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The Evolution of AI-Assisted Cultural Heritage Restoration: A Bibliometric Review of Trends, Hotspots, and Conservation-Oriented Frontiers

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SUMMARY: *Conservation and restoration of cultural heritage are facing more serious problems today due to the degradation of materials, environmental risks, fragmentation of historical evidence, and high demands for data-driven decisions. Although artificial intelligence (AI) has been widely applied in heritage research, most of the existing studies have focused on individual technologies, specific heritage objects or isolated application scenarios, and thus have not comprehensively explored the general development and conservation-oriented value of this field. Bibliometric analysis of applications of AI in cultural heritage conservation and restoration from 2015 to 2025 is conducted in this paper. CiteSpace, VOSviewer and Bibliometrix were used to study changes in publication trends and co-occurrence relationships of related works over time. The above results show that the three stages of development for this field are: exploratory, stable growth and fast development. Research has been conducting damage detection, image completion, generative reconstruction, structural monitoring and preventive conservation recently, away from digital documentation and technical feasibility studies. In addition to mapping the knowledge structure of this field, the research has also connected AI applications to the three restoration-oriented paths and proposed a "restoration task - data type - evidence standard" framework for interpreting AI-assisted heritage restoration. It is proposed that the future application of artificial intelligence (AI) in heritage conservation will be achieved by linking the results of algorithms with other elements such as historical knowledge, expert assessments, and conservation measures on actual heritage objects. This paper reviews the macro-level situation of AI-assisted heritage restoration and offers references for future interdisciplinary research and conservation workflow development.*

KEYWORDS: *Artificial intelligence; Cultural heritage conservation; Heritage restoration; Generative AI; Preventive conservation*

1 Introduction

Cultural heritage is a carrier of history, culture and society; it also has values [1]. Monuments, archaeological sites, historical buildings, artworks, manuscripts, murals, ceramics, and other material remains of human civilisation that document the progress of society are all included here. Cultural heritage is also subject to prolonged physical, chemical, biological and environmental risks [2, 3]. Climate change, floods, urbanisation, tourism pressure, pollution and armed conflict have all increased the vulnerability of heritage objects and sites. Given the above circumstances, conservation and restoration are no longer confined to repairing visible

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damage [4]. Increasingly demanding high-precision documentation and assessment of conditions, risk predictions, material analysis and evidence-based decisions.

Artificial intelligence (AI) has further extended the above possibilities. AI can be used to handle all sorts of complicated visual, spatial and textual data in cultural heritage conservation and restoration [5]. Extract features from images, identify patterns in damage, classify materials, fill in missing visual data, reconstruct three-dimensional shapes, and support conservation-related decisions. AI has a better pattern recognition and data-driven inference capability than the old digital tools [6]. Therefore, it is more practical in cases of fragmented, incomplete or difficult-to-interpret heritage data. Machine learning and deep learning methods have been applied to mural restoration, manuscript damage detection, identification of stone deterioration, monitoring of architectural heritage, and archaeological reconstruction, etc. [7-14] The above applications indicate that AI is moving away from general digital documentation and towards particular conservation and restoration work. Recently, there have been many new developments in generative AI, digital twins, neural rendering and multimodal learning that have expanded the research space. Generative Models are able to perform image completion and visual reconstruction/repair of damaged decorative patterns. Digital Twins and Semantic Models can be used to connect heritage objects with monitoring data, spatial information, and management systems. NeRF-based reconstruction and AI-assisted modelling offer new paths for the three-dimensional documentation of architectural and archaeological heritage. Therefore, the functions of artificial intelligence will also be expanded beyond the previous ones. It is now used to carry out reconstruction, interpretation, supervision and management of cultural heritage sites and objects.

Recently, the two general ways in which research has been conducted on culture and heritage have been systematic reviews and bibliometric analysis. Most of the systematic reviews have concentrated on specific technologies or application scenarios, such as virtual reconstruction, augmented reality, AI/ML-based protection, and HBIM-based heritage documentation [15-19]. The above studies have provided detailed information on individual technologies and clarified their application scenarios for documentation, visualisation, monitoring and repair assistance. Bibliometric analysis has been used to study the publication trends, research hotspots, knowledge structure and cooperation network of related areas in cultural heritage studies. However, most existing research focuses on a single technology, a specific heritage object, a single conservation problem for an individual, or only a small group of AI methods. Although the above studies have explored the progress in technology, they have yet to provide a complete view of the changes in AI applications for broader conservation-oriented research. More significantly, they do not often present the interconnectedness of technological development, restoration tasks, data conditions, evidence standards and conservation decisions. AI output in cultural heritage restoration should not be evaluated solely based on algorithmic accuracy or visual quality. Their contents are derived from correlations with materials and other sources of information, as well as assessments by specialists. Therefore, the main deficiency is not simply the absence of a general overview, but rather the lack of an organized system for studying how AI is used in the evidence chain and workflow of heritage restoration.

Organised bibliometric analysis of AI applications in cultural heritage conservation and restoration from 2015 to 2025 will be conducted in this study. Based on the records retrieved from the Web of Science Core Collection, CiteSpace, VOSviewer and Bibliometrix were employed in this study to conduct multi-faceted analyses of the development of this field. First, how has the quantity of annual publications changed in the past few years, and at what stages of development are they now? Second, which countries, institutions, authors and journals have contributed most actively to this field? Third, what knowledge structures and research hotspots can be obtained by keyword co-occurrence, clustering and burst analysis? Fourth, what emerging themes indicate the future directions of AI-assisted heritage conservation and restoration? Different from other studies, this paper uses a large-scale mapping of academic literature and combines quantitative and qualitative methods to explore the all-round development of artificial intelligence applications in cultural heritage conservation and restoration. To explore how AI can be applied in the diagnostic, reconstruction and prediction stages of restoration and practical restoration work, this paper will conduct an analysis. Further, AI-assisted restoration is explored in terms of diagnosis, reconstruction and prediction, and a macro-level understanding of the change in workflow has been presented from a conservation perspective. At the same time, this paper will investigate how material evidence, historical knowledge and expert judgment influence the workflow of practical restoration work. Briefly introduce the current situation of this field in this paper and put forward some directions for future research to provide support for the integration of interdisciplinary research and the development of new technologies.

2 Materials and Methods

2.1 Data Sources and Search Strategies

Collect and screen the data of this study simultaneously. Web of Science Core Collection (WoSCC) was selected as the main data source [20]. WoSCC is a very stable, high-precision and complete reference database. In the advanced search, only the "Topic" field was restricted for the search string, and records in the titles, abstracts, and keywords were returned. Most of the referenced materials were obtained through WoSCC. The above records were selected to enhance the accuracy of the study. The full search string was as follows: (TS = (“cultural heritage” OR “cultural heritage restoration” OR “cultural heritage conservation”) AND TS = (“artificial intelligence” OR “generative artificial intelligence” OR “machine learning” OR “deep learning”) AND DT = (“Article” OR “Review”). The range of the search will be from January 1, 2015, to December 31, 2025.

2.2 Literature Screening and Data Cleaning

Retrieve the data, and then in accordance with the PRISMA guidelines [21], conduct screening and cleaning of the data. The first search found 583 items. Before thematic screening, 4 duplicate records and 47 non-English records were excluded, and a total of 532 records remained for the next step. Titles, abstracts and author keywords were then manually checked to determine whether the records were relevant to AI applications in cultural heritage restoration, and 161 records were excluded because their research focus did not cover cultural heritage restoration or conservation. The other 371 records were kept as candidates for verification. At this time, 38 records were excluded because they did not investigate AI as an applied tool or present AI-related methods, models, or workflows for heritage restoration and conservation. An additional 30 records were excluded because they had been indexed in Web of Science with a publication year of 2026, although they had been accepted or made available online in 2025. Therefore, this exclusion does not violate the set-up time of the study from 2015-2025. Finally, 303 WoSCC records with the document types of Article or Review were included in the bibliometric analysis and exported as plain-text files in the "Full Record and Cited References" format. Data cleaning addressed inconsistencies in author names and institutional names by correcting them, merged synonymous keywords, and standardising related terms to reduce noise in co-authorship and keyword co-occurrence. The screening process is as follows: Figure 1.

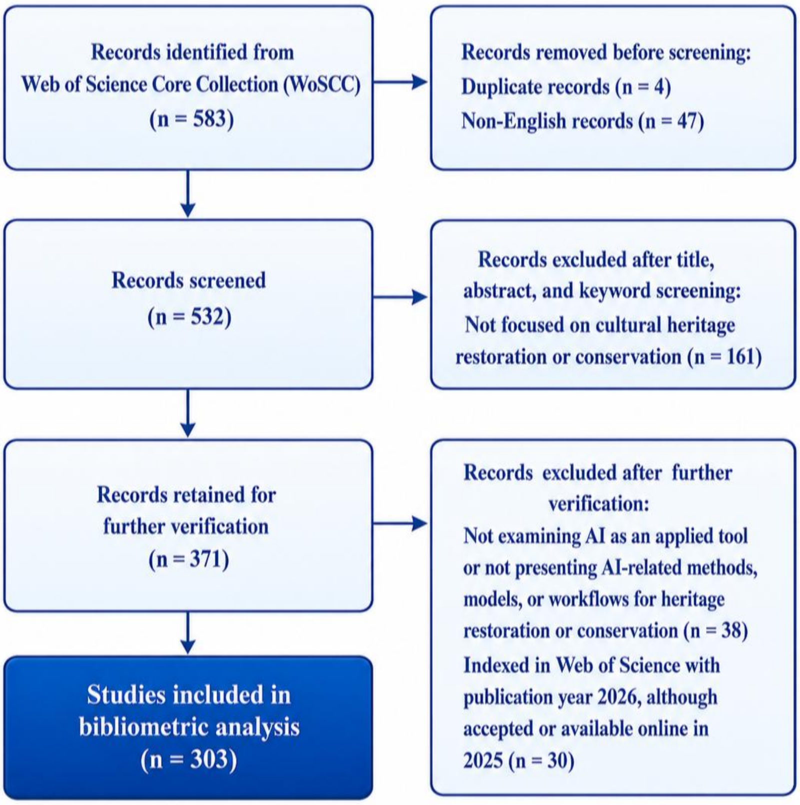


Figure 1: PRISMA Flowchart.

2.3 Bibliometric Tools and Parameter Settings

Bibliometric analysis is a typical method for studying a large body of scholarly works quantitatively. It can show the knowledge structure, research trends and new topics in a certain area [22]. Quantitative relationships among publications, authors, institutions, countries, and keywords in a visual form can also be shown. Some typical bibliometric tools are CiteSpace, VOSviewer, Bibliometrix, HistCite, SciMAT and RefViz. The three bibliometric tools used in this paper are CiteSpace (version 6.4.R1), VOSviewer (version 1.6.20) and Bibliometrix. The above tools were employed together to explore the structure of knowledge, cooperation models and themes in the field. CiteSpace was used to present the collaboration network of authors, institutions and countries, as well as the co-occurrence graph of keywords [23]. VOSviewer (Version 1.6.20) is used to build and display the bibliometric network [24]. The overall strength of the total link was employed to assess the connection strength between nodes. This metric helped identify the leading collaborative groups, thematic clusters, and highly interconnected research topics. In addition, Bibliometrix is based on R and can help organise research topics and concepts to construct maps showing the evolution of these topics over time. Bibliometric statistics were collected using Bibliometrix to show data such as the number of years published per year, source analysis, author output, and initial topic exploration [25]. The above software programs can handle a large amount of data and present it in an easy-to-read graph.

The bibliometric indicators that were shown in the visual analysis are as follows:

(1) $AGR_t = \frac{P_t - P_{t-1}}{P_{t-1}} x\ 100\%$, where P_t denotes the number of publications in year t.

(2) $TLS_i = \sum_{j=1}^{n} w_{ij}$, where w_ij denotes the link weight between node i and node j.

(3) $C_{ab} = \sum_{d=1}^{D} I(a,d)I(b,d)$, where I(a,d) equals 1 when keyword a appears in document d and 0 otherwise.

(4) $BC(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$, where σ_st is the number of shortest paths from s to t and σ_st(v) is the number passing through v.

2.4 Analysis Dimensions and Research Workflow

The four regions of the bibliometric analysis are as follows: First, the distribution of publications over the years was analysed to identify how the field of AI applications in cultural heritage restoration has developed annually. Next, we will jointly analyse whether the authors and other groups are in the same field or country. Keyword co-occurrence and co-citation mapping were employed to perform knowledge structure analysis, and the primary research objects and intellectual foundations were identified. Clustering and burst detection were employed to conduct trend analysis and identify new topics and the future development directions of the data. The whole analysis workflow is as follows: Figure 2.

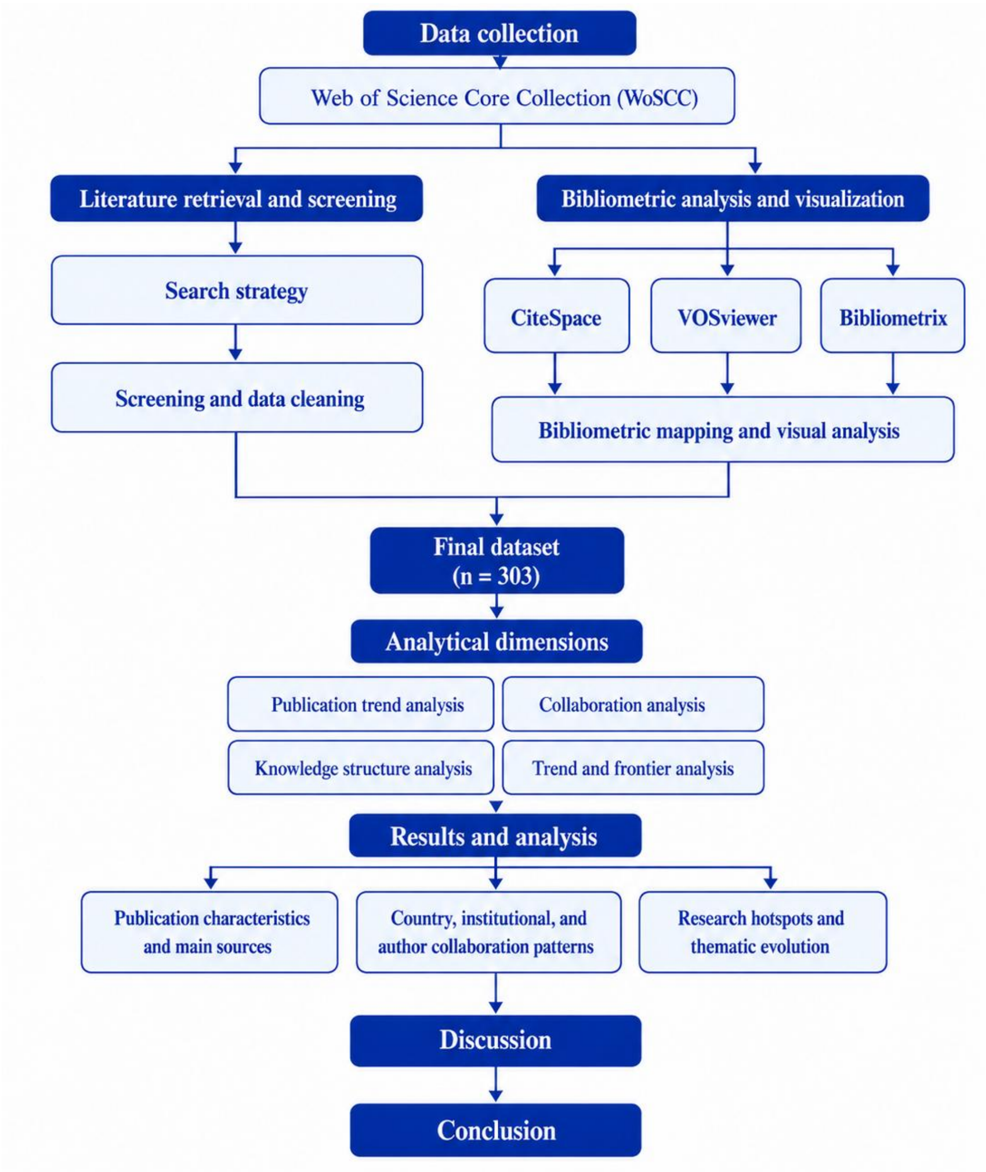


Figure 2: Research Framework.

3 Results and Analysis

3.1 Publication Features and Primary Sources

3.1.1 Trends and Development Stages of Annual Publications

Changes in the number of publications are frequently used to show the development of a research field. The distribution of the publication time can reflect the development progress and various periods of a field. As shown in Figure 3, the annual publication trends provide a basis for identifying the development path of research on AI applications in cultural heritage restoration from 2015 to 2025. Overall, the volume of publications increased during the study period, but the speed of this increase was not uniform each year. Based on changes in annual production and growth trends, three periods of development have been divided for this area: the exploration stage (2015-2019), the stable development stage (2020-2022), and the high-growth stage (2023-2025).

Phase I (2015-2019): Exploration Stage. At that time, the rate of increase per year was low and relatively stable. Technology for cultural heritage and intelligent processing was in its early days and had a relatively small scope of research and application. As a result, the number of related papers is relatively small. The first research by this group mainly focused on computational methods for basic repair and reconstruction. Other studies have explored the feasibility of building a digital platform to connect new technologies and cultural heritage. Therefore, this stage can be viewed as the early stage of the field. At this time, some research started to explore the foundation of AI, model-based methods and cultural heritage. These studies mainly examined the general principles and potential applications of emerging technologies. The content of this study focused on theoretical exploration, feasibility analysis, preliminary image generation and texture synthesis, and early restoration experiments. The first few studies have shown that artificial intelligence can help support the all-round development of cultural heritage protection and restoration.

Phase II (2020-2022): Steady Development Stage. The amount of publication each year gradually increased. In 2020, the number of publications was five per year; by 2021, it reached seven; and finally, by 2022, it was 18. Although the total number of studies remained relatively small, more research has been conducted since the previous stage. At this time, AI methods had started to show better results in image recognition, image correction and digital reconstruction. These ways have been applied to the work of cultural heritage preservation and restoration. At the same time, related studies have begun to explore image generation, restoration of decorative patterns, line drawings, virtual reconstruction and so on, expanding the application of AI in many ways to cultural heritage. In recent years, a large number of restoration-oriented and data-driven applications have been launched.

Phase III (2023-2025): Rapid Expansion Stage. The output of publications in this period increased significantly and reached a high of all time in 2025. Publications in 2023 were 32, increased to 64 in 2024, and then rose to 173 by 2025. Only in 2025 did the number of publications reach over half of all datasets, so scholarly interest was clearly rising. The area of work has been expanding at an accelerating pace due to technological development and an increase in the need for digital preservation of cultural heritage. AI methods have been applied more widely in the field of technical conservation and restoration recently. Research on artificial intelligence is no longer limited to technical tests, and more and more AI applications are being used in the actual work of cultural heritage conservation and restoration. With rapid development, generative AI has also started to be applied in various ways for the protection of intangible cultural heritage. At this time, after a period of steady development, AI applications for cultural heritage conservation and restoration have gradually begun to be introduced in practice.

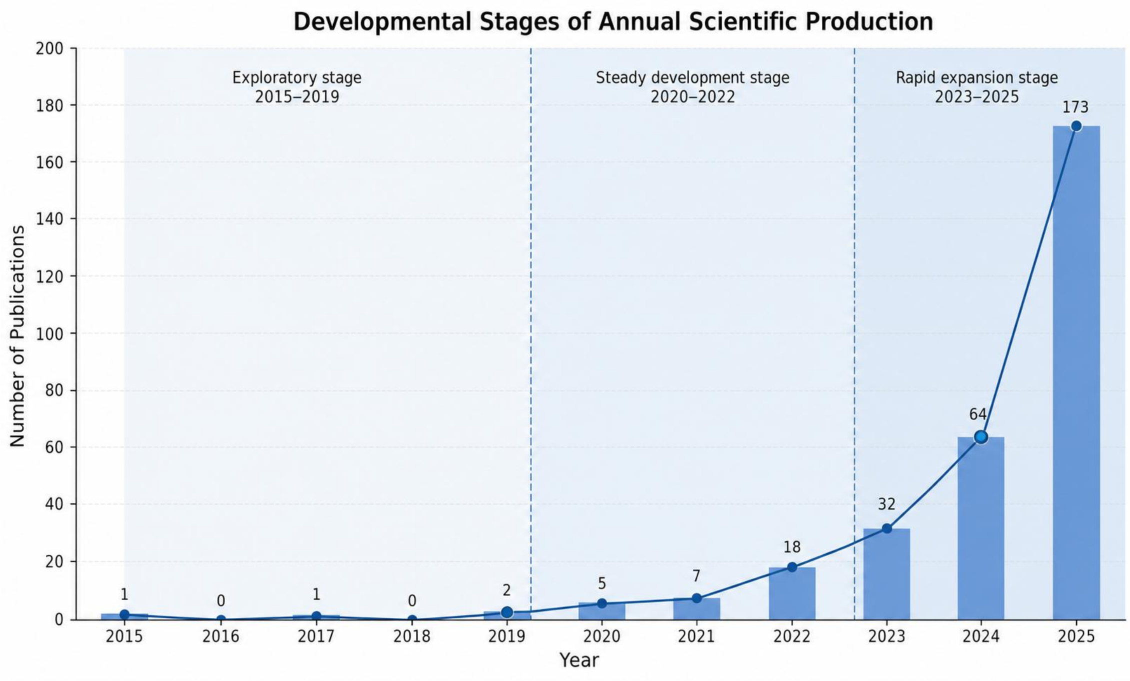


Figure 3: General Trend of Publications (2015-2025).

3.1.2 Disciplinary Distribution and Leading Journals

Based on the distribution of the disciplinary type, research on the application of artificial intelligence in the preservation and renovation of cultural heritage covers all types of subjects. Figure 4 shows the division of disciplines and primary places of publication for research on AI applications in cultural heritage conservation and restoration. Figure 4a is the disciplinary network. The main concentrations of the larger nodes are analytical chemistry, materials science, spectroscopy, archaeology, art, computer science, engineering, geosciences, humanities and construction and building technology. Therefore, this field will not be limited to computer science in the future. The model is suitable for the research of conservation and restoration. Figure 4b is the network of main publication sources. Analyze the distribution of publication sources and the patterns of scholarly contributions and interactions to determine which fields have produced and spread more research results. Publications appear in both heritage-oriented journals and other applications in science. Journal of Cultural Heritage, Heritage Science and Heritage are the main venues directly related to conservation, restoration and heritage science, and journals in applied science, sensing, remote observation, sustainability, construction and information technology indicate the broader methodological scope of the field.

Figure 4c is the trend of production for the main sources over time. The trend of source production is as follows: it was low before 2020, gradually rose from 2020 to 2022, and then increased significantly after 2023. Among the above sources, the Journal of Cultural Heritage has shown one of the strongest growth rates and is expected to lead the way by 2025. Other journals include Sustainability, Applied Sciences, Heritage Science, and Scientific Reports, and these are also on the rise. Therefore, research on AI in cultural heritage preservation and restoration has been given more attention by scholars recently.

Figure 4d shows the most widely cited documents in the dataset. Highly cited papers are spread out across various journals in heritage science, remote sensing, automation, sensing technologies, computer vision, information-related fields, etc. Therefore, influential studies in this area do not belong to one particular subject or type of publication. Generally speaking, as shown in Figure 4, the field of AI applications in cultural heritage conservation and restoration is developing along the lines of several interdisciplinary collaborations, including heritage studies, materials science, engineering, computer science, remote sensing and other applied technologies. The first few leading cited journals by centrality are shown in Table 1.

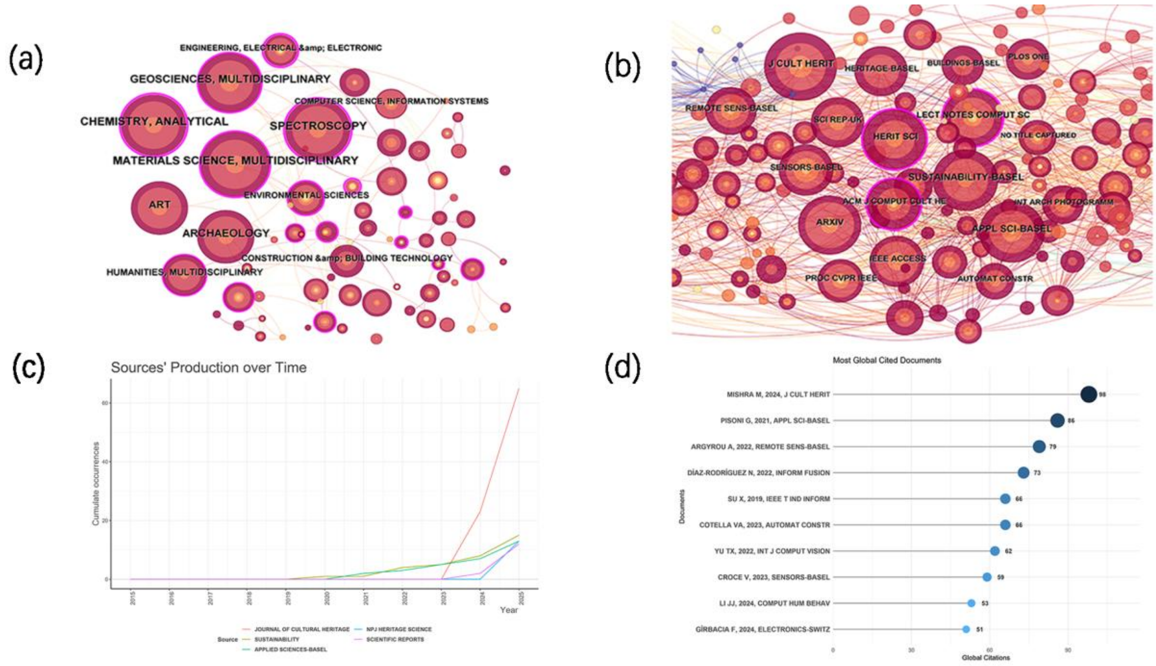


Figure 4: Disciplinary Distribution and Main Publication Sources of AI Applications in Cultural Heritage Conservation and Restoration. (a) Disciplinary Distribution of Publications; (b) Source Network showing relationships among publication venues; (c) Production trends of major sources over time; (d) Most globally cited documents in the dataset.

Table 1: Top 10 Cited Journals by Centrality.

No.	Centrality	Year	Cited Journals
1	0.06	2024	J CULT HERIT
2	0.04	2022	SUSTAINABILITY-BASEL
3	0.06	2021	APPL SCI-BASEL
4	0.01	2022	ARXIV
5	0.11	2023	HERIT SCI
6	0.15	2017	LECT NOTES COMPUT SC
7	0.11	2019	ACM J COMPUT CULT HE
8	0.03	2021	SENSORS-BASEL
9	0.07	2019	IEEE ACCESS
10	0.01	2022	SCI REP-UK

3.2 Country, Institutional and Author Collaboration Patterns

3.2.1 Network of Countries and Institutions

Network analysis can also be applied to identify strong centres of research in this field and determine how widely the results of collaborations at home and abroad have been spread. We need to know where the collaboration zones are located to help promote the spread of educational exchanges abroad, identify research topics with strong support from all over the world, and look ahead to anticipate future collaboration opportunities and paths. Set the node type to "country" and visualize and analyse the national/regional collaborative network for the protection and restoration of cultural heritage in the field of AI. Figure 5 shows the country- and institution-level collaboration patterns of research on AI applications in cultural heritage conservation and restoration. As shown in Figure 5a, the network at the country level is geographically concentrated in terms of publication activities and cooperation. China is the main hub, with the highest number of papers and many connections between the collaborations; Italy, the United States, Spain, South Korea and several other European countries are also relatively active. The global collaboration map also shows that the main links for this cooperation are among China, Europe and North America, and there are other connections with East Asia, Australia and other areas. Instead of spreading evenly around the world, most of the research has focused on a small number of production bases and regional cooperation groups. Figure 5b also shows the time-series production data for the top-producing countries. Before 2020, the main countries had not been published in. From 2020 to 2022, several countries started to show a slow rise, but the total increase was still relatively small. After 2023, China's publication output increased substantially and were now higher than those of other countries. Italy also continued to rise steadily, but Spain, the United States and South Korea had shown relatively lower growth. Therefore, the rapid growth of the field after 2023 has been accompanied by an increase in Chinese publications and ongoing contributions from the research communities in Europe and North America.

Figure 5c shows a collaboration network of some active institutions. Each node in the figure is an institution, and the size of the node generally indicates how much that institution contributes to research in intelligent technologies and sustainable cultural heritage. Zhejiang University and the Consiglio Nazionale delle Ricerche (CNR) are larger nodes in this field and thus relatively central. They are the sources of research results and hubs for cooperation among institutions. Chinese institutions, including the Chinese Academy of Sciences and Zhejiang University, have formed a noticeable and rapidly expanding cluster. European institutions, such as the CNR and several universities in Italy and Spain, are also members of the network. Based on the network structure, several clusters of institutional collaboration have formed, and Chinese institutions are among them. The above institutions work together to form an alliance. As the main institutional units, universities lead this development. Therefore, higher education institutions are among the most active places for this research. The main research institutions are universities and research institutions with strong interdisciplinary capabilities, and six of the top ten institutions in China include Zhejiang University, the Chinese Academy of Sciences, Northwestern Polytechnical University, Chongqing University, Tongji University and Huazhong University of Science and Technology. Some of the institutions are relatively densely connected and are actively collaborating; however, the whole system is still somewhat disjointed, and cooperation is stronger in certain clusters than in the whole network. Figure 5d is the time-series plot of the highest-producing affiliations. The pattern at the national level was similar, and the amount of institutional publication output was also relatively low in the first few years, rising significantly after 2022. Several institutions, particularly the Chinese Academy of Sciences and Zhejiang University, are on a rapid rise towards 2024 and 2025. Figure 5e is the world map of publication distribution and collaboration. The darker shading over China shows that it has published more papers than other places; some active areas also include parts of Europe, the United States, and a few other countries in Asia. Curved links between countries show cross-border cooperation, and some are visible links connecting China with Europe, North America, and other Asian countries. As shown in Figure 5, research on the application of AI in the conservation and restoration of cultural heritage has gradually formed a geographically dispersed but increasingly connected network. Currently, only a small number of countries and institutions have joined this field; although more countries and institutions have participated in various forms of cooperation recently, more collaborative activities are still needed. Table 2 shows the publication frequency and centrality of the main institutions.

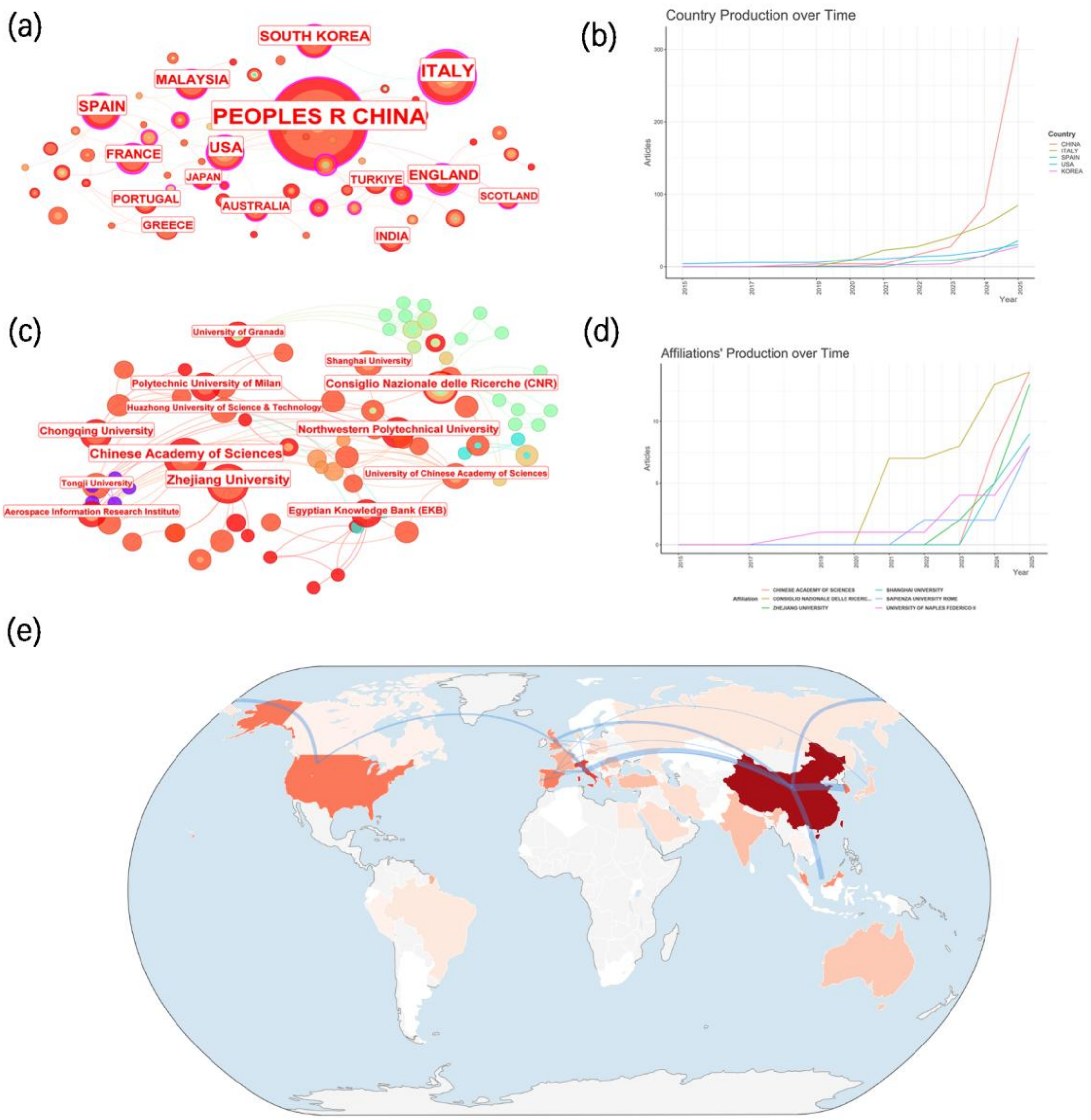


Figure 5: Country and Institutional Collaboration Networks and Production Trends. (a) Collaboration network among contributing countries; (b) Temporal production trends of the most productive countries; (c) Collaboration network among contributing institutions; (d) Temporal production trends of the most productive affiliations; (e) Global distribution and collaboration network of publications.

Table 2: Publication Frequency and Centrality of Major Institutions.

No.	Freq.	Year	University/Institutions
1	10	2024	Zhejiang University
2	10	2024	Chinese Academy of Sciences
3	7	2021	Consiglio Nazionale delle Ricerche(CNR)
4	6	2025	Northwestern Polytechnical University
5	6	2024	Chongqing University
6	5	2022	Sapienza University Rome
7	5	2024	Egyptian Knowledge Bank (EKB)
8	5	2020	Polytechnic University of Milan
9	4	2025	Tongji University
10	4	2019	Huazhong University of Science and Technology

3.2.2 Author Collaboration Characteristics

Co-authorship and cross-country patterns show the contributors of this field. The distribution of corresponding authors (Figure 6a) shows that China leads the way, followed by Italy, South Korea, Spain, Malaysia and the United States. Although single-country publications are still dominant, multiple-country collaborations have begun to emerge in China, Italy, Spain and the United States; at the same time, the national communities are still driving production. Therefore, research on AI applications for the protection and promotion of cultural heritage in China is still concentrated in the country, and international cooperation is in its nascent stage.

The author collaboration network (Figure 6b) uses node size to show the frequency of publication and links to show co-authorship. It has a density of only 0.0161, is very dispersed and has a sparse structure with no wide-spread core clusters. Visible groups focus on Ding Jinghan, Li Xuanhua, Zhao Xichen, Zhu Jinmeng, Ruiz-Agudo Encarnación and Díaz-Rodríguez Natalia. Therefore, author collaboration in this area is still fragmented and largely in the form of teams or projects.

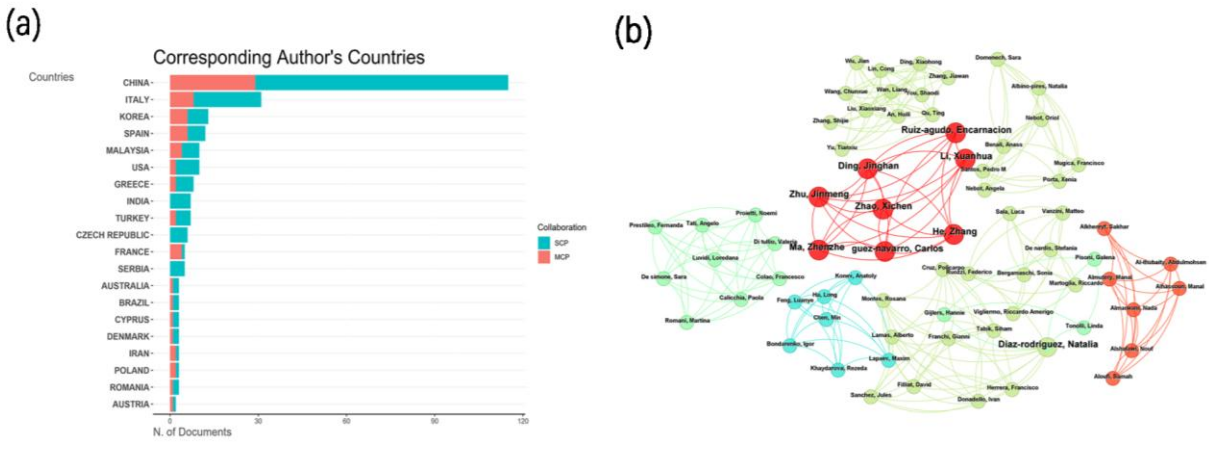


Figure 6: Author collaboration network. (a) Countries of corresponding authors; (b) Author collaboration network.

Figure 7 shows the connections among cited references, authors and keywords. Representative cited references are on the left, active authors are in the middle, and key words are on the right. The group of active authors in the middle column includes Chen W., Li M., Li Y.H., Chen J.M., Chen J., Chen Q., Li L., Cheng Y., Huang J.Z., Liu Y., Zhang R.Y., Zhang Y.J., Wang Y.R., and Liu J.J. The right column shows the main keyword categories for the authors listed above. The first few keywords are classification, ML, AI, intangible cultural heritage, conservation, cultural heritage, generative AI, heritage, art, cultural heritage conservation, and DL. The above links indicate that the main area of current author contributions is at the intersection of AI methods, heritage classification, conservation and digital preservation. The three groups of research topics for the author's groups are as follows. The first group of methods are based on computation and include classification, machine learning, artificial intelligence and deep learning. The second group relates to cultural heritage objects and environments, including cultural heritage, heritage, art and intangible cultural heritage. The third group is related to conservation-oriented applications, and conservation and cultural heritage conservation are examples. Author collaboration is expanding, but most of the work is still concentrated in a few prosperous regions and several small research groups. The foundation of the field's progress is a good-working technical system.

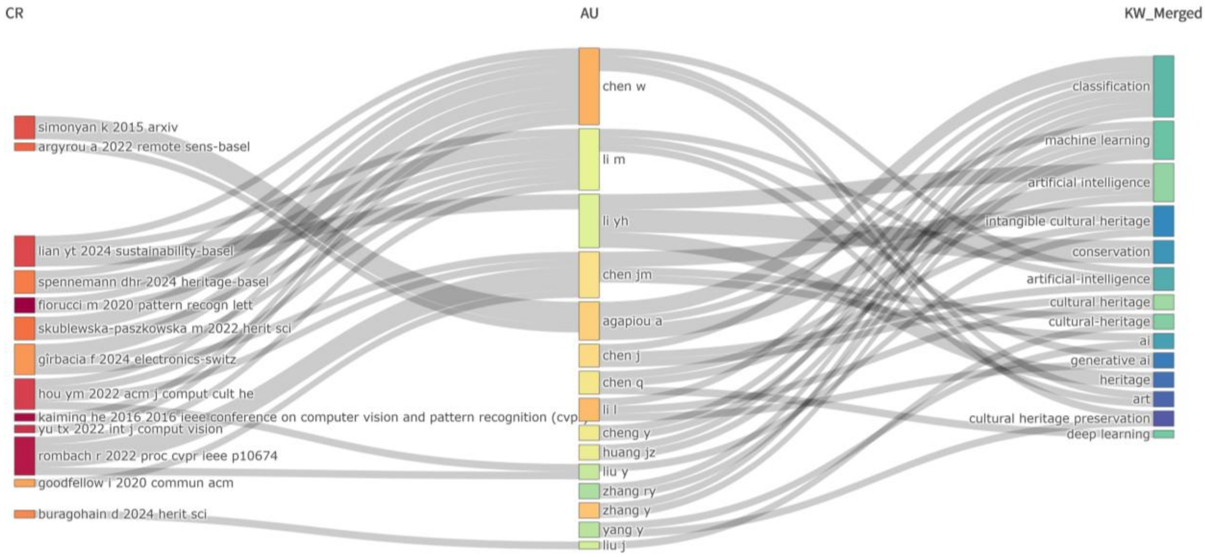


Figure 7: Three-Field Plot of References, Authors and Keywords.

3.3 Research Hotspots and Thematic Evolution

3.3.1 Keyword Co-occurrence and Burst Analysis

Keywords in bibliographic records are used to identify research hotspots and changes in attention to AI-driven heritage conservation. In the co-occurrence network (Figure 8), node size reflects the frequency of occurrence and links are co-occurrence relations. Keyword co-occurrence analysis has been used to divide the literature into several clusters, each of which corresponds to a specific line of research in AI applications for cultural heritage conservation and restoration (Figure 8). The blue cluster is a relatively large set of related terms that collectively represent the overall research field of this work. Based on the above keywords, it can be seen that AI-assisted heritage research is becoming increasingly connected with computational analysis, spatial observation, archaeological interpretation and new generational technologies. The green cluster includes keywords such as "artificial intelligence", "digital heritage", "museum", "photogrammetry", "virtual reality", "augmented reality", "management" and "information", and shows the digital heritage and management aspects of this field. Therefore, this group of activities can be considered as applications of AI for the analysis of restoration work, digital preservation, inheritance management, exhibition design and online display. The red cluster includes conservation and deterioration assessment, and the terms are:

"conservation", "cultural heritage conservation", "computer vision", "quality", "impact", "biodeterioration", and "consolidation". As shown in the keywords above, AI and computer vision are now being used for conditions assessment, damage diagnosis, conservation evaluation and support for repair and restoration. The yellow cluster is focused on recognition and classification tasks, and "deep learning", "classification", "identification", "heritage", and "paintings" are typical examples. The cluster indicates that Deep Learning (DL) has been applied to image-based recognition, object classification and other visual feature extraction tasks in cultural heritage for a long time. Overall, the co-occurrence network shows that the research hot spots are moving away from general digital documentation and recognition towards more integrated applications of conservation assessment, multimodal documentation, and generative reconstruction.

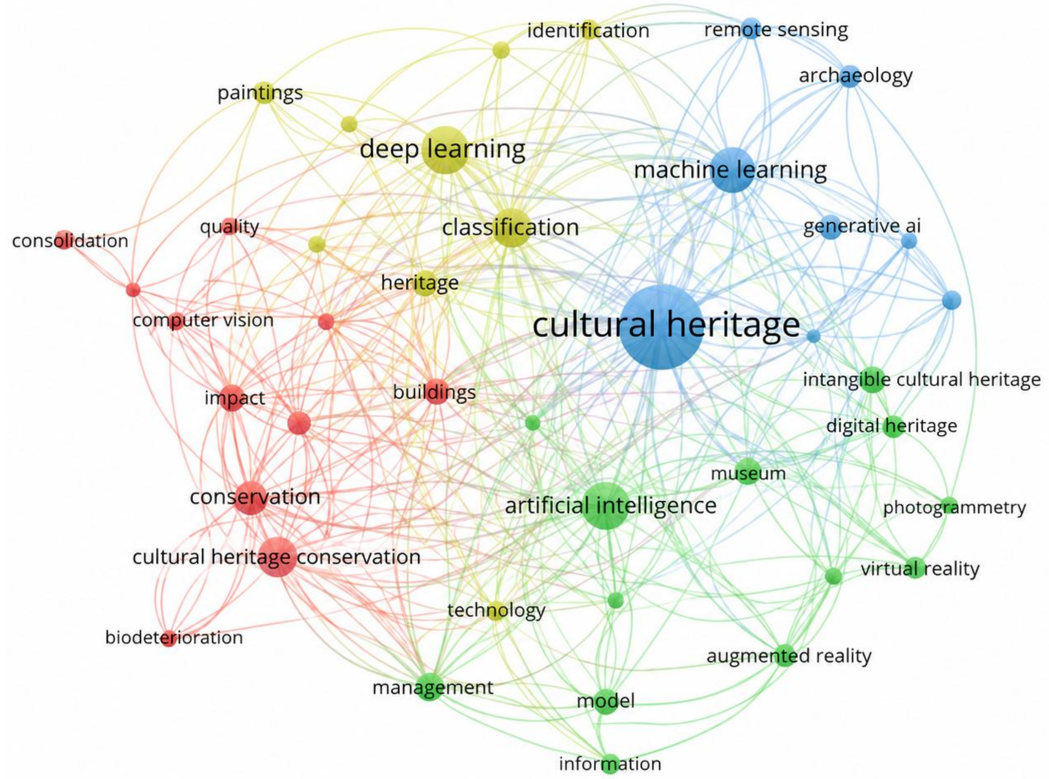
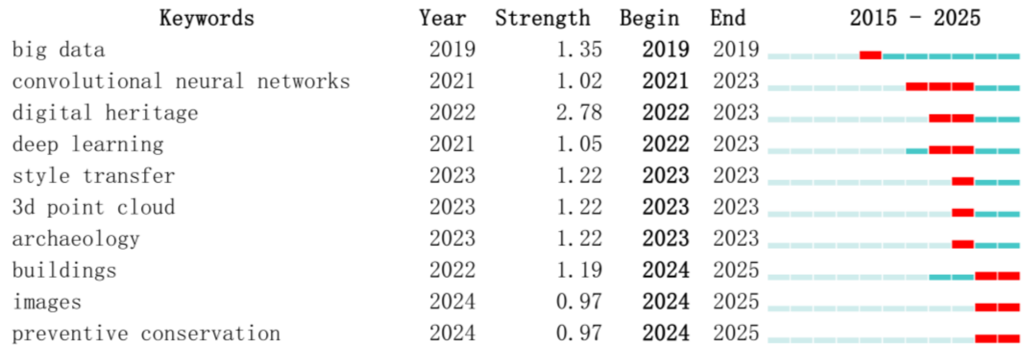


Figure 8: Keyword Co-occurrence Network and Thematic Clusters.

As shown in Figure 9, the keywords with the most significant fluctuations in 2015-2025 and changes in research emphasis over time are presented here. The first burst term was "big data" in 2019, with a burst strength of 1.35; thus, at that time, scholars started to pay more attention to large-scale digital information and data-driven analysis in the study of cultural heritage. From 2021 to 2023, the subjects of the burst terms have shifted towards AI-related computational methods, such as "convolutional neural networks" and "deep learning". At the same time, "digital heritage" had the largest increase in the same period, rising to 2.78 from 2022 to 2023. Therefore, AI methods are gradually being applied to address problems in the digital documentation, recognition and classification of heritage.

In 2023, some short-term burst terms appeared, such as "style transfer", "3D point cloud" and "archaeology", each with a burst strength of 1.22. As shown in the above indicators, the research focus has gradually shifted from general digital documentation to specific technical and application cases. Style transfer refers to changes and enhancements of images; three-dimensional point cloud data, on the other hand, are closely linked to spatial documentation, digital reconstruction and model-making of built heritage. The sudden rise of archaeology has also brought to light more and more applications of AI in interpreting archaeology, analyzing sites and reconstructing heritage.

The most recent surge in terms included "buildings", "images", and "preventive conservation", and these continued from 2024 to 2025. Therefore, some efforts have been made in practice to conserve and restore. The "buildings" now are the focus of interest for studying architectural inheritance, structural assessment, and monitoring the built environment. The emergence of "images" indicates that, at present, image-based analysis still forms a fundamental part of AI-aided heritage studies. At the same time, "preventive conservation" indicates that the field is transitioning from damage repair after the fact to risk monitoring, early warning, and long-term heritage protection.



Keywords	Year	Strength	Begin	End	2015 - 2025
big data	2019	1.35	**2019**	2019	
convolutional neural networks	2021	1.02	**2021**	2023	
digital heritage	2022	2.78	**2022**	2023	
deep learning	2021	1.05	**2022**	2023	
style transfer	2023	1.22	**2023**	2023	
3d point cloud	2023	1.22	**2023**	2023	
archaeology	2023	1.22	**2023**	2023	
buildings	2022	1.19	**2024**	2025	
images	2024	0.97	**2024**	2025	
preventive conservation	2024	0.97	**2024**	2025	

Figure 9: Top Keywords with the Strongest Keyword Bursts.

3.3.2 Thematic Clusters and Frontier Directions

Figure 10 shows the thematic clusters and timeline development of research topics in AI applications for cultural heritage conservation and restoration. As shown in Figure 10a, the keyword clustering results are divided into eight primary theme groups: #0 artificial intelligence, #1 structural health monitoring, #2 cultural heritage preservation, #3 cultural heritage, #4 perceptions, #5 deep learning, #6 prevention, and #7 generative AI. The above groups show that the field has formed a relatively diversified theme system. Among them, AI, DL and generative AI are the leading technological foundations, and structural health monitoring, prevention and cultural heritage protection demonstrate the increasing application of these AI methods in practical conservation work. The clusters of cultural heritage and perceptions also indicate that this field covers more extensive heritage environments, interpretations and user-oriented aspects.

Figure 10b shows a timeline for these thematic clusters and how they have changed over time. Previously, most research has focused on broad issues such as AI, cultural heritage and deep learning (DL), and the initial studies have been general applications of AI, digital documentation and image-based analysis. At the same time, the topics of study also varied. Clusters such as structural health monitoring, cultural heritage preservation and prevention became more prominent, and research gradually expanded to include built-heritage assessment, condition monitoring, risk analysis and preventive conservation. Recently, generative AI has formed an independent cluster and shown new applications in image completion, virtual restoration and generative reconstruction.

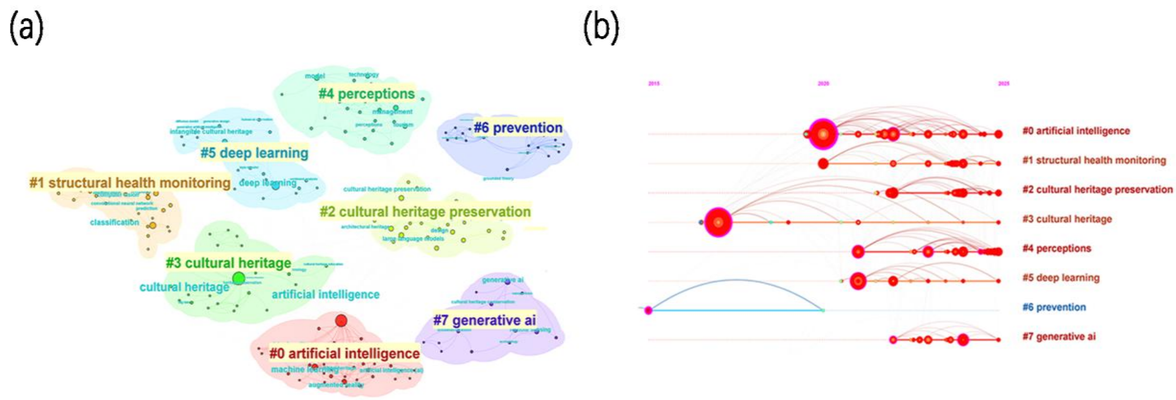


Figure 10: Thematic Clusters and Timeline Evolution of Research Topics. (a) Keyword Cluster Map; (b) Timeline View of Thematic Evolution.

Figure 11 is the trend topics in AI applications for cultural heritage conservation and restoration. The horizontal lines show when each topic was active, and the size of the circle is its frequency. Pattern recognition is the first and oldest topic, running from 2020 to 2024; therefore, it can be concluded that recognition and classification tasks have formed a fundamental methodology in the early development of this field. Starting in 2023, topics such as DL, AI and cultural heritage have become more prominent, and thus AI-based methods are being integrated into broader studies of cultural heritage. Among the above terms, cultural heritage has occurred most frequently and thus is a key content. Around 2024, generative AI, intangible cultural heritage and other clusters of cultural heritage appeared as prominent topics; at this time, applications of AI in the field moved beyond recognition and documentation to content generation, semantic interpretation, etc.

Damage detection was the most recent topic and remained active in 2025.Therefore, the research direction is now closely linked to practical conservation and restoration work. Generally speaking, the trend-topic results indicate a shift from the earlier pattern recognition and deep-learning-based analysis to generative AI, intangible cultural heritage and damage detection. Based on the above results, the research front has moved away from the traditional pattern recognition and classification tasks towards generative restoration, content completion, automated structural damage assessment, intangible cultural heritage digital activation, and prevention-oriented conservation workflows. Thus, these technical demonstrations have moved beyond isolation and now function as integrated preservation systems capable of intelligent reconstruction and active intervention.

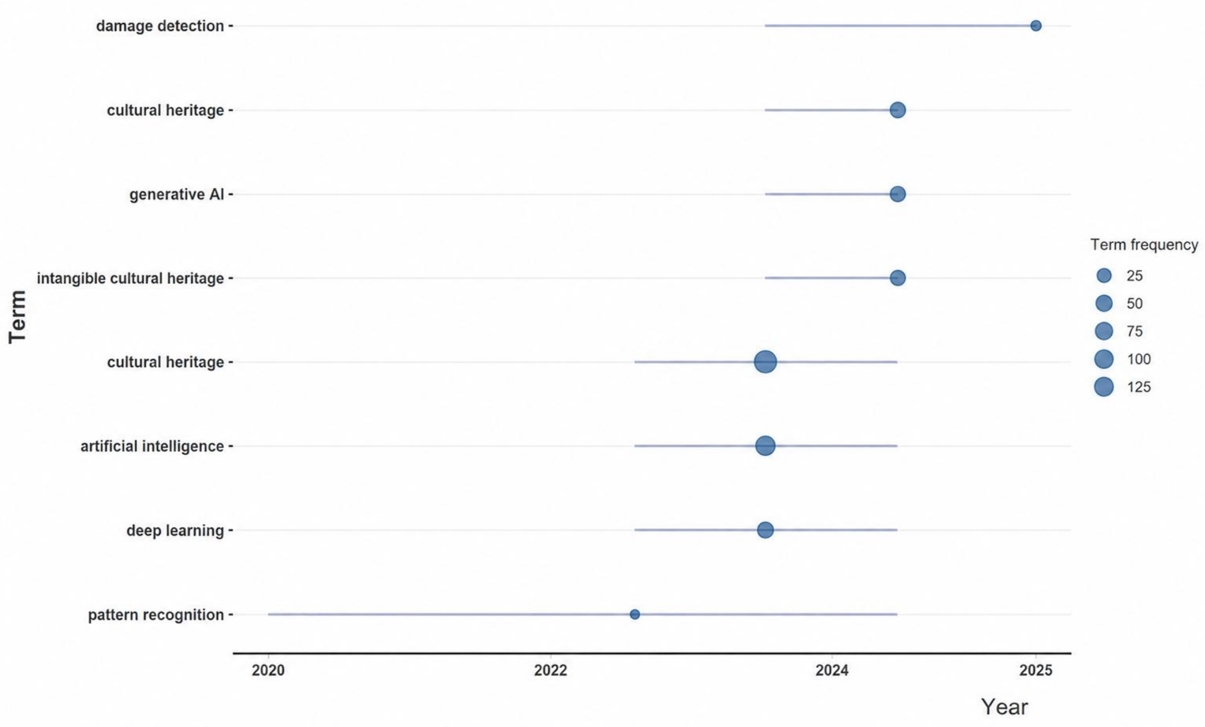


Figure 11: Trend Topics.

4 Discussion

4.1 Key Research Findings

Based on bibliometric methods and visualization tools such as CiteSpace, VOSviewer and Bibliometrix, this study systematically examines the development trends, collaboration patterns, knowledge structure, research hotspots and future directions of artificial intelligence applications in cultural heritage conservation and restoration from 2015 to 2025. Based on the above results, the development of AI-assisted heritage conservation and restoration can be classified into two types: early technical exploration and task-oriented/conservation-related applications. The particular research results are as follows:

A Typical Series of Annual Publication Trends has emerged. During 2015-2019, the number of publications remained relatively low; therefore, it can be assumed that the connection between AI and cultural heritage restoration was still in the initial stages and had not developed into an established research community. From 2020 to 2022, this field was in a period of development; at the same time, the number of publications was increasing steadily, and interest in deep learning, digital recording, image recognition, sensors, and heritage datasets was growing. At this time, feasibility studies have been conducted to test for applications. Since 2023, the amount of published works has risen sharply; thus, it has become a focus of research. With the development of generative AI, multi-modal data, 3D point clouds, HBIM, digital twins and semantic segmentation have all been emerging; thus, research has shifted from general digital analysis to specific conservation and restoration applications.

The distribution of disciplines shows that this field should not be regarded as solely a computer science subject. Instead, it is the result of the integration of materials science, analytical chemistry, spectroscopy, geoscience, archaeology, art history, engineering, computer science and construction technology. Materials science, analytical chemistry and spectroscopy are all required for the role of AI-assisted conservation and restoration, as they need to obtain material evidence, diagnose deterioration and carry out non-destructive examination. Therefore, AI applications in cultural heritage restoration should not be limited to image generation and visual recognition.

The journal's spread also supports this multi-disciplinary nature. The core publication platforms are still the Journal of Cultural Heritage and Heritage Science, and in addition, Sustainability, Applied Sciences, Remote Sensing, Sensors and Automation in Construction have begun to cover the area of remote sensing, sensor-based monitoring, engineering assessment, built heritage studies and applied digital technologies. This distribution of publications indicates that AI-based cultural heritage restoration has developed within heritage conservation journals and is now expanding into applied science, engineering and computational publications. Therefore, the recent growth of this area should not be seen as simply the result of the general expansion of AI. It is also closely related to the rising demands for material diagnosis in cultural heritage conservation and restoration, as well as non-invasive analysis, structural monitoring and evidence-based decision-making.

Collaboration analysis reveals that there is an unevenly distributed, yet expanding, research pattern geographically. Currently, the main output is concentrated in a few productive countries and institutions, with China being the most active contributor, especially after 2023. The Chinese Academy of Sciences and Zhejiang University have also been producing at an increasing rate and are thus contributing to this trend. Italy, Spain, the United States, South Korea, Greece, France and India are also relatively active and have strong traditions of cultural heritage preservation and good technical foundations. The first group of institutional contributors includes top Chinese universities and research institutes, the Italian National Research Council, the Polytechnic University of Milan, and the University of Granada. The above institutions have indicated that the field is influenced by the combination of heritage studies, conservation science, material analysis, computer science, engineering, remote sensing and building technology. The collaborative network remains relatively concentrated and fragmented. Most of the studies are still clustered within the country, institutions or teams, and widespread cross-regional and cross-disciplinary collaboration is lacking. Therefore, there has been no formation of a high-level, interconnected global research community in the field yet.

4.2 Current Research Trends and Stage Characteristics

Rather than being a mere process of technological dissemination, AI-assisted cultural heritage conservation and restoration are evolving from a different perspective in their research logic. In addition to the increase in the number of studies, there has been a change in the focus of these studies.

The number of papers published in the exploratory period of 2015-2019 was relatively small. AI was still being explored as a technical tool for restoration work rather than as an integrated part of the practice, and most of the keywords were related to artificial intelligence, cultural heritage, image generation, texture synthesis, and simple reconstruction. Therefore, the first research did not explore whether to apply AI in the field of restoration. The main reasons for this are that there is a relative shortage of available digital images and early computational models, as well as fragmented heritage datasets. Therefore, most of the studies were only at the level of feasibility testing. The main content of the research in this time was the basic theories and systems for cultural heritage protection. The above studies have shown that it is feasible to use AI for visual feature extraction and restoration reference generation. Their research has shown that AI can be applied to extract and restore visual features for reference generation.

From 2020 to 2022, a period of stable development was achieved due to the emergence of more explicit tasks in conservation and restoration for AI methods. The technical keywords "deep learning" and "machine learning" occurred more frequently and were focused on in research in 2021 and 2022. Application-oriented keywords, such as "architectural heritage" and "augmented reality", have also been rising in this period. The pattern shows that AI has gone from theory to application in practice. Technology is no longer treated as an independent research subject; rather, it has also started to be used in the aims of heritage identification, analysis, conservation and digital presentation. The development of deep learning and the spread of high-resolution photography, photogrammetry, 3D scanning and heritage image databases have all enabled such changes. AI started to be applied to concrete restoration. Recognition and segmentation models can be used to detect cracks, pigment loss, damaged edges of murals, etc., and prepare them for the next round of restoration work. Deep learning and OCR-related methods can be used to enhance the readability of damaged text and strokes in manuscript conservation. Feature matching in ceramic or archaeological restoration can be used to compare fragments by analysing features such as contours, colours, textures and fracture shapes. At this time, AI was no longer performing general image processing but rather evidence extraction and restoration hypothesis support. However, many of these studies were also task-oriented and performance-focused. As a result of this stage, AI shifted from general-purpose image processing to evidence extraction and hypothesis support in the field of restoration.

From 2023 to 2025, as the number of researchers has increased and AI models have strengthened, the field of publication has grown rapidly; at the same time, new kinds of data have been created for risk assessment and mitigation. Research topics became more specific and closely related to actual conservation cases. Generative AI, digital twin technology and MLLMs have all become popular topics recently. The above technologies have expanded the scope of application for basic analysis to include intelligent restoration, digital modelling, content generation and other advanced functions. The Field was no longer well-known or recorded. Now the research direction has moved to restoration and generation, deterioration diagnosis, risk monitoring and prevention intervention. Recently, generative models, multimodal learning, digital twins, and intelligent sensing systems have all been spreading rapidly. Diffusion-based models have been employed to improve the restoration of mural images, and hyperspectral imaging combined with AI has aided in the identification of deterioration in stone heritage. In the future, intelligent systems based on AI and IoT will be added to increase the safety of the site. The above cases are not limited to the recognition of cultural relics by AI. It can be employed in some parts of the repair work, such as damage detection and proposal of restoration plans for damages, and in the planning of long-term preservation.

With the progress of research in recent years, the focus of theme has moved from general technical exploration to specific restoration-oriented applications. First, Artificial Intelligence and digital documentation were studied to some extent to assist with image processing and reconstruction. Recently, a number of studies in deep learning have concentrated on image recognition, virtual restoration, damage detection, structural health monitoring and prevention, and generative AI. Therefore, artificial intelligence will also be used to learn from traditional Chinese characters and develop a new form of language-learning tool. It is now being used more frequently in the practical phase of conservation and restoration for damage diagnosis, missing information inference, structural risk monitoring and decision support. Adjusting will better meet the needs of technological application in conservation. It offers better support for the study of how AI can help with restoration.

4.3 AI-Assisted Restoration Paths and Evidence Requirements

In the keyword co-occurrence network, "deep learning", "classification", "identification" and "computer vision" are closely connected with "conservation", "cultural heritage conservation", "biodeterioration" and "consolidation"; it can be seen that artificial intelligence is being used more and more often for condition assessment, damage recognition, and conservation diagnosis. It will help determine that. Burst-term results also show the appearance of "style transfer" and "3D point cloud", and thematic clusters identify "generative AI" as a new frontier. The above are all associated with image transformation, missing-data completion, virtual restoration and 3D reconstruction, thus providing support for the reconstruction path. In addition, the appearance of "structural health monitoring", "prevention", "buildings" and "preventive conservation" in the clustering, burst and trend-topic results indicates that AI is moving towards risk monitoring, early warning and preventive management. This offers the support for the prediction path. To avoid a technology-only classification, this paper puts forward a framework of "restoration task - data type - evidence standard" for interpreting AI-aided heritage restoration. The system of this framework is that the value of artificial intelligence in conservation and restoration should be assessed based on whether the results can meet specific restoration tasks, use relevant heritage data, and satisfy the criteria of conservation-oriented evidence. Therefore, AI-assisted heritage restoration can be divided into three interconnected paths: diagnostic AI, reconstructive AI and predictive AI. These paths are not only different types of technology but also correspond to different stages of conservation work, require different types of evidence, and have different levels of expert intervention.

The diagnostic pathway is a relatively simple way for AI to be applied in conservation. At this time, the primary purpose is to find visible damage and to determine what kind of problems that damage has caused for the object. Cracks, stains, pigment loss, salt deposits, biological growth, surface detachment and previous repair traces may occur simultaneously, but they often result from different causes of deterioration. CNNs, U-Net, Mask R-CNN, YOLO, Faster R-CNN and Vision Transformers are examples of image-based models that can make these traces more visible and measurable. SVM, Random Forest, KNN and clustering models are also relatively simple machine learning algorithms that can be applied to extract features from spectra, colours, textures and chemicals. Segmentation of the mural restoration can be used to delineate the limits of remaining pigment and damage areas. Spectral classification of stone heritage can be used to differentiate among weathering, salt damage and biological growth. Object detection in architectural heritage can identify damage such as cracks, spalling, missing parts and deformations before repair planning. However, these results are still only at the first level of evidence. A detected crack may be due to a change in moisture, a reduction in structural support, material damage, etc. Therefore, the actual problem is now to make a diagnosis. In the future, AI outputs will be combined with material tests, environmental data, conservation history and field observations in research. A damage-material-cause annotation system would be more practical than simply labelling damage; thus, model outputs could be added to the chain of conservation evidence.

Reconstructive AI raises a different problem. AI can use the existing fragments and styles, as well as old pictures and related cases, to generate a few restoration ideas. Its strength is that it can create possible forms in the absence of information, but its risk is that visual plausibility will be mistaken for truth. Generative models, image inpainting, style transfer, NeRF, point-cloud registration and shape-completion methods can all be applied to mural filling, painting recovery, decorative pattern reconstruction, ceramic fragment matching, inscription recovery and architectural detail reconstruction. The above ways are suitable for damaged, faded or partially lost heritage items. Several types of schemes can be deduced from the above residual signs, repetitive patterns, stylistic characteristics, comparable examples or geometric relationships. However, the value of preservation does not need to be visual harmony. The Pattern of the mural is beautiful, but there is no meaning. A reconstructed ceramic object may appear whole, but it will not be based on the real fracture logic. AI-assisted restoration is not the same as general image completion. Restoration is not to say that the missing is to be rectified.

Adjust the level of inference to some extent. Therefore, the generated output is taken as a hypothesis rather than a reconstruction. The revised workflow should be divided into verified evidence, probable inferences and speculation more distinctively. Link each output to the supporting evidence, and expert review should still be conducted on these results before determining which ones are suitable for the restoration interpretation.

Predictive AI expands the scope of object repair to risk control. Its first function is to adjust the time of the preservation activities. A predictive model can detect an abnormal change in time before it is known to be damaged. Time-series models, anomaly detection methods, digital twins and sensor-based models can all process data on deformation, vibration, humidity, temperature, rainfall, pollution and structural response. The above methods can help monitor crack growth, wall deformation, settlement and vibration alerts in built heritage. At the archaeological site, one or more are used to observe changes in erosion and water damage. Microclimate conditions, such as relative humidity, temperature, light and pollutants, of the museum collection can also be regulated. Prediction is only an early warning signal at present. Only when a risk signal is likely to cause damage will it be identified and managed. Thus, the main purpose will be to improve the model's performance and support the development of conservation. A practical way is to establish a risk threshold-intervention priority-inspection feedback loop. Monitoring results set warning levels, trigger field inspections at the warning level, guide the priorities of intervention based on inspection results, and provide new observations for model updates.

Generally speaking, AI is used in different ways for heritage restoration. Diagnostic AI can show the existing damage more clearly, but it also needs to support material and environmental analysis. Reconstructive AI can make the missing parts seem real, but it must not be presented as facts. Predictive Artificial Intelligence can foresee the future risks in conservation work and take preventive measures in time. Therefore, AI-aided restoration has been further studied in detail. AI is not a general solution for all restoration problems. Its application is generally related to the stage of work, the kind of data and required proof standards.

4.4 Structural Challenges and Future Workflow Integration

Based on the analysis of keyword evolution and thematic clustering, some future directions for the application of AI in cultural heritage conservation and restoration have been put forward. With the continuous development of "deep learning", "generative AI", "damage detection", "structural health monitoring" and "prevention", in the future, more specialised restoration tasks will likely be addressed in the research. Damage diagnosis, virtual reconstruction, risk monitoring and conservation decision support are examples. With the expansion of the application scope, some deficiencies in this field have yet to be resolved.

First, the data are scarce now. Cultural heritage objects are generally scarce, delicate and cannot be replicated easily. Many of the damage processes cannot be replicated in a controlled environment. At the same time, the restoration-related data are also very varied. The above data can help train the AI model, but they are often in various forms and not in line with one another. Therefore, it restricts the reusability of data and model comparison. Therefore, in future research, conservation-oriented datasets will be built that include material type, damage category, acquisition conditions, environmental context, restoration history and expert interpretations.

Second, the standards for evaluation need to be closer to the purpose of preservation. Most studies of artificial intelligence at present use standard computer vision indicators such as accuracy, F1-score, IoU, PSNR, SSIM or prediction error. These indicators are feasible, but they cannot fully meet the requirements for cultural heritage restoration. A high-segmentation-accuracy diagnostic AI does not necessarily know the reasons for the decline in health.

Reconstructive AI does not guarantee the historical truth through visual similarity. Prediction accuracy of the AI does not guarantee that conservation measures will be taken. Therefore, the future assessment will also consider the technical performance and the demands for preservation, such as material relevance, historical consistency, expert approval, and practical conservation effectiveness.

The development of generative AI in recent years has also created new problems of authenticity and evidence control. Generative models can be used to create murals, restore damaged pictures, reconstruct decorative patterns and 3D models without the original data. They can assist in adding more training data due to a lack of real samples. However, generated content may be mistaken for real heritage records if it is not clearly labelled. The issue is more pronounced in restoration because a visually reasonable outcome may be mistaken for historical evidence. Later, distinguish among the categories of definite proof, strong indications, and hypotheses. AI-generated output should be traceable and linked to its data source, and so synthetic content will not reduce the reliability of heritage documentation and restoration interpretation.

Add more AI applications to all links in the conservation workflow. Restoration includes the above, as well as optimisation and prediction. Although the area has grown rapidly since 2023, the authors' collaborative network is still small and dispersed, and research output is concentrated in a few countries and institutions. It can be seen that AI-aided heritage conservation is still relatively focused on a few technical and project-based groups. Conservation-oriented AI is also a collaborative effort by conservators, material scientists, historians, engineers, computer scientists and heritage managers. Therefore, future research should aim to improve algorithms and build a common annotation standard, interdisciplinary datasets, and expert-in-the-loop validation mechanism. A process for gathering evidence, analysing circumstances, constructing a hypothesis for repair, obtaining expert confirmation, designing intervention steps and observing their effects. Future research will develop expert-in-the-loop workflows. Professionals from all fields are requested to participate in all stages of the work, such as data collection and annotation design, model analysis and decision-making, as well as final verification. Autonomous decisions about restoration will not be made by AI in this workflow. It can help organise the evidence, compare the different reasons for it, and support a rational conservation plan.

Future research will move away from task-level AI applications to integrate conservation workflows. The problem is not whether AI can find, create or forecast, but rather whether its output can be connected to materials of life, historical knowledge and expert opinions and subsequently applied in conservation practice. Only when the data structure, evaluation indicators, output results and expert assessments are all interconnected can AI assist in protecting and restoring cultural heritage efficiently.

4.5 Research Limitations

This study has the following defects. First, the dataset was obtained from the Web of Science Core Collection, and only English-language Articles and Reviews were included. Relevant studies indexed in Scopus, Google Scholar, CNKI, conference proceedings, books or non-English sources may therefore have been excluded. Bibliometric tools such as CiteSpace, VOSviewer and Bibliometrix can also be used to analyze the bibliographic data, titles, abstracts, keywords and citation relationships of this paper. Although they can show the large-scale trend and knowledge structure, they are unable to verify the technical feasibility, preservation quality or actual application results of individual AI models and restoration cases. Finally, this paper will use bibliometric mapping and thematic synthesis instead of detailed full-text coding of all the application cases. Future research will integrate several databases, add non-English materials, and perform in-depth qualitative analysis of different types of heritage, as well as the AI method, data mode, evaluation index and expert verification process.

5 Summary

Bibliometric methods and other types of analysis were used to study the development trends, knowledge structure, collaboration patterns and future research directions of artificial intelligence in cultural heritage conservation and restoration from 2015 to 2025. According to the above analysis, the field has expanded rapidly, shifting from the digital documentation of heritage objects and sites towards restoration-oriented applications. Artificial intelligence, deep learning, generative models and intelligent sensing have developed at an accelerated rate, and the demand for evidence-based restoration, risk monitoring and preventative conservation is also growing. Based on the above research, the following general conclusions have been drawn.

Evolution of Research Stages: AI applications in cultural heritage conservation and restoration can be divided into three main stages. From 2015 to 2019, in the exploration phase, a foundation has been laid for applying AI to digital documentation, image processing and preliminary reconstruction. In the period from 2020 to 2022, the steady development stage expanded the above initiatives to include image recognition and correction, virtual restoration and data-driven analysis. From 2023 to 2025, the rapid expansion stage has been marked by an increasing number of applications for generative AI in damage detection, structural health monitoring and preventive conservation.

Collaboration and Interdisciplinary Structure: The field is multidisciplinary to some extent and includes heritage studies, materials science, archaeology, art, computer science, engineering, remote sensing, and building technology. However, research results are still concentrated in a few countries, institutions and author groups. Expand the range of cross-regional and cross-disciplinary cooperation further.

Research Themes and Hotspots: The focus of the research has shifted from general digital documentation and recognition to damage diagnosis, generative reconstruction, risk monitoring and preventive conservation. Based on the above, the three restoration-oriented paths identified in this paper are diagnostic AI, reconstructive AI and predictive AI. It has also put forward a "restoration task - data type - evidence standard" system to show how AI outputs can help support the investigation of conservation evidence and restoration hypotheses, and inform decisions.

Future Research Directions: Future research should focus on building protection-oriented datasets, improving model interpretability, developing methods for integrating multimodal evidence, and establishing workflows that involve experts. Artificial intelligence should not replace professional judgment in the field of cultural heritage conservation. Its long-term value lies in combining technological advancements with physical evidence, historical knowledge, expert assessments, and actual conservation efforts.

Supplementary Materials

Not available.

Author Contributions

Conceptualisation, Y.X. and R.W.; methodology, Y.X.; software, Y.X.; validation, Y.X. and R.W.; formal analysis, Y.X.; investigation, Y.X.; resources, Y.X. and R.W.; data curation, Y.X.;

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The data in this paper were obtained from the Web of Science Core Collection (WoSCC) according to the search plan shown in Section 2. Due to the database licence restrictions, the raw records exported by WoSCC are not available to the public. The processed data that support the results of this study will be provided by the corresponding author upon reasonable request.

Conflicts of interest

The authors have no conflicts of interest.

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