heritage

Article

Will Artificial Intelligence Affect How Cultural Heritage Will Be Managed in the Future? Responses Generated by Four genAI Models

Dirk H. R. Spennemann

Gulbali Institute, Charles Sturt University, P.O. Box 789, Albury, NSW 2640, Australia; dspennemann@csu.edu.au

Abstract: Generative artificial intelligence (genAI) language models have become firmly embedded in public consciousness. Their abilities to extract and summarise information from a wide range of sources in their training data have attracted the attention of many scholars. This paper examines how four genAI large language models (ChatGPT, GPT4, DeepAI, and Google Bard) responded to prompts, asking (i) whether artificial intelligence would affect how cultural heritage will be managed in the future (with examples requested) and (ii) what dangers might emerge when relying heavily on genAI to guide cultural heritage professionals in their actions. The genAI systems provided a range of examples, commonly drawing on and extending the *status quo*. Without a doubt, AI tools will revolutionise the execution of repetitive and mundane tasks, such as the classification of some classes of artifacts, or allow for the predictive modelling of the decay of objects. Important examples were used to assess the purported power of genAI tools to extract, aggregate, and synthesize large volumes of data from multiple sources, as well as their ability to recognise patterns and connections that people may miss. An inherent risk in the 'results' presented by genAI systems is that the presented connections are 'artifacts' of the system rather than being genuine. Since present genAI tools are unable to purposively generate creative or innovative thoughts, it is left to the reader to determine whether any text that is provided by genAI that is out of the ordinary is meaningful or nonsensical. Additional risks identified by the genAI systems were that some cultural heritage professionals might use AI systems without the required level of AI literacy and that overreliance on genAI systems might lead to a deskilling of general heritage practitioners.

Keywords: artificial intelligence; cultural heritage studies; futures studies; strategic foresight

Citation: Spennemann, D.H.R. Will Artificial Intelligence Affect How Cultural Heritage Will Be Managed in the Future? Responses Generated by Four genAI Models. *Heritage* **2024**, *7*, 1453–1471. https://doi.org/10.3390/heritage7030070

Academic Editor: Nicola Masini

Received: 21 December 2023
Revised: 13 February 2024
Accepted: 15 February 2024
Published: 11 March 2024

1. Introduction

Entering public consciousness in late 2022, generative artificial intelligence (genAI) large language models (LLMs) such as ChatGPT, DeepAI, or Google Bard are poised to become the greatest transnational and cross-sectoral disruptors in the way people access information since the invention of the World Wide Web (WWW) in 1993 [1]. With its plain language and human-speech-like interface, the genAI models can provide seemingly comprehensive answers to almost any question and do so within a few seconds. The majority of the population are less concerned with the intricacies of the comprehensiveness, accuracy, and biases in the dataset that enable these genAI systems and are more interested in the convenience that genAI models afford. Given its cross-sectorial appeal, it can be posited that genAI will play a major role in many professions, including cultural heritage studies and cultural heritage management. This paper draws on the capabilities of genAI models to explore how AI may affect the way that cultural heritage will be managed in the near to medium-term future.

1.1. Background to the Generative Artificial Intelligence Language Models

Using transformer architecture, genAI models are designed to detect statistical connections and patterns within textual data. By doing so, they can generate responses that are coherent and pertinent to the received input, resembling human-like responses [2,3]. These models are trained using a vast collection of text materials, such as books (both fiction and non-fiction), articles, and web pages, which serve as a reference dataset for pre-training [4–7]. During this pre-training process, these models 'learn' how to predict the next word in a text string by combining statistical patterns with linguistic and semantic patterns. The capacity of genAI models to provide complex responses is not necessarily proportional to the size and diversity of the resources included in the training dataset [8]. The selection of the sources included in a reference dataset results in biased responses, irrespective of whether the reference dataset has been curated by people (as in closed genAI models) (e.g., political bias [9–12], ethnocentricity [13–15], and sexism [16–18]), or whether genAI models are also enabled to extract of sources from the internet in general (as the latter overrepresents hegemonic viewpoints at the expense of those of marginalized communities [8,19]). This is not the place to discuss the numerous ethical issues that underlie the selection and use of original sources, such as alleged copyright violations [20,21] or whether primary or secondary sources underpin its 'knowledge' base [5,22].

At present, genAI language models rely on statistical connections and patterns within their training data. At the time of writing, they lack reasoning ability [23] and do not possess independent creative thinking abilities, which makes them susceptible to inverted logic phenomena [24]. Despite being capable of producing complex text predictions, any demonstrated creativity in these models is solely dependent on the perception of the human interacting with the language model. Whether a short story written by a generative AI, for example, is considered to be a creative document or perceived as trite 'garbage' depends entirely on the interpretation of the reader, who will judge the story based on their individual experiences and expectations.

ChatGPT/GPT-3.5: GPT-3, launched in June 2020 and was built on a training dataset (time cut-off of 2019) containing 175 billion parameters. This gave it the ability to perform a range of natural language tasks like text classification and sentiment analysis to generate contextually accurate responses to queries or to draft basic contextual texts such as emails and programming code. Its updated version, ChatGPT (GPT-3.5), was made available to the public in November 2022 in a free research preview to stimulate experimentation [25] which was able to communicate in 95 languages [26]. The design reputedly included a safe answer mode to ensure that ChatGPT responded within ethical human values and did not provide harmful content (e.g., planning attacks, hate speech, and advice on suicide), although this is not assured [19,27,28]. Moreover, such filters can be intentionally subverted [29]). The dataset underpinning ChatGPT 3.5, which also relies on 175 billion parameters, had a data cut-off in September 2021, which means they cannot accommodate or comment on events, discoveries, or perspectives that have emerged after this date (Table 1). ChatGPT can, to some degree, incorporate in its responses the context of or prior answers in the same chat and can critique its own response, but is unable to then revise that initial response in a meaningful way [24]. The nature of the training data is not publicly available, with OpenAI noting that ChatGPT 3.5 used "three primary sources of information: (1) information that is publicly available on the internet, (2) information that we license from third parties, and (3) information that our users or our human trainers provide" [30].

GPT-4 and Bing Chat Enterprise: Its successor, GPT-4 was trained on 100 trillion parameters, which allows for more detailed responses. This language model also has a larger memory to better integrate previous answers into revised versions and is able to handle 25 languages other than English [31]. Bing Chat Enterprise uses GPT-4 as its engine (with the above mentioned sources of information), but is also capable of searching the WWW, incorporating data from web resources that have been indexed by Microsoft Bing.

Table 1. Overview of the genAI language models used in this study.

Language Model	Parameters	Training Data Time Cut-Off	Can Search The WWW	Languages
OpenAi ChatGPT 3.5	175 billion	Sep 2021	no	95
DeepAI	175 billion *	2019 + updates *	no	?
GPT-4/BingChat	100 trillion	Sep 2021	no/yes	25
Google Bard	137 billion *	2019 *	yes	>40

* Information obtained by asking the language model to self-report.

DeepAI: The model DeepAI is based on GPT-3 training data (self-reported see Supporting Materials, Conversations 7 and 8) and consequently has the same number and sources of training data and the same time cut-off as ChatGPT. Its language model, which is able to integrate images, differs in its approach and may not always match human-level understanding or context.

Google Bard. This model, developed by Google, relies on a training dataset of 137 billion parameters derived "from publicly available sources" [32] but it has the ability to search the WWW and thus incorporate more recent information, as well as links to web resources indexed by Google (Conversation 6). Google Bard can respond in more than 40 languages [33].

1.2. Use of genAI Language Models in Cultural Heritage Studies

Custom-designed neural networks and machine learning (with AI) have been used for the transcription of digitised sources [34,35]; the reconstruction, interpretation, transcription, and translation of inscriptions [36–39] incl. hieroglyphs [40–42]; and deciphering the text of carbonised scrolls [43] and the authorship attributions of handwritten manuscripts [35,44,45]. In the broader field of material culture, AI systems have been used for the classification and/or reconstruction of pottery [46–55], and provenance studies of pottery [55], as well as the classification of ancient coins [56], constituent materials in shell middens [57], or of cut marks on bones retrieved from archaeological sites sites [58,59]. Custom -designed AI systems have also been used in the field of restoration and conservation [55,60,61].

This contrasts with the 'generic' generative AI language models as summarised in the preceding section, which can reputedly summarise and integrate a wide range of knowledge subject to the extent of their training data. The capabilities of such genAI language models, specifically ChatGPT, have been assessed in a wide range of academic disciplines. A few papers looked at genAI language models such as ChatGPT or Google Bard in the cultural heritage field, such as remote sensing in archaeology [62] and artifact analysis [4]. Digitised physical heritage assets (sites, buildings, and objects) can be utilised within a genAI environment while preserving provenance, authenticity, and veracity [63]. In the museum space, genAI language models can be successfully employed in the creation of exhibit labels and catalogue information [64], developing visitor query systems and guides for museums [65–67], conceptualising entire exhibitions [68], as well as exploring how to approach aspects such as memorialisation [69].

Additionally, in a previous paper, the present author looked at how genAI language models can present a cohesive discussion of values in cultural heritage management [24]. While genAI language models have been shown to be competent at extracting, summarising, and integrating information, they are less suitable (at least in their present configuration) at presenting a critical discussion, as they may suffer from inverted logic [24].

As noted, genAI language models are deemed very capable at collating, extracting, and synthesising text from a range of sources, but are unable to generate independent and creative thoughts. Although publicly accessible generative AI tools, therefore, cannot be relied on to formally develop forecast scenarios based on strategic foresight principles [70,71], they can be used, at this point in their development cycle, to aggregate existing information sources that comment on future opportunities and to summarise the information contained in these. These summations highlight the status quo of possible opportunities that can be drawn on to establish trajectories to develop forecast scenarios.

This paper will examine how four genAI large language models (ChatGPT, GPT4, DeepAI, and Google Bard) responded to prompts that asked (i) whether artificial intelligence would affect how cultural heritage will be managed in the future and (ii) what dangers might emerge when relying heavily on genAI to guide cultural heritage professionals in their actions.

2. Methodology

This study drew on four publicly accessible genAI language models (ChatGPT 3.5, Bing Chat Enterprise, Google Bard, and DeepAI) to engage in a 'conversation' with each as to how genAI could affect how cultural heritage will be managed in the future.

OpenAI's freely available ChatGPT 3.5 (August 3 version) [72] was accessed on 11 September 2023 at 06:08; Google Bard (version 2023.07.13) [73] was accessed on 11 September 2023 at 05:59; Bing Chat Enterprise [74] was accessed on 19 September 2023 at 05:10 (balanced mode) and 05:19 (more creative mode); and DeepAI [75] was accessed in Genius Mode on 20 September 2023 at 21:32 (all times are GMT). All 'conversations' were carried out with the following series of four prompts:

- Will genAI affect how cultural heritage will be managed in the future?
- Can you give me some examples?
- Are there any dangers in relying heavily on genAI to guide cultural heritage professionals in their actions?
- Can you elaborate on [dot point selected from the answer to the previous prompt]?

All conversations with genAI models used in this paper have been documented according to the protocol in [76] and have been archived as a supplementary data document at this DOI: 10.13140/RG.2.2.25648.33285.

For ease of reference, each conversation reproduced in the supplementary data document has been furnished with line numbers, which allow for cross-referencing, as required. In addition, in-text quotes drawn from the AI language models are indicated with the abbreviations BB (Bing Chat, balanced mode), BC (Bing Chat, creative mode), CG (ChatGPT 3.5), DA (DeepAI genius mode), or GB (Google Bard).

3. Results and Discussion

The standard sequence of an academic paper, which calls for a results section to be followed by a discussion section, is unsuitable for the nature of the data in this paper. As a consequence, this results section will not only present excerpts of the texts generated by the genAI language models in relation to a prompt but will also discuss and comment on these before moving onto the description and discussion of the next prompt. This will be followed by a discussion that draws out common threads (Section 4).

3.1. Will genAI Affect How Cultural Heritage Will Be Managed in the Future?

This question was designed to extend the trajectory of current practice in the future. All genAI systems provided a range of possible applications of genAI (Table 2) as well as a series of challenges and issues that need to be considered in the process. The responses can be grouped under the headings of increased digitisation; virtual reconstructions and the creation of interactive and immersive experiences; analysis and interpretation of large volumes of historical data and texts; novel ideas and applications; and blending the old with the new.

Table 2. Opportunities presented by genAI for managing cultural heritage.

Opportunity	ChatGPT 3.5	Bing Chat Balanced—BB	Bing Chat Creative—BC	DeepAI Genius	Google Bard
High quality digital replicas to protect originals	X	X	X	X	X
Restoration/reconstruction of damaged/cultural artifacts	X	X	X	X	X
Digitally restoring faded or damaged text of manuscripts	X				
Reconstruction of historical sites		X			
Interactive/immersive educational tools and experiences	X			X	X
Translation and transcription of texts and manuscripts	X	X			
Analyse and interpret large volumes of historical data and texts	X	X		X	
Create new art, etc., inspired by historical styles and traditions	X		X		
Digital reconstruction of ancient buildings	X				
Language revival and translation incl. synthesising speech	X			X	
Interactive museum exhibits	X				
AI creates historically accurate virtual worlds for gaming	X				
AI image analysis to protect archaeological sites from looting	X				
AI image analysis to assess environmental damage to sites	X			X	
Immersive and informative tourist experiences via mobile apps	X		X	X	
Promoting and disseminating cultural diversity and awareness			X		
Predict effects of time and environmental factors on artifacts				X	
Augment cultural heritage objects with additional information					X
GenAI to authenticate cultural heritage objects					X

3.1.1. Increased Digitisation

It was expected that concepts such as digitisation and digital reconstruction would feature prominently, as they are well discussed in the current literature—although more in terms of general practice [77–80] and less in relation to AI or future manifestations. The concept of digital preservation featured prominently in the responses by all four AI models. BingChat noted that digitisation allowed for increased access (BB), while DeepAI noted that digitisation allowed "physical cultural heritage. . .[to] last longer and be . . .easily shared around the world" (DA). Google Bard stated that genAI "can be used to digitize cultural heritage objects, such as paintings, sculptures, and artifacts [which] can help to preserve these objects from damage and deterioration, and also make them more accessible to the public" (GB), without actually indicating as to how this would help to preserve these objects from damage and deterioration. A similar assertion was made by BingChat, where it claimed that "genAI can use 3D modelling and scanning technology to create accurate digital replicas of physical objects and structures, which can help protect them from damage, decay, or destruction" (BC). It is left to the reader to infer that, presumably, digitisation obviates much of the need to handle objects which would, in consequence, reduce the risk of damage and deterioration. ChatGPT spelled out that "genAI can be used to create high-quality digital replicas of cultural artifacts. . . [and that these] can help preserve cultural heritage by ensuring that even if the original objects deteriorate over time, their digital counterparts can be studied, . . . by future generations" (CG). This assertion ignores the aspects of integrity and authenticity that are fundamental to cultural heritage. Other aspects of materiality embodied in the originals and not on the replicas are also not touched on, let alone critically addressed.

As a management tool, genAI can be employed in the automated transcription of digitised fragile and deteriorating texts by "enhanc[ing] the readability of ancient manuscripts by digitally restoring faded or damaged text" (CG). DeepAI made specific reference to the University of Oxford's independently developed AI tool 'ArchAIDE' [81,82], "which can identify pottery fragments, providing archaeologists with vital information about archaeological sites, reducing the time taken for manual identification" (DA) and Harvard's Semitic Museum's use of AI to reconstruct the appearance of a pottery piece, broken into hundreds of fragments, and to 3D print a restoration (DA) [83]

Several genAI systems also offered the digital restoration and reconstruction of damaged or lost cultural artifacts as a future use of genAI by being able to "restore. . . incomplete artifacts by generating missing parts based on existing fragments" (BB), "fill in missing pieces, restore faded colours, and recreate damaged sculptures or paintings" (CG), "to identify and remove damage from an object" (GB), and to "generate missing parts of damaged artworks based on the style of the original artist" (CG).

3.1.2. Virtual Reconstructions and the Creation of Interactive and Immersive Experiences

The three-dimensional rendering of extant sites, buildings, and shipwrecks, as well as 3D modelled historic reconstructions of these, have become a well-established tool in cultural heritage research, with applications in education and visitor information [84–86]. The ability to aggregate and synthesise data from multiple sources and source types makes genAI a suitable tool to "analyse historical records, architectural drawings, and archaeological findings to create accurate digital reconstructions of ancient buildings and monuments" (CG), including interpretations of "historical sites that have been. . . destroyed" (BC). DeepAI suggested a similar opportunity but went further when suggesting that "AI could help recreate lost cultural heritage, either virtually for study and appreciation or physically using different manufacturing technologies" (DA). The ethical implications of this are discussed further below.

As already explored in the contemporary literature, these 3D modelled historic reconstructions find use in creating interactive educational "materials about an object, or to create interactive experiences that allow people to explore an object in more depth" (GB). The main advantage of genAI language models is their ability to aggregate information based on user queries that can be asked in their natural way of expressing themselves, rather than by entering a series of arcane keyword combinations and to be able to take into account the trajectory of the previous questions. This allows for the development of "AI-powered mobile apps [that] can provide tourists with immersive and informative experiences at cultural heritage sites [with] augmented reality features, historical context, and guided tours tailored to individual interests [and] to explore [them] as they appeared in the past" (CG). Similar concepts were noted by BingChat and DeepAI. Generative AI-powered 3D visualisations could allow us to "overlay text or images on top of physical objects" (GB) and "allow visitors to virtually restore or recreate historical objects" (CG).

While such genAI powered reconstructions are readily imaginable and feasible, neither of the language models raised the issue of 'authenticity' in the reconstruction. While any reconstruction is, by its very nature, to some extent, subjective and informed by conscious and subconscious ethnocentric biases, they are informed by, and modulated by, a researcher's experience, rather that statistical probabilities. Any interpretation of genAI-powered reconstructions that suit the individual interests of tourists still requires contextual knowledge, which non-professionals lack.

ChatGPT provided a more ambitious concept where "virtual reality (VR) and augmented reality (AR) applications, powered by generative AI, can transport users to historical settings or allow them to interact with digital recreations of historical figures" (CG). This can find application in cultural heritage gaming, where "[p]layers can explore ancient civilizations, interact with historical figures, and experience important events through gaming experiences" (CG). Depending on the dataset, genAI language models can not only respond in multiple languages (Table 1) but also adapt their responses to match people's speech patterns (e.g., "speak like/respond like a pirate"). This would allow us to "generate texts in the style of different historical periods and figures, which can help in understanding different writing styles and vernaculars across time" (DA).

ChatGPT extended on the language capabilities by arguing that "genAI can aid in the revival of endangered languages by generating language learning materials, translating texts, and even synthesizing speech in those languages" and thereby "helps [to] preserve linguistic diversity and cultural heritage" (CG).

3.1.3. Blending the Old with the New

Expanding the concept of reconstructions, a theme raised by all four genAI models relates to new forms of heritage derived from a blending of the old with the new. These suggestions seem to have been levered off "The Next Rembrandt" project, whereby a project team trained a neural network on a dataset of 350 Rembrandt paintings and used genAI to create a 3D-printed new painting that was indistinguishable in style from a real Rembrandt [87]. That project was specifically referenced by both Google Bard and DeepAI.

ChatGPT noted that "GenAI can be used to create new artworks, music, literature, and other forms of cultural expression inspired by historical styles and traditions" (CG) with an emphasis on blending "styles of famous composers or artists from different time periods or cultures" (CG). BingChat identified similar opportunities, arguing that this would "showcase and celebrate the richness and variety of different cultures and traditions, as well as foster cross-cultural dialogue and understanding" (BC). DeepAI noted that "AI can create novel representations of existing cultural elements" by "learning the style of one piece and applying it to another" (DA). ChatGPT went further when it posited that this "can breathe new life into traditional cultural practices and help keep them relevant in the modern world" (CG). The mutability of cultural heritage values notwithstanding [88], such suggestions overlook aspects of authenticity and integrity as a basic tenet of cultural heritage management [89–91]. While such 'fusion' is common and a valid line of endeavour in the arts, music, and culinary realms [92–94], it is not *heritage*. This 'error of judgment' again highlights the limitations inherent in genAI language models when generating responses. In the bigger picture, it also raises a spectre of increased misinformation and deliberate fakes generated by malevolent actors employing skewed prompts.

3.1.4. Analysis and Interpretation Large Volumes of Historical Data and Texts

The power of genAI to extract, aggregate, and synthesise large volumes of data from multiple sources and source types has been noted in the literature on genAI. This makes genAI a suitable tool "to process and interpret vast amounts of historical data, such as census records, diaries, and correspondence, to gain insights into past societies, customs, and trends" (CG). DeepAI posits that by being able to "analys[e] a large amount of historical data quickly and accurately, [i]t can recognize patterns and connections that humans may miss, thereby assisting in deeper research and studies" (DA). Whether such patterns are useful depends on the users' interpretation and contextual knowledge.

GenAI models can be interactively trained by academics to interpret and then transcribe "handwritten manuscripts and documents, which may be difficult to read due to age and deterioration" (CG) and then translate these "texts and inscriptions into modern languages" (BB). An example of this is 'Fabricius', a web-based AI tool developed by Google Arts & Culture, which "can decipher Ancient Egyptian Hieroglyphics, which shows promise for potentially decoding other ancient or lost languages" (GB) [95] (see also [96]).

3.1.5. Novel Ideas and Applications

The answers provided so far by the genAI language models about the use of genAI in future heritage studies fit well into the range of the expected and are, by and large, reflective of mainstream explorative thinking at this point of time. Extensions for the range of the expected are few and are primarily based on the predictive modelling of trends derived from existing data. DeepAI, for example, suggested that "[g]enerative AI models could be used to predict the effects of time and environmental factors on cultural artifacts, hence aiding their preservation" and could be used to "monitor cultural sites and provide early warning of deterioration or potential threats" (DA).

In a similar vein to the latter, ChatGPT noted that, coupled with "drones, AI image analysis can be employed to monitor and protect archaeological sites from looting. . .[by] "identify[ing] and report[ing] any unauthorized activity in real-time" (CG). Should theft occur, "[g]enerative AI can be used to authenticate cultural heritage objects, which [could] help to prevent the illegal trafficking of cultural artifacts" (GB).

While ChatGPT provided a closed list of options, the solutions offered by Google Bard concluded with the comment that "[a]s the technology continues to develop, we can expect to see even more innovative and creative ways to use it to protect our cultural heritage for future generations" (GB).

3.1.6. Limitations of genAI in Generating Logical Answers

Previous work had shown that genAI language models are, on occasion, prone to confabulation (or 'hallucinations'), i.e., responses where erroneous 'facts' are being offered [97,98], where answers are provided with inverted logic [24], or where references are invented [5,24]. This confabulation is caused when the predictive contextual modelling goes off on a tangent and then follows that line of 'thought' without reverifying logical coherence [24]. Examples for these were offered both by ChatGPT and DeepAI.

The latter noted, for example, that "genAI can be used in interpreting and translating ancient or lost languages, helping in understanding our past better" (DA). Compared with dead languages (i.e., not the native language of any community) or extinct languages (i.e., without active speakers but 'resurrectable' from books and records that can still be read and understood), lost languages are just that: lost. Inasmuch as books and artifacts or monuments with texts may exist, there are no avenues to access their meaning, as vital contextual information is lacking. While genAI can be deployed to cryptographically examine patterns in word or symbol combinations (akin to decoding hieroglyphics), the contextual key to meaning is lost (unless dual- or multi-text versions exist, e.g., the Rosetta Stone), making translation, let alone interpretation, impossible.

Likewise, ChatGPT noted that "AI algorithms can assist art conservators in the restoration process [as these algorithms] can analyse the chemical composition of pigments to guide restoration work" (CG). This is, of course patent nonsense. GenAI can be trained to classify pigments based of spectrographic data, but without instrumentation will be unable to do so.

3.2. Are There Any Dangers in Relying Heavily on genAI to Guide Cultural Heritage Professionals in Their Actions?

When responding to the initial question prompt, three of the genAI systems (ChatGPT, BingChat, and Google Bard) had already raised ethical challenges and caveats at the end of their responses. The second plank of enquiry specifically prompted the genAI models to consider whether there were any dangers in relying heavily on genAI to guide cultural heritage professionals in their actions. Both the ethical challenges and caveats raised previous answers, and the responses to the second main prompt are discussed below (Table 3). They can be grouped under the headings of 'authenticity', 'biases, misrepresentation, and misinformation' both unintentional and intentional, the 'infringement of intellectual property and moral rights of the creators and owners of the cultural heritage', as well as the 'ownership of AI-generated cultural heritage'.

Table 3. Risk and dangers presented by genAI for managing cultural heritage.

Danger	ChatGPT 3.5	Bing Chat Balanced—BB	Bing Chat Creative—BC	DeepAI Genius	Google Bard
genAI artifacts may lack the authenticity of originals	X		X		X
genAI artifacts may include errors/be inaccurate				X	
difficulty in distinguishing real and genAI artifacts	X				
ownership and control over AI-generated cultural heritage	X			X	X
misrepresentations can perpetuate stereotypes	X				
misrepresentations can disrespect cultural traditions	X		X		
data privacy/need for responsible data management	X		X		
inaccurate, misleading, and distorted representations of heritage		X	X		X
infringe on rights and interests of creators of cultural heritage			X		
infringe on rights and interests of owners of cultural heritage			X	X	
biases in data may favour or exclude certain cultures/narratives			X	X	X
biased outputs in general		X	X	X	X
create fake/misleading content to damage/destroy cultural heritage					X
depersonalisation of cultural interactions	X				
overreliance causes decrease in skills/expertise of CHM professionals	X			X	
diminish skills of artisans, conservators, and restorers	X				
lack of human expertise		X	X		
assumption that AI-generated content is infallible	X				
lack of contextual understanding		X			
loss of jobs				X	
malicious misrepresentation				X	X
loss of control/CHM professionals do not understand how models work					
commodification of heritage					X

3.2.1. Authenticity

Disquiet about the authenticity of genAI-created cultural artifacts was noted by all genAI systems. These were concerns about convincingly generated "reproductions of cultural artifacts and historical content" that may make it "difficult to distinguish between original artifacts and AI-generated replicas" (CG) and that genAI might "produce inaccurate, misleading, or distorted representations of cultural heritage, which may harm the integrity and credibility of the original sources" (BC, likewise DA). Other, more indirect, implications were that such creations might lead to an "oversimplification of the artistic process" (DA) and to the "commodification of cultural heritage" (GB). Among the solutions designed to avoid the confusion and risk that generative AI-generated artifacts might "replace or devalue authentic artifacts", clearly labelling genAI artifacts was deemed 'crucial' (CG).

Of considerable concern, in terms of formulation, is ChatGPT's statement that "generative AI-generated artifacts *may* lack the authenticity of originals" [emphasis the author's]. There can be no doubt that this is the case, which confirms observations of potential logic problems underlying the responses of language models that rely on transformer architecture [24].

3.2.2. Unintentional Biases, Misrepresentation, and Misinformation

The responses of genAI models included commentary on unintentional biases, misrepresentation, and misinformation. DeepAI, for example, stated that "[l]ike all AI, genAI models run the risk of perpetuating and exacerbating existing biases if the data they are trained on is not balanced and diverse" Thus, genAI can not only "produce inaccurate, misleading, or distorted representations of cultural heritage" (BC) which "may harm the integrity and credibility of the original sources" (BC) but also "may favor or exclude certain cultures or groups based on their representation or visibility in the data" (BC) and "propagate harmful narratives or misinterpretations of cultural significance" (CG). DeepAI, exemplified this by noting that "AI trained on Western-centric datasets might have difficulty in correctly identifying, categorizing, or recreating non-western artifacts because of a lack of diverse input data". Similar points were raised by Google Bard when it noted that "if a genAI model is trained on a dataset of paintings that only includes paintings by male artists, then the model is likely to generate new paintings that are also by male artists. This could lead to cultural heritage professionals making decisions that are biased against female artists" (GB).

BingChat placed the responsibility for avoiding such unintentional bias and misrepresentation on the cultural heritage professionals who "have the obligation to use genAI in a way that is ethical, transparent, and respectful of different cultures and perspectives, as well as to address any potential harms or issues that may arise from its use" (BC). But both BingChat and Google Bard also placed emphasis on the creators of the genAI systems. While Google Bard noted that "[i]t is important to develop genAI models that are not biased, or that can be used to identify and mitigate bias", BingChat cited webpages on AI ethics [99,100], noting the need to "us[e] diverse and representative datasets, apply fairness and accountability metrics [and] involv[e] diverse stakeholders and experts in the development and evaluation of generative AI".

3.2.3. Intentional Biases, Misrepresentation, and Misinformation

In addition to unintentional biases, misrepresentation, and misinformation, three of the genAI systems also noted opportunities for malevolent actions. While ChatGPT merely noted that "AI-generated content can propagate harmful narratives or misinterpretations of cultural significance" (CG), Google Bard explicitly stated that "genAI models can be used to create fake or misleading content. This could be used to damage or destroy cultural heritage, or to spread misinformation about it". By way of exemplification, Google Bard noted that "a generative artificial intelligence model could be used to create fake news articles about a cultural heritage site, or to create fake images of a cultural heritage object that has been destroyed [which could] lead to people believing false information about the site or object". While Google Bard also notes that "it is important to develop safeguards to prevent the misuse of generative artificial intelligence for these purposes", there is no indication how that could be given effect. DeepAI, on the other hand, raised concerns about the "risk of digital theft or manipulation of data", noting that digital resources could be "maliciously altered or hacked" to "manipulat[e] historical documents or art [to] misrepresent cultural heritage".

When asked to elaborate on how genAI models can be used to create fake or misleading content, Google Bard responded with a standard set of concerns, including fake news articles, fake images, including deep fakes, and faked audio recordings that represent events that never happened, as well as faked documents and artifacts that may appear genuine.

3.2.4. Infringement of Intellectual Property and Moral Rights of the Creators and Owners of the Cultural Heritage

Both BingChat (balanced mode) and DeepAI raised concerns about genAI models potentially infringing on the intellectual property and moral rights of the creators and owners of the cultural heritage "such as artists, authors, communities, or nations" (BC) by "us[ing] or reproduce[ing] cultural heritage without proper consent or attribution" (BC). Of concern was that genAI "may use or disclose sensitive or confidential data or information related to cultural heritage, such as personal stories, identities, locations, or ownerships" (BC). DeepAI exemplified this with the observation that the "[d]igitization and AI recreation of Native American burial artifacts for public viewing, for instance, could infringe on the cultural rights and traditions of these communities, who often hold such artifacts as sacred and private" (DA).

Neither BingChat nor DeepAI commented on the fact that such infringements are not committed by the genAI algorithm itself, but by the companies who used data encumbered with intellectual property and moral rights in the creation of the datasets (see, for example, [4–7]). BingChat noted, however, that it is "important... to obtain permission and giv[e] credit where due, or by creat[e] fair use policies and exceptions for generative AI".

3.2.5. Ownership of AI-Generated Cultural Heritage

The responses by both Google Bard, ChatGPT, and DeepAI included concerns about the ownership of genAI-created reproductions or adaptations and, thus, can profit from these (CG and GB), and that "there needs to be general consensus on who has access to AI technology and the recreated or restored elements of cultural heritage" (DA) and who "has the authority to create, modify, or share such content" (CG).

3.2.6. Complex and Unpredictable Outputs That May Be Difficult to Understand or Interpret by Humans

An interesting comment was generated by BingChat in its creative mode, which noted that genAI "may produce complex and unpredictable outputs that may be difficult to understand or interpret by humans. For example, genAI may generate outputs that are inconsistent with human expectations or logic. Therefore, it is important to ensure explainability and transparency of the outputs and processes of generative AI, such as by providing clear explanations and feedback for the generated content, [and] documenting and disclosing the methods and assumptions used by generative AI". In a similar vein, Google Bard noted that "genAI models are complex... [and] that it can be difficult for cultural heritage professionals to understand how the models work and how they make decisions. This could lead to cultural heritage professionals losing control over the decisions that are made by the models".

3.2.7. Perception of Infallibility

Both ChatGPT and BingChat in its balanced mode raised the spectre that users may be in "the mistaken belief or assumption that AI-generated content, recommendations, or decisions are always accurate, unbiased, and free from errors" (BB). The main concern was that "AI systems [may] become more advanced and integrated into various aspects of our lives, including cultural heritage management, [that] people may begin to trust AI's output without critically evaluating it, [based on] the perception that AI is based on objective algorithms and data, and therefore, it must be infallible" (BB). As genAI systems "inherit biases from their training data and algorithms" (BB, similarly CG) and "can struggle with complex or ambiguous tasks" (BB), they "can make mistakes, misinterpret information, or produce results that are unintended or inaccurate". A perception of infallibility may make it "challenging to attribute responsibility or accountability when errors occur", especially "in cases where AI-generated content or decisions have negative consequences" (BB).

3.2.8. Overreliance on genAI and the Deskilling of Humans

All four genAI systems commented on the dangers inherent in an overreliance on genAI and the associated deskilling of cultural heritage professionals. Noted, in particular, was the possible degradation of critical thinking and interpretation skills (CG, BB, and DA) as well as a reduction in "intuition and creativity which are essential for interpreting and preserving cultural artifacts" (BB, similarly DA) thereby potentially "lead[ing] to a loss of the nuanced understanding and care that experts bring to their work" (BB). An overreliance on genAI may "lead to a decrease in the skills and expertise of cultural heritage professionals due to losses in, and preservation techniques . . . including the skills of artisans, conservators, and restorers" (CG).

Beyond the deskilling, "an increased reliance on genAI and a perception of its infallibility may result in the expertise of cultural heritage professionals being undervalued or [even] overlooked" (DA), which could then "lead to job losses in sectors that traditionally required human input" (DA). In particular, "museum curators, tour guides, restorers, etc., could potentially lose their jobs with the advent of AI/AR/VR technology, which can replicate or even enhance many of their responsibilities" (DA).

When DeepAI was asked to expand on the risks and consequences of the deskilling of humans in the cultural heritage management process, it noted that human skills and expertise continued to be of importance not only to quality assure the genAI-created outputs in order to avoid negative outcomes (e.g., misidentification of an artifact and subsequent distortion of historical facts), but also in order to ensure that the decisions are ethical and to be able to react to unforeseen circumstances. DeepAI noted that "[c]ultural heritage management involves complex ethical considerations, such as respecting cultural sensitivities, addressing historical injustices, and ensuring equitable access to cultural resources [and that] human professionals are better equipped to navigate these ethical challenges and make decisions that align with societal values". DeepAI further indicated that "[c]ultural heritage management often requires adaptability and flexibility in response to changing circumstances or new discoveries. [While h]uman professionals can quickly adapt their approaches, modify strategies, and incorporate new information into their decision-making process, genAI may struggle to adapt to novel situations or unexpected challenges".

3.2.9. Depersonalisation of Cultural Heritage

BingChat (creative mode) noted that "[c]ultural heritage professionals have the skills and experience to interpret and communicate cultural heritage in a way that is respectful, engaging, and relevant to different audiences". Both ChatGPT and BingChat (creative mode) raised concerns that an increased reliance on genAI may lead to the depersonalisation of experiences gained while on "guided tours, educational materials, or cultural interactions [due to the lack of] human touch, empathy, and cultural expertise that professionals bring to interpreting and sharing cultural heritage" (CG), in particular as genAI "may not be able to capture the subtleties and nuances of cultural heritage, such as the emotions, meanings, values, and contexts that are embedded in it" (BC).

3.2.10. Balancing the Dangers in Relying Heavily on genAI to Guide Cultural Heritage Professionals

In order to balance any dangers emanating from relying heavily on genAI to guide them, all four genAI models provided some suggestions, placing the responsibility squarely on the cultural heritage professionals themselves. They need to regard and use genAI as a tool (CG and DA) rather than replacing human expertise (BB), and to ensure that genAI is used responsibly (BB) and ethical guidelines are being followed (CG). It was deemed important that cultural heritage professionals maintain oversight when integrating AI into cultural heritage management (DA, CG) and responsibly curate AI-generated content (CG), for example by "using transparency and clear labelling to distinguish AI-generated content from original artifacts" (CG), by "educating the public about the role of AI in cultural heritage management" (CG) and by "putting in place safeguards to prevent the misuse of generative AI" (GB).

In addition, cultural heritage professionals need to develop literacy in genAI systems, in order to be able to "carefully weigh the potential benefits and risks of using this technology before making a decision" (GB), to "understand how the models work and how they make decisions" (GB), and to make an informed choice of genAI models, "using [those] that are transparent and auditable" (GB). The latter assertion is somewhat oxymoronic, as the exact nature of training data has never been made public for *any* of the genAI models.

Furthermore, Google Bard deemed it desirable for cultural heritage professionals to "be involved in the development and implementation of genAI systems" (BB) to "strike a balance between harnessing the potential of AI and preserving the authenticity and cultural significance of heritage artifacts and traditions" (GB).

3.2.11. Data and Privacy

On a more generic level, all genAI systems apart from Google Bard raised concerns about data security and privacy with the need to secure the data from "[u]nauthorized access or breaches of sensitive data [which] could result in the misuse or theft of valuable cultural information" (CG), by "applying access control and consent mechanisms, or following ethical data collection and sharing practices" (BC), and by ensuring that "[c]ultural heritage professionals [understand that they] have the duty to protect the security and privacy of the data and information they handle, as well as to comply with the relevant laws and regulations" (BC). In addition, there needs to be some form of quality control over the possible output of genAI, as it "may use or disclose sensitive or confidential data or information related to cultural heritage, such as personal stories, identities, locations, or ownerships" (BC).

4. Discussion and Conclusions

A common tenet is that genAI large language models are deemed capable of extracting and synthesising text [101–103]. As this is methodologically based on semantic proximity constructs, the results are not prone to biases [10,104], but may suffer from inverted logic [24]. Moreover, the effective summation and synthesis of text requires judgment as to which element to include, even if they are less dominant in terms of the overall bulk of text to be condensed. This necessitates, at least at present, human oversight of the output. Furthermore, genAI large language models are, at present, unable to purposively generate creative or innovative thoughts. It is left to the reader to determine whether any text that is provided by genAI, which is out of the ordinary, is considered nonsensical or meaningful. Consequently, genAI models cannot predict the future even if they are tasked to do so. The 'projections' offered by genAI models are summaries of extant information in their dataset that are both factual and actual uses of AI in the cultural heritage field, as well as data on the potential uses of AI in general. By combining both, genAI models create examples of possible future uses of AI in cultural heritage, as well as possible future problems and dangers.

The projections offered are, by and large, extensions of existing concepts such as increased digitisation, virtual reconstruction, and the creation of interactive and immersive experiences. A number of novel concepts were offered. Some of these were realistic, such as the predictive modelling of the decay of objects, while others, such as blending the old with the new, run against the philosophy of heritage management. Overall, however, the examples put forward were far fewer than expected.

Among the potential future uses of AI that were not mentioned by the genAI models, but that can be envisaged, would be an extension of handwriting analysis from forensic science [105] into archival studies. It is commonplace that drafts of official historic correspondence exhibit marginal notes and annotations in varied handwriting. Automated transcription coupled with identification and classification of the handwriting as to potential authors would allow for a more nuanced understanding of historic decision-making processes.

DeepAI noted that power of genAI to extract, aggregate, and synthesise large volumes of data from multiple sources may allow genAI models "to recognize patterns and connections that humans may miss". This is a significant 'observation.' Depending on the training data, genAI models may generate seemingly random combinations derived from statistical correlations of extracted data that may be unexpected and, at first sight, non-sensical. Whether such patterns are useful depends on the user's contextual knowledge and this interpretation of the pattern. Here, we need to distinguish between 'generic' genAI systems, such as ChatGPT, and bespoke models designed specifically for document analysis. When considering the latter, the training process is critical as it will influence the validity of the generated text and, thus, will restrict the range of responses. It may well prove to be beneficial to develop models with two modes, one that responds in a more constrained 'logical' manner and one where responses are more speculative to generate a left-of-field output.

Without doubt, AI tools will revolutionise the execution of repetitive and mundane tasks, such as the classification of small pottery fragments or the identification and classification of bone fragments, such as fishbones, in archaeological sites—and they will be able to do so with more rigorous standards than human actions. But in this may also lie some shortcomings. For example, the AI driven classification of pottery may not be able to recognise differences in quality as expressed in the texture of its surface, aspects that have a tactile dimension where haptic interaction is required. Likewise, depending on the way the AI system is trained, it may attempt to unequivocally classify elements that may be more ambiguous, instances where human intuition would lead to further investigation and examination. In essence, care must be taken that the selection of the dataset is not subconsciously biased and that the training of the models does not result in a built-in confirmation bias.

As noted by Google Bard, it is likely that at least some cultural heritage professionals will use AI systems without the required level of AI literacy, i.e., without the detailed understanding of its internal processes. There is an inherent risk that a successful classification system will be adopted and adapted to new areas of enquiry without questioning the underlying training process of the original models. As a consequence, underlying classification biases may go unnoticed, resulting in erroneous classification, which, in turn, may result in erroneous or biased interpretations. While, at first sight, this seems to place the responsibility on the user, this is an instance of 'caveat emptor'—as is the case with all computerised support and data management systems. Given that much of this occurs, at least for the user, in a seemingly impenetrable 'black box scenario', there is a need that designers of AI systems clearly and unequivocally spell out both the exact nature of the training data employed, as well as the nature and extent of the system's limitations.

Beyond the realm of custom-tailored AI, genAI language models can be used to generate text from a wide range of input data. These texts can be written in a language suitable for different audiences, ranging from contemporary languages (e.g., English and Mandarin) or in terms of reading age or level of educational achievement. Underlying this, however, any level of output can only ever be as good as the nature, diversity, quantity, and quality of the training data that were supplied, as well as any ethical frameworks that may have been deployed in the training and quality assurance process. Users need to be cognisant of the biases derived from the curation of the training sets [10,12], which requires transparency by the companies offering the AI products. It is not well understood, for example, that current models of genAI, such as ChatGPT, draw on 'authoritative' sources, which are, in fact, gleaned from the web, such as Wikipedia [5].

It is clear that genAI models are here to stay and that they will be increasingly integrated into general productivity tools (e.g., word processing and image manipulation programs) and information and query systems. While it is highly unlikely that "museum curators [or] restorers... could potentially lose their jobs", as posited by DeepAI, cost cutting measures may well see reductions in generic tour guides and other customer-facing staff. It can be posited that specialised and customised applications will be developed at a rapid rate. The examples generated by these four genAI systems, as limited as they may be, highlight the need for the cultural heritage profession to be AI literate. The training of present and future cultural heritage professionals in the fields of archaeology and historic preservation/cultural heritage management, as well as museology must include AI literacy as part of the generic skill set. This AI literacy needs to augment and be in parallel with the continued training in 'traditional' investigative, analytical, and interpretive skills.

All genAI systems raised the issue that overreliance on genAI without AI literacy runs the risk of deskilling human users, which has parallels with current increased reliance on other technologies.

Drawing on Inayatullah's concept of Future Avoiders, Migrants and Natives [106], we can posit a generation of AI natives that knows no other world and who are, by and large, unable to use alternative technologies. This is not far-fetched, as example can be found in the current reality, where a generation of World Wide Web and smart phone natives are unable to execute even basic calculations in their head or on paper, or are able to read a paper-based street map.

Supplementary Materials: https://researchoutput.csu.edu.au/en/datasets/will-generative-ai-affect-how-cultural-heritage-will-be-being-man.

Funding: This research received no external funding.

Data Availability Statement: https://researchoutput.csu.edu.au/en/datasets/will-generative-ai-affect-how-cultural-heritage-will-be-being-man (accessed on 10 February 2024).

Conflicts of Interest: The author declares no conflict of interest.

References

1. Spennemann, D.H.R. Will the age of generative Artificial Intelligence become an age of public ignorance? *Preprint* **2023**, 1–12. [CrossRef]
2. Markov, T.; Zhang, C.; Agarwal, S.; Eloundou, T.; Lee, T.; Adler, S.; Jiang, A.; Weng, L. New and Improved Content Moderation Tooling. Available online: https://openai.com/blog/new-and-improved-content-moderation-tooling/ (accessed on 28 June 2023).
3. Collins, E.; Ghahramani, Z. LaMDA: Our Breakthrough Conversation Technology. Available online: https://web.archive.org/web/20230130233845mp_/https://openai.com/blog/new-and-improved-content-moderation-tooling/ (accessed on 1 September 2023).
4. Frąckiewicz, M. ChatGPT-4 for Digital Archaeology: AI-Powered Artifact Discovery and Analysis. Available online: https://ts2.space/en/chatgpt-4-for-digital-archaeology-ai-powered-artifact-discovery-and-analysis/ (accessed on 29 June 2023).
5. Spennemann, D.H.R. What has ChatGPT read? References and referencing of archaeological literature by a generative artificial intelligence application. *arXiv* **2023**, arXiv:2308.03301.
6. Reisner, A. Revealed: The authors whose pirated books are powering generative Ai. *Atlantic* **2023**. Available online: https://www.theatlantic.com/technology/archive/2023/08/books3-ai-meta-llama-pirated-books/675063/ (accessed on 29 June 2023).
7. Reisner, A. What I Found in a Database Meta Uses to Train Generative AI. *Atlantic* **2023**. Available online: https://www.theatlantic.com/technology/archive/2023/09/books3-ai-training-meta-copyright-infringement-lawsuit/675411/ (accessed on 29 June 2023).
8. Bender, E.M.; Gebru, T.; McMillan-Major, A.; Shmitchell, S. On the dangers of stochastic parrots: Can language models be too big? In Proceedings of the 2021 ACM conference on fairness, accountability, and transparency, Virtual, 3–10 March 2021; pp. 610–623.
9. Rozado, D. The political biases of chatgpt. *Soc. Sci.* **2023**, *12*, 148. [CrossRef]
10. Rutinowski, J.; Franke, S.; Endendyk, J.; Dormuth, I.; Pauly, M. The Self-Perception and Political Biases of ChatGPT. *arXiv* **2023**, arXiv:2304.07333. [CrossRef]
11. Ferrara, E. Should chatgpt be biased? challenges and risks of bias in large language models. *arXiv* **2023**, arXiv:2304.03738.
12. McGee, R.W. Is chat gpt biased against conservatives? An empirical study (February 15, 2023). *SSRN* **2023**. [CrossRef]
13. Kamran, A. Decolonizing Artificial Intelligence: Unveiling Biases, Power Dynamics, and Colonial Continuities in AI Systems. *RMS J.* **2023**. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4610643 (accessed on 15 September 2023).
14. Paradis, K. More Than Ones and Zeros: Developing an Intersectional Framework for Artificial Intelligence. *J. Inf. Ethics* **2023**, *32*, 70–83.
15. Mbalaka, B. Epistemically violent biases in artificial intelligence design: The case of DALLE-E 2 and Starry AI. *Digit. Transform. Soc.* **2023**, *2*, 376–402. [CrossRef]
16. Tamkin, A.; Brundage, M.; Clark, J.; Ganguli, D. Understanding the capabilities, limitations, and societal impact of large language models. *arXiv* **2021**, arXiv:2102.02503.

17. Kuck, K. Generative Artificial Intelligence: A Double-Edged Sword. In Proceedings of the 2023 World Engineering Education Forum-Global Engineering Deans Council (WEEF-GEDC), Cape Town, South Africa, 23–27 October 2023; pp. 1–10.
18. Gross, N. What ChatGPT Tells Us about Gender: A Cautionary Tale about Performativity and Gender Biases in AI. *Soc. Sci.* **2023**, *12*, 435. [CrossRef]
19. Head, C.B.; Jasper, P.; McConnachie, M.; Raftree, L.; Higdon, G. Large language model applications for evaluation: Opportunities and ethical implications. *New Dir. Eval.* **2023**, *2023*, 33–46. [CrossRef]
20. Lucchi, N. ChatGPT: A case study on copyright challenges for generative artificial intelligence systems. *Eur. J. Risk Regul.* **2023**, 1–23. [CrossRef]
21. Chesterman, S. Good Models Borrow, Great Models Steal: Intellectual Property Rights and Generative AI. *Policy Soc.* **2023**, puae006. [CrossRef]
22. Chang, K.K.; Cramer, M.; Soni, S.; Bamman, D. Speak, memory: An archaeology of books known to chatgpt/gpt-4. *arXiv* **2023**, arXiv:2305.00118.
23. Bang, Y.; Cahyawijaya, S.; Lee, N.; Dai, W.; Su, D.; Wilie, B.; Lovenia, H.; Ji, Z.; Yu, T.; Chung, W. A multitask, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity. *arXiv* **2023**, arXiv:2302.04023.
24. Spennemann, D.H.R. ChatGPT and the generation of digitally born "knowledge": How does a generative AI language model interpret cultural heritage values? *Knowledge* **2023**, *3*, 480–512. [CrossRef]
25. Ray, P.P. ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet Things Cyber-Phys. Syst.* **2023**, *3*, 121–154. [CrossRef]
26. Flensted, T. How Many Languages Does ChatGPT Support? The Complete ChatGPT Language List. Available online: https://seo.ai/blog/how-many-languages-does-chatgpt-support#:~:text=Unlock%20the%20Power%20of%20ChatGPT,list%20of%20supported%20languages%20below (accessed on 1 October 2023).
27. Hua, S.; Jin, S.; Jiang, S. The Limitations and Ethical Considerations of ChatGPT. *Data Intell.* **2023**, 1–38. [CrossRef]
28. Ferrara, E. GenAI against humanity: Nefarious applications of generative artificial intelligence and large language models. *arXiv* **2023**, arXiv:2310.00737. [CrossRef]
29. Spennemann, D.H.R. Exploring ethical boundaries: Can ChatGPT be prompted to give advice on how to cheat in university assignments? *Preprint* **2023**, 1–14. [CrossRef]
30. OpenAI. How ChatGPT and Our Language Models Are Developed. Available online: https://help.openai.com/en/articles/7842364-how-chatgpt-and-our-language-models-are-developed (accessed on 1 February 2024).
31. Vaughan-Nichols, S. GPT-3.5 vs GPT-4: Is ChatGPT Plus Worth Its Subscription Fee? Available online: https://www.zdnet.com/article/gpt-3-5-vs-gpt-4-is-chatgpt-plus-worth-its-subscription-fee/ (accessed on 15 September 2023).
32. Manyika, J.; Hsiao, S. *An Overview of Bard: An Early Experiment with Generative AI [Version 19 October 2023]*; Google LLC: Mountain View, CA, USA, 2023.
33. Google. Bard FAQ. Available online: https://bard.google.com/faq (accessed on 12 October 2023).
34. Griffin, G.; Wennerström, E.; Foka, A. AI and Swedish Heritage Organisations: Challenges and opportunities. *AI Soc.* **2023**. [CrossRef]
35. Cuéllar, Á. Artificial Intelligence to the Rescue of the Spanish Golden Age: Automatic Transcription and Modernization of One Thousand Three Hundred Theatrical Prints and Manuscripts. *Hipogrifo. Rev. De Lit. Y Cult. Del Siglo De Oro* **2023**, *11*, 101–115.
36. Assael, Y.; Sommerschield, T.; Shillingford, B.; Bordbar, M.; Pavlopoulos, J.; Chatzipanagiotou, M.; Androutsopoulos, I.; Prag, J.; de Freitas, N. Restoring and attributing ancient texts using deep neural networks. *Nature* **2022**, *603*, 280–283. [CrossRef]
37. Sanders, D.H. Neural Networks, AI, Phone-based VR, Machine Learning, Computer Vision and the CUNAT Automated Translation App–not your father's archaeological toolkit. In Proceedings of the 2018 3rd Digital Heritage International Congress (DigitalHERITAGE) held jointly with 2018 24th International Conference on Virtual Systems & Multimedia (VSMM 2018), San Francisco, CA, USA, 26–30 October 2018; pp. 1–5.
38. Roueché, C. AI minds the gap and fills in missing Greek inscriptions. *Nature* **2022**, *603*, 235–236. [CrossRef]
39. Locaputo, A.; Portelli, B.; Colombi, E.; Serra, G. Filling the Lacunae in ancient Latin inscriptions. In Proceedings of the CEUR Workshop Proceedings, Leipzing, Germany, 20–22 September 2023; pp. 68–76.
40. Guidi, T.; Python, L.; Forasassi, M.; Cucci, C.; Franci, M.; Argenti, F.; Barucci, A. Egyptian hieroglyphs segmentation with convolutional neural networks. *Algorithms* **2023**, *16*, 79. [CrossRef]
41. León, R.B.; Peña, C.A.; Moreno, G.G. Advances in the Development of an Algorithm for Parametric Identification of Egyptian Hieroglyphs Using Artificial Vision. *J. Adv. Inf. Technol.* **2023**, *14*, 788–795. [CrossRef]
42. Fu, X.; Yang, Z.; Zeng, Z.; Zhang, Y.; Zhou, Q. Improvement of Oracle Bone Inscription Recognition Accuracy: A Deep Learning Perspective. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 45. [CrossRef]
43. Marchant, J. AI reads text from ancient Herculaneum scroll for the first time. *Nature* **2023**. [CrossRef]
44. Shaus, A.; Gerber, Y.; Faigenbaum-Golovin, S.; Sober, B.; Piasetzky, E.; Finkelstein, I. Forensic document examination and algorithmic handwriting analysis of Judahite biblical period inscriptions reveal significant literacy level. *PLoS ONE* **2020**, *15*, e0237962. [CrossRef] [PubMed]
45. Chammas, M.; Makhoul, A.; Demerjian, J.; Dannaoui, E. A deep learning based system for writer identification in handwritten Arabic historical manuscripts. *Multimed. Tools Appl.* **2022**, *81*, 30769–30784. [CrossRef]
46. Cardarelli, L. A deep variational convolutional Autoencoder for unsupervised features extraction of ceramic profiles. A case study from central Italy. *J. Archaeol. Sci.* **2022**, *144*, 105640. [CrossRef]

47. Argyrou, A.; Agapiou, A.; Papakonstantinou, A.; Alexakis, D.D. Comparison of Machine Learning Pixel-Based Classifiers for Detecting Archaeological Ceramics. *Drones* **2023**, *7*, 578. [CrossRef]
48. Bickler, S.H. Machine learning identification and classification of historic ceramics. *Archaeology* **2018**, *20*, 20–32.
49. Aoulalay, A.; El Makhfi, N.; Abounaima, M.C.; Massar, M. Classification of Moroccan decorative patterns based on machine learning algorithms. In Proceedings of the 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), Kenitra, Morocco, 2–3 December 2020; pp. 1–7.
50. Kuntitan, P.; Chaowalit, O. Using deep learning for the image recognition of motifs on the Center of Sukhothai Ceramics. *Curr. Appl. Sci. Technol.* **2022**, *22*, 1–15. [CrossRef]
51. Chetouani, A.; Treuillet, S.; Exbrayat, M.; Jesset, S. Classification of engraved pottery sherds mixing deep-learning features by compact bilinear pooling. *Pattern Recognit. Lett.* **2020**, *131*, 1–7. [CrossRef]
52. Cintas, C.; Lucena, M.; Fuertes, J.M.; Delrieux, C.; Navarro, P.; González-José, R.; Molinos, M. Automatic feature extraction and classification of Iberian ceramics based on deep convolutional networks. *J. Cult. Herit.* **2020**, *41*, 106–112. [CrossRef]
53. Ostertag, C.; Beurton-Aimar, M. Matching ostraca fragments using a siamese neural network. *Pattern Recognit. Lett.* **2020**, *131*, 336–340. [CrossRef]
54. Marie, I.; Qasrawi, H. Virtual assembly of pottery fragments using moiré surface profile measurements. *J. Archaeol. Sci.* **2005**, *32*, 1527–1533. [CrossRef]
55. Anglisano, A.; Casas, L.; Queralt, I.; Di Febo, R. Supervised Machine Learning Algorithms to Predict Provenance of Archaeological Pottery Fragments. *Sustainability* **2022**, *14*, 11214. [CrossRef]
56. Aslan, S.; Vascon, S.; Pelillo, M. Two sides of the same coin: Improved ancient coin classification using Graph Transduction Games. *Pattern Recognit. Lett.* **2020**, *131*, 158–165. [CrossRef]
57. Bickler, S.H. Prospects for machine learning for shell midden analysis. *Archaeol. New Zealand* **2018**, *61*, 48–58.
58. Byeon, W.; Dominguez-Rodrigo, M.; Arampatzis, G.; Baquedano, E.; Yravedra, J.; Maté-González, M.A.; Koumoutsakos, P. Automated identification and deep classification of cut marks on bones and its paleoanthropological implications. *J. Comput. Sci.* **2019**, *32*, 36–43. [CrossRef]
59. Domínguez-Rodrigo, M.; Cifuentes-Alcobendas, G.; Jiménez-García, B.; Abellán, N.; Pizarro-Monzo, M.; Organista, E.; Baquedano, E. Artificial intelligence provides greater accuracy in the classification of modern and ancient bone surface modifications. *Sci. Rep.* **2020**, *10*, 18862. [CrossRef] [PubMed]
60. Jiang, D.; Li, P.; Xie, H. Research into Digital Oil Painting Restoration Algorithm Based on Image Acquisition Technology. In Proceedings of the 2022 International Conference on 3D Immersion, Interaction and Multi-sensory Experiences (ICDIIME), Madrid, Spain, 27–29 June 2022; pp. 65–68.
61. Sizyakin, R.; Voronin, V.; Pižurica, A. Virtual restoration of paintings based on deep learning. In Proceedings of the Fourteenth International Conference on Machine Vision (ICMV 2021), Rome, Italy, 8–12 November 2021; pp. 422–432.
62. Agapiou, A.; Lysandrou, V. Interacting with the Artificial Intelligence (AI) Language Model ChatGPT: A Synopsis of Earth Observation and Remote Sensing in Archaeology. *Heritage* **2023**, *6*, 4072–4085. [CrossRef]
63. Graham, D. The Use of Generative AI in an Interdisciplinary Approach for Cultural Preservation. *Qeios* **2023**. [CrossRef]
64. Merritt, E. Chatting about Museums with ChatGPT. Available online: https://www.aam-us.org/2023/01/25/chatting-about-museums-with-chatgpt (accessed on 29 June 2023).
65. Trichopoulos, G.; Konstantakis, M.; Alexandridis, G.; Caridakis, G. Large Language Models as Recommendation Systems in Museums. *Electronics* **2023**, *12*, 3829. [CrossRef]
66. Trichopoulos, G.; Konstantakis, M.; Caridakis, G.; Katifori, A.; Koukouli, M. Crafting a Museum Guide Using GPT4. *Bid Data Cogntiive Comput.* **2023**, *7*, 148. [CrossRef]
67. Trichopoulos, G. Large Language Models for Cultural Heritage. In Proceedings of the 2nd International Conference of the ACM Greek SIGCHI Chapter, CHIGREECE 2023, Athens, Greece, 27–28 September 2023; Article 33. pp. 1–5.
68. Spennemann, D.H.R. Exhibiting the Heritage of COVID-19—A Conversation with ChatGPT. *Heritage* **2023**, *6*, 5732–5749. [CrossRef]
69. Makhortykh, M.; Zucker, E.M.; Simon, D.J.; Bultmann, D.; Ulloa, R. Shall androids dream of genocides? How generative AI can change the future of memorialization of mass atrocities. *Discov. Artif. Intell.* **2023**, *3*, 28. [CrossRef]
70. Hines, A.; Bishop, P.J.; Slaughter, R.A. *Thinking about the Future: Guidelines for Strategic Foresight*; Social Technologies: Washington, DC, USA, 2006.
71. Van Duijne, F.; Bishop, P. *Introduction to Strategic Foresight*; Future Motions, Dutch Futures Society: Den Haag, The Netherlands, 2018; Volume 1, p. 67.
72. OpenAI. ChatGPT 3.5 (August 3 Version). Available online: https://chat.openai.com (accessed on 11 September 2023).
73. Google. Google Bard Version 2023.07.13. Available online: https://bard.google.com (accessed on 19 October 2023).
74. Microsoft. Bing Chat Enterprise. Available online: https://www.bing.com/chat (accessed on 19 September 2023).
75. DeepAi. DeepAi. Available online: https://deepai.org/chat (accessed on 19 September 2023).
76. Spennemann, D.H.R. Children of AI: A protocol for managing the born-digital ephemera spawned by Generative AI Language Models. *Publications* **2023**, *11*, 45. [CrossRef]
77. Jadresin Milic, R.; McPherson, P.; McConchie, G.; Reutlinger, T.; Singh, S. Architectural history and sustainable architectural heritage education: Digitalisation of heritage in New Zealand. *Sustainability* **2022**, *14*, 16432. [CrossRef]

78. Maietti, F. Digital Documentation for Enhancement and Conservation of Minor or Inaccessible Heritage Sites. In *Cultural Leadership in Transition Tourism: Developing Innovative and Sustainable Models*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 139–156.
79. Comes, R.; Neamțu, C.G.D.; Grec, C.; Buna, Z.L.; Găzdac, C.; Mateescu-Suciu, L. Digital Reconstruction of Fragmented Cultural Heritage Assets: The Case Study of the Dacian Embossed Disk from Piatra Roșie. *Appl. Sci.* **2022**, *12*, 8131. [CrossRef]
80. Popova, D. Digital Reconstruction of Lost Architectural Heritage on the Case Study of Two 19th Century Houses. *Digit. Present. Preserv. Cult. Sci. Herit.* **2023**, *13*, 117–126. [CrossRef]
81. Anichini, F.; Banterle, F.; Buxeda i Garrigós, J.; Callieri, M.; Dershowitz, N.; Dubbini, N.; Diaz, D.L.; Evans, T.; Gattiglia, G.; Green, K. *Developing the ArchAIDE Application: A Digital Workflow for Identifying, Organising and Sharing Archaeological Pottery Using Automated Image Recognition*; Internet Archaeology nº 52; University of York: York, UK, 2020.
82. Anichini, F.; Dershowitz, N.; Dubbini, N.; Gattiglia, G.; Itkin, B.; Wolf, L. The automatic recognition of ceramics from only one photo: The ArchAIDE app. *J. Archaeol. Sci. Rep.* **2021**, *36*, 102788. [CrossRef]
83. Neumüller, M.; Reichinger, A.; Rist, F.; Kern, C. 3D printing for cultural heritage: Preservation, accessibility, research and education. In *3D Research Challenges in Cultural Heritage: A Roadmap in Digital Heritage Preservation*; Ioannides, M., Quak, E., Eds.; Springer: Berlin/Heidelberg, Germany, 2014; pp. 119–134.
84. Koutsoudis, A.; Arnaoutoglou, F.; Chamzas, C. On 3D reconstruction of the old city of Xanthi: A minimum budget approach to virtual touring based on photogrammetry. *J. Cult. Herit.* **2007**, *8*, 26–31. [CrossRef]
85. Amakawa, J.; Westin, J. New Philadelphia: Using augmented reality to interpret slavery and reconstruction era historical sites. *Int. J. Herit. Stud.* **2018**, *24*, 315–331. [CrossRef]
86. Tschirschwitz, F.; Richerzhagen, C.; Przybilla, H.-J.; Kersten, T.P. Duisburg 1566: Transferring a historic 3d city model from google earth into a virtual reality application. *PFG–J. Photogramm. Remote Sens. Geoinf. Sci.* **2019**, *87*, 47–56. [CrossRef]
87. Korsten, B.; Haanstra, B. The Next Rembrandt. Available online: www.nextrembrandt.com (accessed on 1 September 2023).
88. Spennemann, D.H.R. The Shifting Baseline Syndrome and Generational Amnesia in Heritage Studies. *Heritage* **2022**, *5*, 2007–2027. [CrossRef]
89. Labadi, S. *UNESCO, Cultural Heritage, and Outstanding Universal Value: Value-Based Analyses of the World Heritage and Intangible Cultural Heritage Conventions*; UNESDOC: New York, NY, USA, 2013.
90. Deacon, H.; Smeets, R. Authenticity, value and community involvement in heritage management under the world heritage and intangible heritage conventions. *Herit. Soc.* **2013**, *6*, 129–143. [CrossRef]
91. Jigyasu, N. Authentic versus staged identity–problematizing tourism interventions for authenticity and integrity in historic cities. *J. Cult. Herit. Manag. Sustain. Dev.* **2022**. [CrossRef]
92. Katz, R.; Katz, E. Evaluating culture: World music and fusion food. *Int. J. Cult. Stud.* **2015**, *18*, 155–165. [CrossRef]
93. Erdem, B.; Dogdubay, M.; Sarıoglan, M. The relationship between product innovation and fusion cuisine in food and beverage establishments: A discussion on Turkish cuisine. In *Current Issues in Hospitality and Tourism Research and Innovations*; Radzi, S.M., Chik, C.T., Hashim, R., Abu, R., Zainal, A., Eds.; CRC Press: Boca Raton, FL, USA, 2012; pp. 213–218.
94. Sutton, R.A. "Fusion" and questions of Korean cultural identity in music. *Korean Stud.* **2011**, *35*, 4–24. [CrossRef]
95. Google Arts & Culture. Fabricius. Available online: https://experiments.withgoogle.com/fabricius (accessed on 1 February 2024).
96. Plecher, D.A.; Eichhorn, C.; Seyam, K.M.; Klinker, G. ARsinoë—Learning Egyptian Hieroglyphs with Augmented Reality and Machine Learning. In Proceedings of the 2020 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), Recife, Brazil, 9–13 November 2020; pp. 326–332.
97. Alkaissi, H.; McFarlane, S.I. Artificial hallucinations in ChatGPT: Implications in scientific writing. *Cureus* **2023**, *15*, e35179. [CrossRef] [PubMed]
98. Emsley, R. ChatGPT: These are not hallucinations–they're fabrications and falsifications. *Schizophrenia* **2023**, *9*, 52. [CrossRef]
99. Hiter, S. Generative AI Ethics: Concerns and Solutions. Available online: https://www.eweek.com/artificial-intelligence/generative-ai-ethics/ (accessed on 1 October 2023).
100. Shi, M. The ethics of generative AI: How we can harness this powerful technology. Available online: https://www.zdnet.com/article/how-we-can-harness-the-power-of-generative-ai-ethically/ (accessed on 1 October 2023).
101. Boyko, J.; Cohen, J.; Fox, N.; Veiga, M.H.; Li, J.I.; Liu, J.; Modenesi, B.; Rauch, A.H.; Reid, K.N.; Tribedi, S. An interdisciplinary outlook on large language models for scientific research. *arXiv* **2023**, arXiv:2311.04929.
102. Tang, L.; Sun, Z.; Idnay, B.; Nestor, J.G.; Soroush, A.; Elias, P.A.; Xu, Z.; Ding, Y.; Durrett, G.; Rousseau, J.F. Evaluating large language models on medical evidence summarization. *Npj Digit. Med.* **2023**, *6*, 158. [CrossRef]
103. Babl, F.E.; Babl, M.P. Generative artificial intelligence: Can ChatGPT write a quality abstract? *Emerg. Med. Australas.* **2023**, *35*, 809–811. [CrossRef]
104. Messner, W.; Greene, T.; Matalone, J. From Bytes to Biases: Investigating the Cultural Self-Perception of Large Language Models. *arXiv* **2023**, arXiv:2312.17256.

105. Marcinowski, M. Evaluation of neural networks applied in forensics; handwriting verification example. *Aust. J. Forensic Sci.* **2022**, *55*, 745–754. [CrossRef]
106. Inayatullah, S. Future Avoiders, Migrants and Natives. *J. Futures Stud.* **2004**, *9*, 83–86.