrossRef]
11. Belhi, A.; Ahmed, H.O.; Alfaqheri, T.; Bouras, A.; Sadka, A.H.; Foufou, S. An integrated framework for the interaction and 3D visualization of cultural heritage. *Multimed. Tools Appl.* **2024**, *83*, 46653–46681. [CrossRef]
12. Rauterberg, G.W.M. From personal to cultural computing: How to assess a cultural experience. In *UDayIV: Information Nutzbar machen: Information Der Beiträge Zum Usability Day IV 09. Juni 2006*; Pabst Science Publishers: Lengerich, Germany, 2015; pp. 13–21.
13. Gîrbacia, F. An analysis of research trends for using artificial intelligence in cultural heritage. *Electronics* **2024**, *13*, 3738. [CrossRef]
14. Harisanty, D.; Obille, K.L.B.; Anna, N.E.V.; Purwanti, E.; Retrialisca, F. Cultural heritage preservation in the digital age, harnessing artificial intelligence for the future: A bibliometric analysis. *Digit. Libr. Perspect.* **2024**, *40*, 609–630. [CrossRef]
15. Kotulski, M.; Kotulska, J. Digitization of cultural heritage as a form of its protection. In *Public Policy, Governance and Communications in the EU Member States and Candidate Countries: Post-Conference Monograph*; National University of Kyiv-Mohyla Academy (NaUKMA): Kyiv, Ukraine, 2023; pp. 63–77. Available online: <https://ekmair.ukma.edu.ua/handle/123456789/26945> (accessed on 10 March 2026).
16. Haznedar, B.; Bayraktar, R.; Ozturk, A.E.; Arayici, Y. Implementing PointNet for point cloud segmentation in the heritage context. *Herit. Sci.* **2023**, *11*, 2. [CrossRef]
17. Vazquez de Ágredos Pascual, M.L.; Fantoni, R.; Francucci, M.; Guarneri, M.; Mongelli, M.; Pierattini, S.; Gil Bordallo, J.M. 3D model acquisition and image processing for the virtual musealization of the Spezeria di Santa Maria Della Scala, Rome. *Heritage* **2022**, *5*, 1253–1275. [CrossRef]
18. Münster, S.; Maiwald, F.; di Lenardo, I.; Henriksson, J.; Isaac, A.; Graf, M.M.; Oomen, J. Artificial intelligence for digital heritage innovation: Setting up a R&D agenda for Europe. *Heritage* **2024**, *7*, 794–816. [CrossRef]
19. Blessing, O.O. Human-AI collaboration systems. *J. Sci. Technol. Soc. Transform.* **2025**, *1*, 26–33.
20. Puerta-Beldarrain, M.; Gómez-Carmona, O.; Sánchez-Corcuera, R.; Casado-Mansilla, D.; Lopez-de-Ipina, D.; Chen, L. A multifaceted vision of the human-AI collaboration: A comprehensive review. *IEEE Access* **2025**, *13*, 29375–29405. [CrossRef]
21. Tong, R.J. From augmentation to symbiosis: A review of human-AI collaboration frameworks, performance, and perils. *arXiv* **2025**, arXiv:2601.06030. [CrossRef]

22. Foroughi, M.; Andrade, B.; Roders, A.P. Capturing experts' knowledge in heritage planning enhanced by AI: A case study of windcatchers in Yazd, Iran. *J. Cult. Herit.* **2024**, *67*, 1–8. [\[CrossRef\]](#)
23. Schindler, J. Expertise and tacit knowledge in artistic and design processes: Results of an ethnographic study. *J. Res. Pract.* **2015**, *11*, M6.
24. Phillips, P.J.; Hahn, C.A.; Fontana, P.C.; Yates, A.N.; Greene, K.; Przybocki, M.A. *Four Principles of Explainable Artificial Intelligence*; NIST Interagency/Internal Report (NISTIR) 8312; National Institute of Standards and Technology: Gaithersburg, MD, USA, 2021. [\[CrossRef\]](#)
25. Holter, S.; El-Assady, M. Deconstructing human-AI collaboration: Agency, interaction, and adaptation. In *Proceedings of the Computer Graphics Forum*; Wiley-Blackwell: Hoboken, NJ, USA, 2024; Volume 43, p. e15107. [\[CrossRef\]](#)
26. Mamidala, J.V.; Bitkuri, V.; Attipalli, A.; Kendyala, R.; Kurma, J.; Enokkaren, S.J. Machine learning approaches to salary prediction in human resource payroll systems. *J. Comput. Sci. Technol. Stud.* **2024**, *6*, 341–349. [\[CrossRef\]](#)
27. Attipalli, A.; Bitkuri, V.; Kurma, J.; Enokkaren, S.; Kendyala, R.; Mamidala, J.V. A survey of artificial intelligence methods in liquidity risk management: Challenges and future directions. *SSRN* **2021**, 5741342. [\[CrossRef\]](#)
28. Ene, D. Cultural heritage representation in databases. In *Proceedings of the 7th Balkan Conference on Informatics Conference*, Craiova, Romania, 2–4 September 2015; pp. 1–4. [\[CrossRef\]](#)
29. Qingqing, L.; Anwar, R.B.; Vermol, V.V. Research status and design strategies of culture-based porcelain design. *Int. J. Creat. Change Manag.* **2025**, *17*, 39–51.
30. Michel, J.B.; Shen, Y.K.; Aiden, A.P.; Veres, A.; Gray, M.K.; The Google Books Team; Pickett, J.P.; Hoiberg, D.; Clancy, D.; Norvig, P.; et al. Quantitative analysis of culture using millions of digitized books. *Science* **2011**, *331*, 176–182. [\[CrossRef\]](#) [\[PubMed\]](#)
31. Hassija, V.; Chamola, V.; Mahapatra, A.; Singal, A.; Goel, D.; Huang, K.; Hussain, A. Interpreting black-box models: A review on explainable artificial intelligence. *Cogn. Comput.* **2024**, *16*, 45–74. [\[CrossRef\]](#)
32. Dong, Z. Exploring cross-cultural communication content adaptability through advanced natural language processing and sentiment analysis. *Syst. Soft Comput.* **2025**, *7*, 200290. [\[CrossRef\]](#)
33. Sowa, K.; Przegalinska, A. From expert systems to generative artificial experts: A new concept for human-AI collaboration in knowledge work. *J. Artif. Intell. Res.* **2025**, *82*, 2101–2124. [\[CrossRef\]](#)
34. Fragiadakis, G.; Diou, C.; Kousiouris, G.; Nikolaidou, M. Evaluating human-AI collaboration: A review and methodological framework. *arXiv* **2024**, arXiv:2407.19098. [\[CrossRef\]](#)
35. Molina, D.A.; Kharlov, V.; Chen, J.S. Towards effective human-AI collaboration in decision-making: A comprehensive review and conceptual framework. In *Proceedings of the 2024 Portland International Conference on Management of Engineering and Technology (PICMET)*, Portland, OR, USA, 4–8 August 2024; pp. 1–6. [\[CrossRef\]](#)
36. Hu, Y.; Yu, S.; Qin, S.; Chen, Y. How to extract traditional cultural design elements from a set of images of cultural relics based on F-AHP and entropy. *Multimed. Tools Appl.* **2021**, *80*, 5833–5856. [\[CrossRef\]](#)
37. Wang, Q.; Yang, L. Model analysis of communication entropy of intangible cultural heritage within a smart ecosystem framework. In *Proceedings of the 2025 4th International Symposium on Computer Applications and Information Technology (ISCAIT)*, Xi'an, China, 21–23 March 2025; pp. 1658–1662. [\[CrossRef\]](#)
38. Han, R.; Li, W.C. A study on the quantitative analysis of typological Tupu and the form of ceramic stemmed cups in the Yuan Dynasty. *Art. Des.* **2014**, *9*, 1–3. (In Chinese)
39. Saragusti, I.; Karasik, A.; Sharon, I.; Smilansky, U. Quantitative analysis of shape attributes based on contours and section profiles in artifact analysis. *J. Archaeol. Sci.* **2005**, *32*, 841–853. [\[CrossRef\]](#)
40. Zheng, L.; Chiang, W.-L.; Sheng, Y.; Zhuang, S.; Wu, Z.; Zhuang, Y.; Lin, Z.; Li, Z.; Li, D.; Xing, E.; et al. Judging LLM-as-a-judge with MT-bench and Chatbot Arena. In *Advances in Neural Information Processing Systems (NeurIPS 2023)*, New Orleans, LA, USA, 10–16 December 2023; Neural Information Processing Systems Foundation, Inc.: La Jolla, CA, USA, 2023; Volume 36, pp. 46595–46623. Available online: https://ui.adsabs.harvard.edu/link_gateway/2023arXiv230605685Z/ (accessed on 2 March 2026).
41. Nuthalapati, A.; Hinds, N.; Lim, B.Y.; Wang, Q. Enhancing XAI interpretation through a reverse mapping from insights to visualizations. In *Proceedings of the 2025 IEEE Visualization and Visual Analytics (VIS)*, St. Pete Beach, FL, USA, 16–21 November 2025; pp. 41–45. [\[CrossRef\]](#)
42. Wang, W.; Lu, Z. Few-shot bronze vessel classification via siamese fourier networks. *Sci. Rep.* **2024**, *14*, 18011. [\[CrossRef\]](#) [\[PubMed\]](#)
43. Yan, D. From physical to virtual: Enhancing the representation of intangible cultural heritage using mixed reality. *J. Posthumanism* **2025**, *5*, 1541–1556. [\[CrossRef\]](#)
44. De Regt, H.W. Visualization as a tool for understanding. *Perspect. Sci.* **2014**, *22*, 377–396. [\[CrossRef\]](#)
45. Li, M.H.; Pan, G. Visualization analysis of museum collection data. *Comput. Digit. Eng.* **2019**, *47*, 1–6. (In Chinese) [\[CrossRef\]](#)

46. Yi, J.H.; Kang, W.; Kim, S.E. Smart culture lens: An application that analyzes the visual elements of ceramics. *IEEE Access* **2021**, *9*, 42868–42883. [[CrossRef](#)]
47. Tosa, N.; Matsuoka, S.; Thomas, H. Inter-Culture Computing: ZENetic Computer. In *Intelligent Agent*; ACM: New York, NY, USA, 2004; Volume 6.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.