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Accessible Cultural Heritage through Explainable Artificial Intelligence

Natalia Díaz-Rodríguez

natalia.diaz@ensta-paris.fr ENSTA, Institut Polytechnique Paris & INRIA Flowers,
France

Galena Pisoni

galena.pisoni@univ-cotedazur.fr, Université Côte d'Azur, Nice, France

Abstract

Ethics Guidelines for Trustworthy AI advocate for AI technology that is, among other things, more inclusive. Explainable AI (XAI) aims at making state of the art opaque models more transparent, and defends AI-based outcomes endorsed with a *rationale explanation*, i.e., an explanation that has as target the non-technical users. XAI and Responsible AI principles defend the fact that the audience expertise should be included in the evaluation of explainable AI systems. However, AI has not yet reached all public and audiences, some of which may need it the most. One example of domain where accessibility has not much been influenced by the latest AI advances is cultural heritage. We propose including minorities as special user and evaluator of the latest XAI techniques. In order to define catalytic scenarios for collaboration and improved user experience, we pose some challenges and research questions yet to address by the latest AI models likely to be involved in such synergy.

Keywords: Explainable Artificial Intelligence, Generative Models, Natural Language Processing, Image Captioning, Cultural Heritage

1. Introduction

The European Commission Ethics Guidelines for Trustworthy Artificial Intelligence (AI) [1] and Responsible AI principles [2] advocate for lawful



Figure 1: Left: *3 Graces*. Middle: *Monet* from the series *People matching artworks*. Right: *People touching artworks*. Reproduced with permission from ©Stefan Draschan www.StefanDraschan.com.

4 AI technology that is, among other things, more inclusive. *EXplainable* AI
5 (XAI) aims at making state of the art opaque models more transparent, and
6 defends AI-based outcomes endorsed with a *rationale explanation*, i.e., an
7 explanation that has as target the non-technical users. The latest XAI tech-
8 niques [2, 3, 4, 5] could bring art closer to new audiences. By increasing
9 the accessibility of cultural heritage to collectives not fully able to enjoy it
10 today, missing gaps in technology could be identified. One example of such
11 innovations is the smartphone app MonuMAI¹, which has already demon-
12 strated how to put together technological innovation to actively approach
13 different perspectives in science and art dissemination to the public [6, 7].
14 Based on deep neural networks (DNNs), MonuMAI classifies photos taken
15 (e.g. of a facade) according to different architectonic styles, providing visual
16 explanations on the elements contributing to the detected style.

17 Such examples show that technology can yet have a lot more of impact
18 than currently has. Models able to switch among input/output modalities
19 (in terms of the data they are able to process) could have a crucial role. The
20 role is actively approaching art to minorities not having it accessible (since
21 blind people can listen and read, the deaf can read, etc.). The latest advances
22 in natural language processing (NLP), computer vision (CV) and XAI could
23 disruptively innovate the ways in which we teach, learn, and approach art to

¹MonuMAI = Monuments + Maths + AI + Dissemination

24 society.

25 For instance, people with visual impairments take and share photographs
26 for the same reasons that sighted people do, but as they find many more
27 difficulties, methods have been developed to assist blind photography (in-
28 cluding audio feedback that facilitates aiming the camera) [8]. Generating
29 descriptions helps visually impaired people better browse and select photos
30 based on human-powered photo descriptions and computer-generated photo
31 descriptions. Could such human computation-generated visual explanations
32 also help completely blind users, e.g. to navigate? Could these help any
33 user that wants to learn from first-hand experts how a given artwork is in-
34 terpreted, or what it conveys, providing the right context of its time? If
35 the answer is positive, perhaps a DNN could be trained with all generated
36 data to avoid the arduous task of labelling data so that eventually, the blind
37 would not require human assistance. In this paper we put ourselves in the
38 shoes of particular collectives such as the blind, or the deaf, and pose a set
39 of settings we consider worth exploring in the intersection of art and science.
40 In particular, we propose using cultural heritage as a playground for (X)AI,
41 and suggest a list of challenges and research questions (RQs) showing why
42 inclusive art needs XAI, and why XAI may find on minority audiences, the
43 right manner to evaluate where AI can have more impact.

44 2. EXplainable AI (XAI)

45 *Given an audience, an **eXplainable AI** (XAI) is a suite of machine*
46 *learning techniques that produces details or reasons to make its functioning*
47 *clear or easy to understand* [2]. XAI draws insights from Social Sciences and
48 the psychology of explanation, and its objective is to (1) produce more ex-
49 plainable models maintaining high level performance, and (2) enable humans
50 to understand, trust, and manage the emerging generation of artificially in-
51 telligent partners.

52 Given the inherent subjectivity of an explanation, current discussions ad-
53 vocate for rethinking interpretability, involving the audience expertise. When
54 AI becomes ubiquitous across domains, it is specially important to follow the
55 EU Ethics Guidelines for Trustworthy AI [1], Guidelines for Responsible AI
56 and interpretable AI models [2]. Equally important is accounting for inter-
57 ests, demands and requirements of the different stakeholders interacting with
58 the system to be explained. In cultural heritage contexts, accounting for the

59 target audience is equally important from both evaluation and personalisa-
60 tion points of view [9].

61 **3. Unconventional interfaces for art accessibility**

62 Groups of visitors inside museums have been a focus of ongoing research
63 for a long time [10, 11, 12]. Some systems allowed for visitor collaboration
64 by supporting shared listening or leaving messages between visitors [11]. In
65 order to facilitate the process of engagement and collaboration between co-
66 visitors, narratives are often introduced in museum contexts. Narratives are
67 responsible for mental immersion through which users can be engaged and in-
68 volved in the experience, increasing their sense of mediated presence as well.
69 Visitors preferences have been studied [13], and more engaging approaches
70 have been proposed for stimulating the visitor interests by using presenta-
71 tions such as film or drama [14]. The drama was adapting to the visitors so
72 that different available independent drama segments were played to be group
73 based on characteristics of the group of visitors, the specific context of the
74 visit, and implicit input from the visitors themselves. Results showed that
75 drama, when designed for small groups, and combined with the raw emotion
76 of onsite visitors being in front of actual original artifacts, can emotionally
77 engage distant visitors with mobility constrains [15].

78 Another way to alleviate mobility disadvantages for challenged individ-
79 uals and to allow them still to enjoy art is through the use of virtual envi-
80 ronments. Virtual environments offer the possibility to navigate in new or
81 known environments and contexts, and interacting with people in different
82 locations. Virtual environments can provide a realistic experience, or the
83 participant’s feeling of “being there” in an environment, also defined as a
84 sense of presence. Previous studies have investigated if and how challenged
85 individuals can access and appreciate museum contents, and the best suited
86 interface designs for this [16, 17]. The results have been positive with first
87 results indicating that challenged individuals could indeed understand the
88 virtual tours and engage in contextual conversations, while the ability to fol-
89 low the tour depended on the level of the “interactivity” of the prototype.
90 The more complex the interaction, the least possible it was for challenged
91 individuals to follow the museum visit.

92 For those with cognitive disabilities and the elderly, the ability to consume
93 cultural contents and to independently consult information about museums
94 from home is even more limited. Previous applications that understand the

95 cognitive barriers and propose solutions to present information so to cope
96 with the reduced cognitive loads have been developed and tested with users
97 [16, 18]. The majority of studies focus on developing or using AR technologies
98 to support blind or visually impaired users. Successful steps towards this
99 future have been made, with the possibilities for shared experiences already
100 available also for people with cognitive disabilities.

101 *3.1. Storytelling and audience engagement*

102 Approaching art to different audiences should consider culture and back-
103 ground. Culture traditions can disruptively change the idea of a museum
104 activity since early ages. For instance, opinion towards museums can be seen
105 by kids very differently. A great example is how kids loudly enjoy and see
106 museums as a fun place for kids when allowed to paint and talk inside (as
107 in UK National Gallery). The idea of museum becomes that one of a ludic
108 place, transmitting the idea that art can be a fun activity to play with. Such
109 context makes kids at ease to approach and feel curious about heritage, leav-
110 ing room for creativity. A very different idea of art is what often is formed
111 in children when museums do not allow touching, loud speaking, nor interac-
112 tion, linking the idea of museum more to a temple, or an activity that many
113 may find boring.

114 Studying mechanisms to bring closer the artistic heritage to a target
115 audience shows that, in art, the audience plays a central element, and can
116 change the vision of society towards art dramatically. Likewise in XAI, not
117 placing the audience in a centric role risks AI losing its deserved trust.

118 In order to renew the ways of thinking about art,

119 **Challenge 1.** *Could AI help deliver art, personalize or write new rules on*
120 *what is possible to do with cultural heritage?*

121 Neural symbolic computation [19, 20] includes methods to embed symbolic
122 and neural representations to learn and reason with different levels of ab-
123 straction [21].

124 **RQ 1.** *Does embedding of expert/domain knowledge into DL models [22] help*
125 *explain such models? Can XAI help encode such prior knowledge [22]?*

126 **Use Case 1.** *Juan Jesus Pleguezuelos, History teacher and podcast author*
127 *of Art History for entrance exams to University²: The challenge I pose is to*

²<https://www.instagram.com/historiaarte.selectividad>

128 *make others see an historical image only through words. It is clear that this*
129 *requires an exhaustive description of the masterpiece, but you should also*
130 *try to make others feel the latent soul in it, and decipher the intention of*
131 *the author. And if you could also convey the emotion that this work is able*
132 *to cause, it can be that words may be more than enough to make a listener*
133 *understand an artistic work that he is not seeing in that moment.*

134 **Challenge 2.** *Could XAI exhibit the level of detail and engagement required*
135 *to effectively convey a style, or the spirit represented in the times of an art-*
136 *work?*

137 **4. Explaining art through language**

138 Unlike math, art may not always be understood, and may require extra
139 (objective and subjective) interpretations to be able to effectively convey its
140 message. We believe art and the story accompanying it could be made more
141 widely understood if they would be more easily accessible.

142 **Hypothesis 1.** *If AI models can assist generation of content- and interpretation-*
143 *wise explanations, art can be more widely understood and accessible.*

144 One difficulty to convey the style of art eras consists of the ability to
145 express what that era meant. E.g., Renaissance’s works show people’s joy,
146 elegance, etc. AI not only should recognize the style but also the spirit
147 present in the era. For instance, given *Venus Birth*, how is to be understood
148 the Renaissance period? How to understand the ideas and spirit of the time?
149 What was the intention of the author? XAI may be a well-fitting candidate
150 tool to help this objective, being a catalyst for on-demand interfaces to truly
151 adapt to every active audience.

152 Producing textual explanations through NLP is a way of explaining AI
153 models [2]. Image captioning, visual question answering (VQA) and tex-
154 tual advisable explanations are different ML tasks considered. An example
155 of advisable explanations is on computer vision scene understanding for au-
156 tonomous driving learning models [23].

157 *4.1. Image captioning models*

158 Image captioning models produce a text describing the scene given an
159 input image. With the aim of producing clarifying explanations on why a

160 particular image caption model fails or succeeds, since a deep neural network
161 (DNN) is considered a black box model hard to inspect, recent strategies
162 make sure that the objects the captions talk about are indeed detected in
163 the images [24, 25]. Textual explanations can also contribute to make vision
164 and language models more robust, in the sense of being more semantically
165 grounded [26].

166 Since image captioning models pretrained on datasets outside the art do-
167 main fail completely at describing out of distribution inputs (e.g., pictorial
168 compositions not found in natural images), some metrics evaluating the se-
169 mantic fidelity of the model have been devised [24]. These call for models
170 more semantically faithful to the input information, in order to reduce the
171 bias that image caption models suffer [27], as well as object hallucination.
172 The latter is a well-known phenomenon where image captioning models cap-
173 tion an image with objects not present in the image [28].

174 Captioning models including sentiment have also been developed [29],
175 either using the viewer’s attitude and emotions towards the image [30], or
176 including emotional content inherent to the artwork image [31].

177 **Hypothesis 2.** *(X)AI can explain art.*

178 Content vs Form

179 **RQ 2.** *Could (X)AI distinguish among a) content vs b) form explanations?*
180 *Could (X)AI produce a) content and b) form explanations?*

181 The above RQs highlight the challenge of synthesizing figurative sense
182 (interpretation) vs literary sense (content) explanations of an artwork.

183 4.2. Visual Question Answering models

184 Another NLP model to produce explanations about an image is tackled by
185 the problem of visual question answering [32], specially useful for the blind³
186 or image captioning projects⁴⁵⁶. Generating questions that can be answered

³<https://vizwiz.org/>

⁴lens.google.com Google Lens is an *image recognition technology designed to bring up relevant information related to objects it identifies using visual analysis based on a neural network.*

⁵Google Goggles was an image recognition mobile app used for searches based on pictures taken by handheld devices.

⁶<https://lazarilloproject.github.io/>

187 by a DNN’s output caption can improve explainability and quality of image
188 captioning models [33].

189 **RQ 3.** *Could art explanations be generated on request, i.e., using visual ques-*
190 *tion answering (VQA)?*

191 Advisable text explanations have shown to be useful when teaching mod-
192 els to drive autonomously [23].

193 **RQ 4.** *Could advisable explanations increase the engagement and interest in*
194 *artwork?*

195 To enrich the experience of a user when observing art, an advisable interactive
196 introspection explanation could be: *Pay attention to where the light is set in*
197 *this painting. What is the center of focus the author is highlighting as such?*
198 *Why?*

199 **RQ 5.** *Should only objective or also subjective information be part of an*
200 *artistic explanation?*

201 **5. Explaining visual art through generative and multimodal models**

202 Generative adversarial networks (GANs) are considered a form of artifi-
203 cial curiosity [34]. Generative models have been successfully used for image
204 inpainting [35, 36] or image reconstruction. A potential application of in-
205 painting, i.e., filling the gaps in a given image, could be 2D or 3D restora-
206 tion [37]. For instance, DAFNE (Digital Anastylis of Frescoes challeNgE)
207 dataset⁷[38] allows to design methods to aid conservators and restorers per-
208 form fresco reconstruction when pieces are missing, spurious or suffer erosion.

209 Another application of generative models is performing style transfer.
210 Style transfer models successfully disentangle the data generating factors [39]
211 such as content and style when synthesizing paintings [40]. Similarly, music
212 instruments can be extracted from videos [41] using multimodal CNNs.

213 **RQ 6.** *Can XAI disentangle the underlying data generating (historical, stylis-*
214 *tic, spiritual) factors behind a generative model output?*

⁷It considered inclusion of autism users https://vision.unipv.it/DAFchallenge/DAFNE_dataset/.

215 *Edmond Bellamy* (Fig. 2) was the first piece of AI (GAN)-generated art
216 to come to auction at Christie’s, demonstrating that algorithms are able to
217 emulate creativity⁸.



Figure 2: *Edmond de Belamy*. Credit: ©Obvious, 2018 (instagram: @obvious_art)

218 Explainable AI techniques could assist explaining what artists and styles
219 influenced the model training the most, in order to apply feature attribution
220 methods to rate most prominent influence, helping perhaps understanding
221 what elements made it succeed.

222 **Challenge 3.** *Can XAI explain a given artwork’s success in terms of the*
223 *underlying influencing artistic styles?*

224 For instance, what makes disruptive and interesting Trina Mery artistic
225 body painting compositions⁹, Stefan Draschan’s photography, or Prof.
226 Pleguezuelos’s History podcasts¹⁰, or *Edmond Bellamy*?

227 Dreaming machines using multimodal data fusion and information re-
228 trieval are an example of neural-symbolic cognitive agent that can halluci-
229 nate visual input when it is completely or partially blanked (mimicking loss
230 of vision) [43].

231 **RQ 7.** *Could models learn to hallucinate a missing data modality given a*
232 *lack of the privileged information [44]?*

⁸Sold at \$432,500 [42] <https://www.christies.com/features/A-collaboration-between-two-artists-one-human-one-a-machine-9332-1.aspx>

⁹<https://www.trinamerry.com/>

¹⁰<https://www.instagram.com/elprofesorinquieta>

233 Biologically plausible models such as Deep Boltzman Machines’ sensory
234 hallucinations could be generalized to potentially validate the understanding
235 of a deep neural network (DNN) and verify whether its output is faithful to
236 the original content of the artwork. Perhaps in the same manner a machine
237 can learn to explain non regular input modalities, e.g. touch-based artwork,
238 through words or sounds.

239 6. Art and Robotics

240 Creativity is consider a driver for research in robotics in open ended
241 learning environments [45], because performance is not the only criteria to
242 be assessed on robots when they must learn to deal with new situations. In
243 these cases, creativity can quantitatively measure progress, define diversity-
244 driven behaviours, or deal with unforeseen damages [46].

245 In terms of accessibility, technological advancements have brought “telep-
246 resence” or mobile remote presence (MRP) systems as another opportunity
247 for bridging social and spatial barriers for people with mobility constrains.
248 MRPs are designed to be teleoperated and are used to improve communica-
249 tion between individuals. They were found to have the potential to assist
250 challenged individuals in instrumental activities of daily living as well as
251 to foster social interaction between people. A number of qualitative stud-
252 ies where people with mobility constrains used an MRP system identified
253 benefits for the participants such as being able to see and to be seen, reduc-
254 ing costs and hassles associated with traveling, and reducing social isolation
255 [47]. Experiences with an interactive museum tour-guide robot have been
256 described in previous literature [48]. Questions on how to provide the same
257 user experience, while users teleoperate a robot to make the experience as
258 close as possible as if they were there physically are still to be solved.

259 Learning joint representation models from vision and language is useful
260 for navigation of embodied robotics [49]. On the other hand, robotics can be
261 thought of as delivery means for art explanations. For instance, a robot can
262 sense when the group he is leading in Seville’s Alcazaba tour is getting bored,
263 and change, e.g., the length of its explanations based on the movement of
264 the visitors [50, 51]. In this context, it is worth investigating the utility of
265 such robots in terms of:

266 **RQ 8.** *Do remotely operated mobile robots increase virtual visits to a cultural*
267 *site, with respect to static browser-based virtual tours?*

268 **RQ 9.** *Do robot guides [50] improve the visitors rating when no human guide*
269 *is available? Is their user experience rated better than walkytalky guides?*

270 **RQ 10.** *Can AI provide guide explanations that reduce the boredom of the*
271 *visitors?*

272 There could be a value in having a AI-empowered robots visiting together
273 the cultural heritage site with the humans as well. One potential application
274 and advantage of using robots and AI in cultural heritage is with respect to
275 language: e.g., a robot like C-3PO that speaks all languages can make the
276 tour anytime in any language, including sign language. This has a value with
277 respect to a human tour guide and can be seen as a next step in innovation
278 in the field of guide systems, as the incarnation of audio guides.

279 Other types of robots have created art on their own. A Russian research
280 group developed a robot which incorporates a novel colour-mixing device that
281 can, in principle, create any shade or hue. The researchers used both off-the-
282 shelf components and 3D-printed parts to build their robot. It includes an
283 algorithm that transforms a photographic image into a set of vectors that
284 programs the robot’s brush to imitate human brushstrokes [52].

285 **7. A call for a multidisciplinary collaboration**

286 The presented challenges aim at stimulating a call for collaborators in a
287 joint effort to mutually learn from other domains, and form an interdisci-
288 plinary research consortium aggregating a diverse set of collective and sym-
289 biotic needs:

- 290 • Art historians: can gain visibility by making art accessible, building
291 a portfolio, e.g. as gallery guides, art podcast content generators, etc.
292 Humanities students could better learn by teaching their lessons outside
293 humanities and generating AI-consumable data.
- 294 • Artists and story tellers could earn an audience willing to learn about
295 a niche passion.
- 296 • Disabled and minorities: The blind could get access to art explana-
297 tions through audio or text resources, the deaf through the latter’s
298 transcriptions.

- 299 • Computer scientists would use the generated data to build robust ma-
300 chine learning models that (1) explain art, and (2), are explainable.

301 The ultimate aim is that all content would facilitate anyone to understand
302 any art with the right context.

303 7.1. *Impact of AI on Technological Domains*

304 We envision a set of domain areas where the symbiosis among art and
305 (X)AI could be further exploited. In order to guarantee Responsible AI
306 guidelines [2], provenance specification of XAI training and generated re-
307 sources should be a requirement.

308 Recommendation systems and personalization services may optimize match-
309 ing art-tellers and art-listeners, and suggest new artworks likely to be appre-
310 ciated by a given public.

311 Educators and developmental psychologists could find in XAI a support
312 tool to convey humanities, social sciences and history in terms of the align-
313 ment of explanation facts with the mental model and cultural background of
314 the learner.

315 After all these technologies are put into place, and human in the loop ma-
316 chine learning systems have gathered enough data, a new wave of creative AI
317 algorithms will emerge. All byside data generated through Human-Machine
318 collaborations involving the stakeholders above could train deep models to
319 capture the underlying generating factors that make humans interpret art
320 the way they do.

321 However, language could perhaps transfer art across domains, adapting
322 accordingly to the requested format and medium at each time.

323 Because language cannot express art, but is the closest mean for univer-
324 sal communication, we expect art expression through deep and word-based
325 representations to be one form of universal intermediate language allowing
326 to sing a painting, or to draw a song.

327 **Challenge 4.** *Tackling the lack of personal touch in technology*

328 During quarantine/crises, diverse cultural agendas are made available for
329 free (operas, museums, virtual tours, circus, libraries, etc.). At-home vs on-
330 site experiences can degrade the experience of culture, perhaps due to lacking
331 the social touch involved in the original experience. Human computation,
332 art-history and humanities expertise on the approach to such cultural offer

333 could not only serve the purpose of bringing art home, but also set the
334 basis for future ML models that could generate personalized explanations
335 about a given artwork. A hypothesis is that museum experiences require of a
336 personalized, social or physical involvement experience in order to maximize
337 the inherent pleasure of enjoying cultural heritage sites, with everything that
338 it conveys.

339 ML algorithms generate sketches [53], steerable playlists [54], music [55],
340 and incite creativity through editing tools [56]. Since machine discriminators
341 outperform humans in detecting generated text [57],

342 **RQ 11.** *Could AI recognize XAI generated explanations better than humans?*

343 **RQ 12.** *Can human testimony personalized art explanations stimulate en-
344 gagement and discovery of art by society?*

345 **RQ 13.** *Could artist voice note explanations uplift the lack of social touch
346 in traditional virtual/ audio guides?*

347 We hypothesize:

348 **Hypothesis 3.** *Digitized artwork personal reviews can enrich access to cul-
349 tural heritage based on artists audio/transcriptions, making it available to
350 any art consumer, including the deaf and the blind.*

351 **Challenge 5.** *Evaluating AI-generated art explanations*

352 **RQ 14.** *Is XAI being evaluated in the right tasks and with the right audi-
353 ence?*

354 **RQ 15.** *Can we evaluate AI generated text explanations' quality in a quan-
355 titative manner that is both user questionnaire-free and audience-specific?*

356 In order to assess story quality, word embeddings can be used to estimate
357 cognitive interest [58, 59, 60]. Fashion styles and its social media tags can be
358 used to predict subjective influence and novelty [61]. Could such influence
359 and novelty metrics correlate with actionable or useful explanations?

360 **RQ 16.** *Could AI explain what makes an artwork appreciated or liked? Could
361 we quantify the amount of surprise or originality it conveys?*

362 **Challenge 6.** *Defining explanation standards*

363 **RQ 17.** *Can we define standards for XAI explanations, including those sub-*
364 *ject to subjectivity?*

365 General XAI techniques usually evaluate XAI techniques on their ability
366 to generate visual or textual explanations [2]. However, the requirements
367 to evaluate an explanation positively by a blind or deaf person are likely to
368 require very different criteria.

369 **RQ 18.** *Can we always provide automatic satisfying answers when the ob-*
370 *server is unable to see/ visually impaired?*

371 **Challenge 7.** *Explaining concepts hard to visually grasp*

372 A single format may not fit to convey all art modalities. At times, some
373 modalities, e.g., sound, may be a better format to translate into. However,
374 visual-textual semantic embedding [62] and retrieval [63] is possible. In the
375 latter case, without labelled cultural heritage data thanks to transfer learn-
376 ing.

377 If *what is essential is invisible to the eyes*¹¹, symbols such as words or
378 knowledge graphs could act as intermediate proxy representation to verbalize
379 complex abstract concepts.

380 **RQ 19.** *Can multimodal deep representations be an intermediate language*
381 *to universally convey art? Could these generate text explanations for tech*
382 *and non technical audiences?*

383 *7.2. XAI as a medium, rather than a menace to human creativity*

384 Historians can argue that humanities education can currently abuse the
385 use of images to teach. This is demonstrated by the success of an influenc-
386 ing teacher’s podcast that prepares for History university entrance exams.
387 *While the use of words stimulates the imagination and keeps the mind work-*
388 *ing, providing an image to explain the same concept keeps the mind static and*
389 *inactive.* This is why teacher Pleguezuelos points to the images correspond-
390 ing to the podcast explanations in *Instagram*¹² only after students had to

¹¹*It is only with the heart that one can see rightly; what is essential is invisible to the eye.* -Antoine de Saint-Exupéry

¹²<https://www.instagram.com/historiaarte.selectividad>

391 imagine the described period, era, or artwork, exclusively with words. Could
392 a machine learn the same way? Could it reinforce the knowledge through
393 later confirmation with a different learning modality?

394 **Challenge 8.** *What is the key role that AI can play in bringing heritage*
395 *closer to the viewer?*

396 An artwork can inspire our mind if we are taught in what epoch it was
397 represented, and in what context it was created. If AI models could ever be
398 powerful enough to make us re-live that era, the inspiration they transmitted,
399 and even imagine the spirit of the age,

400 **Challenge 9.** *Could AI destroy the creativity of the viewer, that part that*
401 *inspires the audience?*

402 We argue that since AI can learn from a multimode of inputs, it can provide
403 interesting analogies or links to other artworks that a human could not do.
404 XAI techniques should explore ways in which AI could be not a threat to
405 the development of creativity that the artwork itself implies, but rather a
406 facilitation medium that suggests questions, allows exploring unknowns, and
407 further stimulates scientific curiosity and hunger for knowledge. In this con-
408 text, artificial models of computational curiosity [64] could align with those
409 of humans, to guide the latter to improve its mental model, trust, and cu-
410 riosity [65]. Curiosity increase could act as metric of positive understanding
411 of art and its whole context.

412 8. Discussion and Conclusions

413 Panels discussing the abilities of computational creativity involving scien-
414 tists and humanities can results in fiery discussion¹³. Research labs in Digital
415 Humanities investigate perceptual and cognitive tasks related to human cre-
416 ativity. This shows that, as in developmental robotics where robot models
417 are trained for open-ended learning [45], having to perform life-long learning
418 [66] continually, both humans and machines can learn from each other, better
419 inform hypotheses and experiments, and allow synergistic research.

¹³*Computational Creativity: Art through the Eyes of Computation* (panel arranged by N Díaz-Rodríguez & S Tomkins, Data Science Santa Cruz initiative, including art historians, computer scientists, musicians and humanists): <http://ihr.ucsc.edu/event/quantifying-creativity-art-through-the-eyes-of-computation/> Video: <http://travellingscholar.com/qcreativity/>

Challenge	Dimensions	Concerns
Augmenting accessibility to minorities or users with physical & cognitive disabilities	Interface and content personalisation, Generative and Multimodal AI	Inclusion, AI Ethics
Making AI explainable	Explainable & Interpretable AI	FAT ML, Responsible AI
Explaining art with AI	Human computation, Human in the loop, [Multimodal, Generative] AI	Trust, Responsible AI
Creativity as research engine, AI for content synthesis	Engagement, Curiosity, Computational creativity	Trust, Subjectivity Metrics

Table 1: (X)AI for Cultural Heritage Challenges.

420 We summarized hypothesis and RQs into challenges, discipline dimensions
421 affected and concerns to address such challenges in Table 8. We presented
422 some disruptive art settings as motivating examples where AI and XAI could
423 have novel research playgrounds to validate models. Since concerns involve
424 fairness, accountability, transparency (FAT) in ML, we gave a first step listing
425 questions that need to be addressed to obtain insights on how AI can best
426 help accessibility to audiovisuals.

427 Despite having presented here challenges and opportunities focused on
428 how AI (and robotics) can help access cultural heritage and the digital hu-
429 manities, this is just an application domain where the limits of current AI
430 models can be stress-tested. The existing challenges to attain explainable
431 AI in any real-life problem are equally relevant and should be explored, es-
432 pecially in practical applications of AI safety and AI for social good (from
433 elderly telepresence robots [67] to epidemic and hospital crisis management
434 [68]).

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