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► **To cite this version:**

Natalia Díaz-Rodríguez, Galena Pisoni. Accessible Cultural Heritage through Explainable Artificial Intelligence. PATCH 2020 - 11th Workshop on Personalized Access to Cultural Heritage, Jul 2020, Genova / Virtual, Italy. hal-02864501

**HAL Id: hal-02864501**

**<https://hal.archives-ouvertes.fr/hal-02864501>**

Submitted on 11 Jun 2020

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# Accessible Cultural Heritage through Explainable Artificial Intelligence

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## 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

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## 1. Introduction

2 The European Commission Ethics Guidelines for Trustworthy Artificial  
3 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](http://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 MonuMAI<sup>1</sup>, 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

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<sup>1</sup>MonuMAI = 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 University<sup>2</sup>: The challenge I pose is to*

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<sup>2</sup><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 blind<sup>3</sup>  
186 or image captioning projects<sup>456</sup>. Generating questions that can be answered

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<sup>3</sup><https://vizwiz.org/>

<sup>4</sup>[lens.google.com](https://lens.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.*

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

<sup>6</sup><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 dataset<sup>7</sup>[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?*

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<sup>7</sup>It considered inclusion of autism users [https://vision.unipv.it/DAFchallenge/DAFNE\\_dataset/](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 creativity<sup>8</sup>.



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 compositions<sup>9</sup>, Stefan Draschan’s photography, or Prof.  
226 Pleguezuelos’s History podcasts<sup>10</sup>, 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]?*

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

<sup>9</sup><https://www.trinamerry.com/>

<sup>10</sup><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 interdis-  
288 ciplinary 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*<sup>11</sup>, 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*<sup>12</sup> only after students had to

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

<sup>12</sup><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 discussion<sup>13</sup>. 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.

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<sup>13</sup>*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/>



<b>Challenge</b>	<b>Dimensions</b>	<b>Concerns</b>
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]).

## 435 9. Acknowledgements

436 We thank Juan Jesús Pleguezuelos for the motivating testimonies, Stefan  
437 Draschan and OBVIOUS collective for borrowing illustrating images, and  
438 Pranav Agarwal, Siham Tabik, Francisco Herrera, Alberto Castillo Lamas,  
439 Mario Romero, Serena Ivaldi and Paris Cité Universitaire friends for inspiring  
440 brainstormings.

## 441 References

- 442 [1] High Level Expert Group on Artificial Intelligence, Ethics Guidelines  
443 for Trustworthy AI, Technical Report, European Commission, 2019.
- 444 [2] A. B. Arrieta, N. Díaz-Rodríguez, J. D. Ser, A. Bennetot, S. Tabik,  
445 A. Barbado, S. Garcia, S. Gil-Lopez, D. Molina, R. Benjamins,  
446 R. Chatila, F. Herrera, Explainable artificial intelligence (xai):  
447 Concepts, taxonomies, opportunities and challenges toward re-  
448 sponsible ai, *Information Fusion* (2019). URL: [http://www.  
449 sciencedirect.com/science/article/pii/S1566253519308103](http://www.sciencedirect.com/science/article/pii/S1566253519308103).  
450 doi:<https://doi.org/10.1016/j.inffus.2019.12.012>.
- 451 [3] R. Guidotti, A. Monreale, S. Ruggieri, F. Turini, F. Giannotti, D. Pe-  
452 dreschi, A survey of methods for explaining black box models, *ACM  
453 computing surveys (CSUR)* 51 (2018) 1–42.

- 454 [4] D. Gunning, Explainable artificial intelligence (xAI), Technical Report,  
455 Defense Advanced Research Projects Agency (DARPA), 2017.
- 456 [5] S. T. Mueller, R. R. Hoffman, W. J. Clancey, A. Emrey, G. Klein,  
457 Explanation in human-ai systems: A literature meta-review, synopsis  
458 of key ideas and publications, and bibliography for explainable  
459 AI, CoRR abs/1902.01876 (2019). URL: <http://arxiv.org/abs/1902.01876>. arXiv:1902.01876.
- 461 [6] F. Herrera, A. Martínez-Sevilla, S. Tabik, R. Montes, A. Castillo, T. C.  
462 Sánchez, J. P. Cruz, Competición caepia-app: Monumai, una app para  
463 incrementar el valor social del patrimonio-arquitectónico andaluz (2018).
- 464 [7] F. Fernández Morales, J. Valderrama Ramos, S. Luque López,  
465 A. Martínez Sevilla, J. Policarpo Cruz Cabrera, P. Alvito, Paseos  
466 Matemáticos por Granada: Un estudio entre arte, ciencia e historia,  
467 Editorial Universidad de Granada, 2017. URL: <https://dialnet.unirioja.es/servlet/libro?codigo=701550>. doi:10.1007/978-3-030-22327-4\_13.
- 470 [8] Y. Zhao, S. Wu, L. Reynolds, S. Azenkot, The effect of computer-  
471 generated descriptions on photo-sharing experiences of people with vi-  
472 sual impairments, CoRR abs/1805.01515 (2018). URL: <http://arxiv.org/abs/1805.01515>. arXiv:1805.01515.
- 474 [9] C. Rocchi, O. Stock, M. Zancanaro, M. Kruppa, A. Krüger, The mu-  
475 seum visit: generating seamless personalized presentations on multiple  
476 devices, in: Proceedings of the 9th international conference on Intelli-  
477 gent user interfaces, 2004, pp. 316–318.
- 478 [10] O. Stock, M. Zancanaro, PEACH-Intelligent interfaces for museum vis-  
479 its, Springer Science & Business Media, 2007.
- 480 [11] T. Kuflik, O. Stock, M. Zancanaro, A. Gorfinkel, S. Jbara, S. Kats,  
481 J. Sheidin, N. Kashtan, A visitor’s guide in an active museum: Pre-  
482 sentations, communications, and reflection, Journal on Computing and  
483 Cultural Heritage (JOCCH) 3 (2011) 11.
- 484 [12] P. M. Aoki, R. E. Grinter, A. Hurst, M. H. Szymanski, J. D. Thornton,  
485 A. Woodruff, Sotto voce: exploring the interplay of conversation and

- 486 mobile audio spaces, in: Proceedings of the SIGCHI conference on  
487 Human factors in computing systems, ACM, 2002, pp. 431–438.
- 488 [13] G. Kostoska, D. Fezzi, B. Valeri, M. Baez, F. Casati, S. Caliari, S. Tarter,  
489 Collecting memories of the museum experience, in: CHI'13 Extended  
490 Abstracts on Human Factors in Computing Systems, 2013, pp. 247–252.
- 491 [14] C. Callaway, O. Stock, E. Dekoven, Experiments with mobile drama  
492 in an instrumented museum for inducing conversation in small groups,  
493 ACM Trans. Interact. Intell. Syst. 4 (2014). URL: [https://doi.org/](https://doi.org/10.1145/2584250)  
494 [10.1145/2584250](https://doi.org/10.1145/2584250). doi:10.1145/2584250.
- 495 [15] G. Pisoni, F. Daniel, F. Casati, C. Callaway, O. Stock, Interactive  
496 remote museum visits for older adults: an evaluation of feelings of pres-  
497 ence, social closeness, engagement, and enjoyment in a social visit, in:  
498 2019 IEEE International Symposium on Multimedia (ISM), IEEE, 2019,  
499 pp. 99–993.
- 500 [16] G. Kostoska, M. Baez, F. Daniel, F. Casati, Virtual, remote partici-  
501 pation in museum visits by older adults: a feasibility study, in: 8th  
502 International Workshop on Personalized Access to Cultural Heritage  
503 (PATCH 2015), ACM IUI 2015, 2015, pp. 1–4.
- 504 [17] G. Kostoska, A. P. Vermeeren, J. Kort, C. Gullström, Video-mediated  
505 participation in virtual museum tours for older adults, in: 10th In-  
506 ternational Conference on Design & Emotion, 27-30 September 2016,  
507 Amsterdam, The Design & Emotion Society,, 2016.
- 508 [18] M. Gea, X. Alaman, P. Rodriguez, V. Rodriguez, Towards smart  
509 & inclusive society: building 3d immersive museum by children with  
510 cognitive disabilities, in: Proceedings of the EDULEARN16: 8th In-  
511 ternational Conference on Education and New Learning Technologies,  
512 Barcelona, Spain, 2016, pp. 4–6.
- 513 [19] T. R. Besold, A. d'Avila Garcez, S. Bader, H. Bowman, P. Domin-  
514 gos, P. Hitzler, K.-U. Kuehnberger, L. C. Lamb, D. Lowd, P. Machado  
515 Vieira Lima, L. de Penning, G. Pinkas, H. Poon, G. Zaverucha, Neural-  
516 Symbolic Learning and Reasoning: A Survey and Interpretation, 2017.  
517 [arXiv:1711.03902](https://arxiv.org/abs/1711.03902).

- 518 [20] G. Marra, F. Giannini, M. Diligenti, M. Gori, Integrating learning and  
519 reasoning with deep logic models, 2019. [arXiv:1901.04195](https://arxiv.org/abs/1901.04195).
- 520 [21] A. Bennetot, J.-L. Laurent, R. Chatila, N. Díaz-Rodríguez, Towards  
521 explainable neural-symbolic visual reasoning, in: NeSy Workshop IJCAI  
522 2019, Macau, China, 2019.
- 523 [22] M. Diligenti, S. Roychowdhury, M. Gori, Integrating prior knowledge  
524 into deep learning, in: 2017 16th IEEE International Conference on  
525 Machine Learning and Applications (ICMLA), IEEE, 2017, pp. 920–  
526 923.
- 527 [23] J. Kim, A. Rohrbach, T. Darrell, J. Canny, Z. Akata, Textual ex-  
528 planations for self-driving vehicles, in: Proceedings of the European  
529 conference on computer vision (ECCV), 2018, pp. 563–578.
- 530 [24] P. Agarwal, A. Betancourt, V. Panagiotou, N. Díaz-Rodríguez,  
531 Egoshots, an ego-vision life-logging dataset and semantic fidelity metric  
532 to evaluate diversity in image captioning models, in: Machine Learn-  
533 ing in Real Life (ML-IRL) Workshop at the International Conference  
534 on Learning Representations (ICLR), 2020. URL: [https://arxiv.org/  
535 abs/2003.11743](https://arxiv.org/abs/2003.11743).
- 536 [25] J. Lu, J. Yang, D. Batra, D. Parikh, Neural Baby Talk, 2018 IEEE/CVF  
537 Conference on Computer Vision and Pattern Recognition (2018) 7219–  
538 7228.
- 539 [26] R. R. Selvaraju, S. Lee, Y. Shen, H. Jin, D. Batra, D. Parikh, Tak-  
540 ing a HINT: Leveraging Explanations to Make Vision and Language  
541 Models More Grounded, 2019 IEEE/CVF International Conference on  
542 Computer Vision (ICCV) (2019) 2591–2600.
- 543 [27] L. A. Hendricks, K. Burns, K. Saenko, T. Darrell, A. Rohrbach, Women  
544 also snowboard: Overcoming bias in captioning models, in: European  
545 Conference on Computer Vision, Springer, 2018, pp. 793–811.
- 546 [28] A. Rohrbach, L. A. Hendricks, K. Burns, T. Darrell, K. Saenko, Object  
547 Hallucination in Image Captioning, CoRR [abs/1809.02156](https://arxiv.org/abs/1809.02156) (2018). URL:  
548 <http://arxiv.org/abs/1809.02156>. [arXiv:1809.02156](https://arxiv.org/abs/1809.02156).

- 549 [29] I. Hrga, M. Ivašić-Kos, Deep image captioning: An overview, in:  
550 2019 42nd International Convention on Information and Communication  
551 Technology, Electronics and Microelectronics (MIPRO), IEEE, 2019, pp.  
552 995–1000.
- 553 [30] A. P. Mathews, L. Xie, X. He, Senticap: Generating image descriptions  
554 with sentiments, in: Thirtieth AAAI conference on artificial intelligence,  
555 2016.
- 556 [31] O. M. Nezami, M. Dras, P. Anderson, L. Hamey, Face-cap: Image cap-  
557 tioning using facial expression analysis, in: Joint European Conference  
558 on Machine Learning and Knowledge Discovery in Databases, Springer,  
559 2018, pp. 226–240.
- 560 [32] D. Gurari, Q. Li, A. J. Stangl, A. Guo, C. Lin, K. Grauman, J. Luo,  
561 J. P. Bigham, VizWiz Grand Challenge: Answering Visual Questions  
562 from Blind People, 2018 IEEE/CVF Conference on Computer Vision  
563 and Pattern Recognition (2018) 3608–3617. URL: [https://arxiv.org/  
564 abs/1802.08218](https://arxiv.org/abs/1802.08218).
- 565 [33] J. Wu, Z. Hu, R. J. Mooney, Generating question relevant captions to  
566 aid visual question answering, arXiv preprint arXiv:1906.00513 (2019).
- 567 [34] J. Schmidhuber, Generative adversarial networks are special cases of  
568 artificial curiosity (1990) and also closely related to predictability mini-  
569 mization (1991), Neural Networks (2020).
- 570 [35] D. Pathak, P. Krahenbuhl, J. Donahue, T. Darrell, A. A. Efros, Context  
571 encoders: Feature learning by inpainting, in: Proceedings of the IEEE  
572 conference on computer vision and pattern recognition, 2016, pp. 2536–  
573 2544.
- 574 [36] O. Elharrouss, N. Almaadeed, S. Al-Maadeed, Y. Akbari, Image in-  
575 painting: A review, Neural Processing Letters (????) 1–22.
- 576 [37] A. F. Abate, S. Barra, G. Galeotafore, C. Díaz, E. Aura, M. Sánchez,  
577 X. Mas, E. Vendrell, An augmented reality mobile app for museums:  
578 Virtual restoration of a plate of glass, in: Euro-Mediterranean Confer-  
579 ence, Springer, 2018, pp. 539–547.

- 580 [38] V. Cantoni, L. Lombardi, G. Mastrotisi, A. Setti, The DAFNE Project:  
581 Human and Machine Involvement, volume 99, Electronic Imaging & the  
582 Visual Arts: EVA 2019, Florence. Firenze University Press, 2019.
- 583 [39] A. Achille, S. Soatto, Emergence of invariance and disentanglement in  
584 deep representations, *The Journal of Machine Learning Research* 19  
585 (2018) 1947–1980.
- 586 [40] L. A. Gatys, A. S. Ecker, M. Bethge, A neural algorithm of artistic  
587 style, arXiv preprint arXiv:1508.06576 (2015).
- 588 [41] O. Slizovskaia, E. Gómez, G. Haro, Musical instrument recognition in  
589 user-generated videos using a multimodal convolutional neural network  
590 architecture, in: *Proceedings of the 2017 ACM on International Con-*  
591 *ference on Multimedia Retrieval*, 2017, pp. 226–232.
- 592 [42] G. Vernier, H. Caselles-Dupré, P. Fautrel, Electric dreams of ukiyo: A  
593 series of japanese artworks created by an artificial intelligence, *Patterns*  
594 1 (2020) 100026.
- 595 [43] L. de Penning, A. D. Garcez, J.-J. C. Meyer, Dreaming Ma-  
596 chines: On multimodal fusion and information retrieval using neural-  
597 symbolic cognitive agents, in: A. V. Jones, N. Ng (Eds.),  
598 2013 Imperial College Computing Student Workshop, volume 35  
599 of *OpenAccess Series in Informatics (OASICs)*, Schloss Dagstuhl-  
600 Leibniz-Zentrum fuer Informatik, Dagstuhl, Germany, 2013, pp. 89–  
601 94. URL: <http://drops.dagstuhl.de/opus/volltexte/2013/4276>.  
602 doi:10.4230/OASICs.ICCSW.2013.89.
- 603 [44] D. Lopez-Paz, L. Bottou, B. Schölkopf, V. Vapnik, Unifying distillation  
604 and privileged information, arXiv preprint arXiv:1511.03643 (2015).
- 605 [45] S. Doncieux, D. Filliat, N. Díaz-Rodríguez, T. Hospedales, R. Duro,  
606 A. Coninx, D. M. Roijers, B. Girard, N. Perrin, O. Sigaud, Open-  
607 ended learning: A conceptual framework based on representational re-  
608 description, *Frontiers in Neurobotics* 12 (2018) 59. URL: [https://](https://www.frontiersin.org/article/10.3389/fnbot.2018.00059)  
609 [www.frontiersin.org/article/10.3389/fnbot.2018.00059](https://www.frontiersin.org/article/10.3389/fnbot.2018.00059). doi:10.  
610 3389/fnbot.2018.00059.
- 611 [46] S. Doncieux, Creativity: A driver for research on robotics in open envi-  
612 ronments, *Intellectica* 65 (2016) 205–219.

- 613 [47] J. M. Beer, L. Takayama, Mobile remote presence systems for older  
614 adults: acceptance, benefits, and concerns, in: Proceedings of the 6th  
615 international conference on Human-robot interaction, 2011, pp. 19–26.
- 616 [48] M. K. Ng, S. Primatesta, L. Giuliano, M. L. Lupetti, L. O. Russo, G. A.  
617 Farulla, M. Indaco, S. Rosa, C. Germak, B. Bona, A cloud robotics  
618 system for telepresence enabling mobility impaired people to enjoy the  
619 whole museum experience, in: 2015 10th International Conference on  
620 Design & Technology of Integrated Systems in Nanoscale Era (DTIS),  
621 IEEE, 2015, pp. 1–6.
- 622 [49] F. Landi, L. Baraldi, M. Corsini, R. Cucchiara, Embodied vision-  
623 and-language navigation with dynamic convolutional filters, CoRR  
624 abs/1907.02985 (2019). URL: <http://arxiv.org/abs/1907.02985>.  
625 arXiv:1907.02985.
- 626 [50] V. Evers, N. Menezes, L. Merino, D. Gavrila, F. Nabais, M. Pantic,  
627 P. Alvito, D. Karreman, The development and real-world deployment  
628 of frog, the fun robotic outdoor guide, in: Proceedings of the 2014  
629 ACM/IEEE international conference on Human-robot interaction, 2014,  
630 pp. 100–100.
- 631 [51] V. Evers, N. Menezes, L. Merino, D. Gavrila, F. Nabais, M. Pantic,  
632 P. Alvito, The development and real-world application of frog, the fun  
633 robotic outdoor guide, in: Proceedings of the Companion Publication of  
634 the 17th ACM Conference on Computer Supported Cooperative Work &  
635 Social Computing, CSCW Companion '14, Association for Computing  
636 Machinery, New York, NY, USA, 2014, p. 281–284. URL: <https://doi.org/10.1145/2556420.2557638>. doi:10.1145/2556420.2557638.
- 638 [52] A. I. Karimov, E. E. Kopets, V. G. Rybin, S. V. Leonov, A. I.  
639 Voroshilova, D. N. Butusov, Advanced tone rendition technique for  
640 a painting robot, Robotics and Autonomous Systems 115 (2019) 17–27.
- 641 [53] J. F. J. Mellor, E. Park, Y. Ganin, I. Babuschkin, T. Kulkarni, D. Rosen-  
642 baum, A. Ballard, T. Weber, O. Vinyals, S. M. A. Eslami, Unsupervised  
643 doodling and painting with improved spiral, 2019. arXiv:1910.01007.
- 644 [54] F. Maillet, D. Eck, G. Desjardins, P. Lamere, et al., Steerable playlist  
645 generation by learning song similarity from radio station playlists., in:  
646 ISMIR, 2009, pp. 345–350.



- 647 [55] C.-Z. A. Huang, A. Vaswani, J. Uszkoreit, N. Shazeer, C. Hawthorne,  
648 A. M. Dai, M. D. Hoffman, D. Eck, An improved relative self-attention  
649 mechanism for transformer with application to music generation, ArXiv  
650 abs/1809.04281 (2018).
- 651 [56] A. Roberts, J. Engel, Y. Mann, J. Gillick, C. Kayacik, S. Nørly,  
652 M. Dinculescu, C. Radebaugh, C. Hawthorne, D. Eck, Ma-  
653 genta studio: Augmenting creativity with deep learning in ableton  
654 live, in: Proceedings of the International Workshop on Musical  
655 Metacreation (MUME), 2019. URL: [http://musicalmetacreation.  
656 org/buddydrive/file/mume\\_2019\\_paper\\_2/](http://musicalmetacreation.org/buddydrive/file/mume_2019_paper_2/).
- 657 [57] D. Ippolito, D. Duckworth, C. Callison-Burch, D. Eck, Human and  
658 automatic detection of generated text, arXiv preprint arXiv:1911.00650  
659 (2019).
- 660 [58] M. Behrooz, J. Robertson, A. Jhala, Story quality as a matter of percep-  
661 tion: Using word embeddings to estimate cognitive interest, in: Proceed-  
662 ings of the AAAI Conference on Artificial Intelligence and Interactive  
663 Digital Entertainment, volume 15, 2019, pp. 3–9.
- 664 [59] M. Behrooz, A. Jhala, Modeling social interestingness in conversational  
665 stories, in: Proceedings of the Australasian Computer Science Week  
666 Multiconference, 2017, pp. 1–6.
- 667 [60] M. Behrooz, Curating Interest in Open Story Generation, Ph.D. thesis,  
668 UC Santa Cruz, 2019.
- 669 [61] K. Bollacker, N. Díaz-Rodríguez, X. Li, Extending Knowledge  
670 Graphs with Subjective Influence Networks for Personalized Fash-  
671 ion, Springer International Publishing, Cham, 2019, pp. 203–  
672 233. URL: [https://doi.org/10.1007/978-3-030-00317-3\\_9](https://doi.org/10.1007/978-3-030-00317-3_9). doi:10.  
673 1007/978-3-030-00317-3\_9.
- 674 [62] T. Ramalho, T. Kociský, F. Besse, S. M. A. Eslami, G. Melis, F. Viola,  
675 P. Blunsom, K. M. Hermann, Encoding spatial relations from natu-  
676 ral language, CoRR abs/1807.01670 (2018). URL: [http://arxiv.org/  
677 abs/1807.01670](http://arxiv.org/abs/1807.01670). arXiv:1807.01670.

- 678 [63] M. Cornia, M. Stefanini, L. Baraldi, M. Corsini, R. Cuc-  
679 chiara, Explaining digital humanities by aligning images and tex-  
680 tual descriptions, *Pattern Recognition Letters* 129 (2020) 166 –  
681 172. URL: [http://www.sciencedirect.com/science/article/pii/](http://www.sciencedirect.com/science/article/pii/S0167865519303381)  
682 [S0167865519303381](http://www.sciencedirect.com/science/article/pii/S0167865519303381). doi:[https://doi.org/10.1016/j.patrec.2019.](https://doi.org/10.1016/j.patrec.2019.11.018)  
683 [11.018](https://doi.org/10.1016/j.patrec.2019.11.018).
- 684 [64] P.-Y. Oudeyer, Computational theories of curiosity-driven learning,  
685 arXiv preprint arXiv:1802.10546 (2018).
- 686 [65] R. R. Hoffman, S. T. Mueller, G. Klein, J. Litman, Metrics for explain-  
687 able ai: Challenges and prospects, arXiv preprint arXiv:1812.04608  
688 (2018).
- 689 [66] T. Lesort, V. Lomonaco, A. Stoian, D. Maltoni, D. Filliat, N. Díaz-  
690 Rodríguez, Continual learning for robotics: Definition, framework,  
691 learning strategies, opportunities and challenges, *Information Fusion*  
692 58 (2020) 52 – 68. URL: [http://www.sciencedirect.com/science/](http://www.sciencedirect.com/science/article/pii/S1566253519307377)  
693 [article/pii/S1566253519307377](http://www.sciencedirect.com/science/article/pii/S1566253519307377). doi:[https://doi.org/10.1016/j.](https://doi.org/10.1016/j.inffus.2019.12.004)  
694 [inffus.2019.12.004](https://doi.org/10.1016/j.inffus.2019.12.004).
- 695 [67] N. Pérez-Higueras, R. Ramón-Vigo, I. P. Hurtado, J. Capitán, F. Ca-  
696 ballero, A social navigation system in telepresence robots for elderly,  
697 2016.
- 698 [68] G.-Z. Yang, B. J. Nelson, R. R. Murphy, H. Choset, H. Christensen,  
699 S. H. Collins, P. Dario, K. Goldberg, K. Ikuta, N. Jacobstein, D. Kragic,  
700 R. H. Taylor, M. McNutt, Combating covid-19—the role of robotics  
701 in managing public health and infectious diseases, *Science Robotics*  
702 5 (2020). URL: [https://robotics.sciencemag.org/content/5/40/](https://robotics.sciencemag.org/content/5/40/eabb5589)  
703 [eabb5589](https://robotics.sciencemag.org/content/5/40/eabb5589). doi:[10.1126/scirobotics.abb5589](https://doi.org/10.1126/scirobotics.abb5589).