

Boundary Between Art and Pornography: Differences in Image Identification Between Artificial Intelligence and Human Intelligence

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ABSTRACT

This study examined whether Microsoft Azure and human participants differed significantly in their judgment of controversial image content (e.g., adult and violent content). Significant differences were observed between the Azure- and participant-awarded scores on all four indexes—Adult, Racy, Gore, and Event Description. The artificial intelligence made stricter judgments than did the participants. The introduction of artificial intelligence may facilitate the efficient judgment of images by website administrators. However, the standards upheld by artificial intelligence appear to be unique and stricter than those upheld by people. In the short term, the boundary between art and pornography may remain difficult to identify. Assessing the difference in judgments between artificial and human intelligence should be a topic of continual concern.

Keywords: Artificial intelligence, image works, infringement analysis, image identification.

INTRODUCTION

Since a breakthrough was made in computing technologies, artificial intelligence has developed rapidly and now has diverse practical applications. Related studies have demonstrated that artificial intelligence has begun to be applied in various industries and domains such as agriculture [1], physics [2], freight safety [3], and human face recognition [4,5]. Major breakthroughs have also led to wide application to image identification [6,7], natural language [8], and speech recognition [9,10]. For image identification, from machine learning [11] to deep learning [12,13], convolutional neural network (CNN) technology has played a crucial role [14,15]. Most systems rely on matrix decomposition for information filtering [16].

Since the computing mechanism breakthrough, researchers have introduced artificial intelligence to fields and applications related to intellectual property rights [17], such as trademark inspection [18], trademark identification [19], and trademark search [20]. Regarding copyright, artificial intelligence has been applied effectively in the fields of web page infringement [21], file protection [22], and multimedia copyright [23]. Image identification and protection and related applications, such as in image labeling [24], image descriptions [25], and

image fingerprints [26], have also begun to be emphasized. However, studies on image protection issues related to intellectual property rights, such as image processing [27] and image infringement [28], remain noncomprehensive and insufficient. Websites are increasingly using artificial intelligence for image identification to prevent pornographic images from being viewed by children. Whether the standard of judgment exacted by artificial intelligence is consistent with that of a real person is a long-standing point of intention. This study explored the difference in image identification between artificial intelligence and human intelligence. The results can serve as a reference for webpage administrators.

METHODS

Whether online images feature adult content has been gaining attention recently. Multiple social media companies such as Facebook have employed artificial intelligence calculations to assist website administrators in identifying and filtering out images that may feature adult content. Microsoft Azure (hereafter Azure) provides a basic image identification function. A user applies Azure to uploaded images, and the program judges the objects in the images and provides the probability that the objects have been correctly judged through artificial intelligence calculation.

This study examined whether Azure and human participants differed significantly in their judgment of controversial content, such as adult and violent content. Artworks identified as pornographic or controversial and were thus removed by Facebook were collected. By taking well-known works as examples, the actual effect of the image judgments made by the artificial intelligence applied by web administrators was determined.

Participants

To assess the cognitive experience of a real person viewing artworks, the “Difference in Image Identification between Artificial Intelligence and Real Person” questionnaire was administered. A total of 175 people completed the questionnaire in April and May 2021.

Samples

The images identified by Facebook as featuring adult content were coded A1–A9. They were mainly images of photographs and paintings and were as follows: A1—Etude de nu [29], A2—Odalisque [30], A3—Ice Cream [31], A4—The Origin of the World [32], A5—The Kiss [33], A6—La Grande Odalisque [34], A7—Adam and Eve [35], A8—Amor Victorious [36], and A9—Liberty Leading the People [37].

Materials

Nine famous artworks, most of which have appeared in international mainstream media, were used.

Descriptions of and news on the research sample are presented in Table 1.

Table 1: Descriptions of and news on the artworks examined.

Code	Description	News
A1	This photograph was taken by Laure Albin Guillot, who was the first in France to capture decorative microscopic images,	Facebook caused outrage among French art lovers in blocking the webpage of a Parisian art gallery for 24 hours after a photograph study of a nude posted on the

	which she called micrographie, combining science with visual art [38].	webpage was deemed by the social network to be in violation of its community standards [39].
A2	In this painting, a voluptuous woman lies prone on a divan, showing her backside and turning her head flirtatiously to the viewer but averting her eyes slightly as if to maintain a coy demeanor. Surrounded by lush fabrics of deep blue, the creamy tones of her skin and dressing gown are thrown into sharp contrast [40].	—
A3	This photograph presents an active, confident young woman with bright orange hair against a bright green, yellow, and blue background. She pursues satisfaction on her own terms, unabashedly enjoying her dessert. Equally, this photograph prompts debate about depictions of women [41].	Facebook removed a Philadelphia Museum of Art post of Evelyne Axell's painting <i>Ice Cream</i> , stating that it featured "excessive amounts of skin or suggestive content [42]."
A4	In 1866, Gustave Courbet—a French painter who led the realism movement in the 19th century— painted <i>L'Origine du monde</i> , a famous painting also known as <i>The Origin of the World</i> . Depicting a naked woman lying on a bed with her legs spread, it was relatively controversial for its time [43].	In 2011, a French teacher posted on his personal Facebook account an image of <i>The Origin of the World</i> with a link to a related article. Consequently, his account was deactivated without warning or justification [44].
A5	This oil-on-canvas painting by Gustav Klimt, to which was added gold leaf, silver, and platinum, depicts a couple embracing each other, their bodies entwined in elaborate beautiful robes decorated in an Art Nouveau-influenced style and the organic forms of the earlier Arts and Crafts movement [45].	—
A6	This painting depicts a nude woman lying on a bed that is covered with fabrics. The scene is occupied by only her body, a feather fan, the turban she wears on her head, and a few other details indicating her provenance from an exotic country [46].	—
A7	This panel depicts the fall from grace of the first humans, Adam and Eve [47].	Flemish artists such as Peter Paul Rubens (1577– 1640), Anthony van Dyck (1599–1641), and Jan Brueghel the Elder (1568–1625) are considered influential masters. Because most of their artworks address topics such as religion and mythology, nude figures are commonly featured in their paintings. Facebook bans all advertisements containing nudity. Belgium's government and museums have thus faced some difficulties in promoting paintings, which are an integral part of the country's cultural heritage [48].
A8	In this painting, Cupid, the god of love, stands upon the trampled symbols of music, science, war, and government, illustrating Virgil's line "love conquers all; let us all yield to love!" [49].	Cupid is shown nude, with his legs splayed; for that reason, Facebook informed Filho that the image violated Facebook's community standards [50].

A9	The 1830 artwork depicts a rebellion during the July Revolution led by Marianne, France's most famous national heroine. Personifying the concept of Liberty, a woman brandishes the flag of the French Revolution in the center of the painting, reflecting the energy and excitement of the Revolution [51].	This 19th-century masterpiece was featured in an online campaign for a play showing in Paris when it was blocked on Facebook, the play's director Jocelyn Fiorina said. "A quarter of an hour after the advert was launched, it was blocked, with the company telling us we cannot show nudity," Fiorina said. She then posted a new advertisement for the play with the same painting but with the woman's breasts covered by a banner saying "censored by Facebook." This image was not banned [52].
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RESULTS

Computer vision API of Azure

After the Computer Vision Application Programming Interface (API; v. 3.1) of Azure identifies an image, it presents the type of object predicted to be depicted in the image. Table 2 shows the object prediction scores (ranging from 0 to 1) provided by Azure for the sample (images A1–A9).

Table 2: Object prediction scores for the sample images, as evaluated by Azure.

Code	Event Description	Confidence in the Event	Objects	Confidence in the Objects
A1	A man lying on a bed	0.8003	Indoor scene Bed Nude Lying down Hospital room	0.9435 0.9389 0.8646 0.8013 0.6563
A2	A person sleeping in a dog bed	0.6550	Painting Dog Human face Clothing Person Art Woman Sofa Clothes	0.9516 0.9136 0.9031 0.8355 0.8173 0.7389 0.6479 0.3897 0.2123
A3	A person holding a sign	0.3714	Drawing Painting Art Child's art Sketch Illustration Cartoon Person Text Acrylic	0.9911 0.9823 0.9762 0.9629 0.9585 0.9531 0.9513 0.8883 0.8385 0.6911
A4	A dog sleeping on a bed	0.6017	Indoor Nude Belly Lying down Sleeping Baby Arm	0.9865 0.9318 0.8755 0.8746 0.7239 0.6353 0.5588

A5	A close-up of a painted wall	0.6698	Painting Drawing Art Colorful	0.9442 0.7595 0.6354 0.3967
A6	A woman lying on a bed	0.8762	Person Indoor Bed Human face Lying down Painting Text	0.9874 0.9247 0.8952 0.8588 0.6389 0.7102 0.5871
A7	A group of people posing for the camera	0.9089	Person Art Outdoor-scene Nude Posing Standing Swimsuit Swimming	0.9750 0.9726 0.9464 0.9442 0.8643 0.8506 0.7661 0.6571
A8	A woman sitting in a chair	0.6737	Painting Indoor scene Art Person Drawing Text Human face Cartoon Poster Museum Nude Sketch	0.9847 0.9488 0.9296 0.9285 0.8952 0.8495 0.8412 0.8381 0.6856 0.5689 0.5361 0.5082
A9	A group of people wearing military uniforms	0.7928	Text Book Painting Person Art Drawing Cartoon Group Man Clothing Poster Posing Dressed Several	0.9989 0.9908 0.9694 0.9641 0.9002 0.8254 0.8126 0.8093 0.7379 0.7278 0.6730 0.3683 0.2620 0.1076

According to the official website of the Computer Vision API of Microsoft Azure, Computer Vision is able to detect adult content in images. The relevant index can serve as a reference by website administrators to help determine whether images have controversial content and should thus be restricted.

Azure distinguishes controversial (pornographic and violent) content and other in-appropriate content as follows: (1) Adult images with clear nudity and showing sexual behavior are marked with an Adult Score. (2) Indecent images with suggestive content are marked with a Racy Score.

(3) Violent images are marked with a Gore Score. Azure detects whether images have these types of content and awards a score from 0 to 1 (up to four decimal places in this study). Table 3 presents the scores awarded by Azure for images A1–A9.

Table 3: Scores for images A1–A9, as awarded by Azure.

Code	Adult Score	Adult (True or False)	Racy Score	Racy (True or False)	Gore Score	Gore (True or False)
A1	0.0908	False	0.1176	False	0.5862	False
A2	0.9336	True	0.9603	True	0.8847	True
A3	0.5872	False	0.6033	True	0.0027	False
A4	0.9999	True	0.9999	True	0.3364	False
A5	0.0054	False	0.0096	False	0.5991	False
A6	0.9031	True	0.9938	True	0.3679	False
A7	0.9790	True	0.9968	True	0.5002	False
A8	0.9858	True	0.9948	True	0.2777	False
A9	0.0174	False	0.0201	False	0.7601	True

Recognition by Human Participants

The questionnaire, which was distributed online, was divided into two parts. The first part contained the letter of consent for the experiment, as well as questions on basic demographic data. The second part concerned the identification of images A1–A9. The participants were asked to award Adult, Racy, and Gore scores and to evaluate the Event Description provided by Azure.

The questionnaire comprises the following questions: (1) “What level of pornography do you think this image has? Please award a score of 1–10 where 1 means not porno-graphic at all whereas 10 means the highest level of pornography.” (2) “What level of in-decency do you think this image has? Please award a score of 1–10 where 1 means not indecent at all whereas 10 means the highest level of indecency.” (3) “What level of violence do you think this image has? Please award a score of 1–10 where 1 means not violent at all whereas 10 means the highest level of violence.” (4) “Do you think the Event Description provided by the Computer Vision API of Azure is accurate? Please award a score of 1–10 where 1 means very inaccurate whereas 10 means very accurate.”

In total, 175 questionnaires were collected, 33 from men (18.9%) and 142 from women (81.1%). All participants with valid responses were required to complete a letter of consent that stated the following: “I agree to conduct this experiment and understand that the questionnaire may involve nudity and sexual issues. Even if I check Agree, I can still stop answering at any stage while I am completing the questionnaire.”

This study tested four scores: The Adult, Racy, Gore, and Event Description scores. Adult referred to an image appearing to be pornographic; Racy referred to an image having suggestive and sexual content; and Gore referred to an image portraying violence. The Event Description score indicated whether the participants considered the description provided by the Computer Vision API of Azure to be accurate. Table 4 shows the participants’ scores for images A1–A9.

Table 4: Participants' scores for images A1–A9.

Code	Adult		Racy		Gore		Event Description	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A1	3.00	1.88	2.11	1.68	1.34	0.91	3.79	2.22
A2	3.46	2.35	1.53	1.22	3.54	2.20	4.71	2.69
A3	1.70	1.32	6.91	2.46	6.34	2.70	2.65	2.34
A4	1.83	1.56	2.06	1.72	1.63	1.36	2.49	1.67
A5	2.50	1.90	1.37	0.91	3.16	2.01	3.17	1.97
A6	1.67	1.25	2.98	2.12	2.73	1.99	2.16	1.81
A7	1.54	1.19	1.49	1.27	4.22	2.75	6.26	2.63
A8	3.45	2.46	1.79	1.39	1.81	1.58	4.77	2.93
A9	7.38	2.60	3.49	2.49	1.69	1.31	4.76	2.72

Computer Vision API of Azure

This study took the Azure score as the basic score and employed the one-sample t test to determine whether a difference was present between the Adult, Racy, Gore, and Event Description scores awarded by Azure and by the participants (A= Azure; R= Real person; p= p value). Significant differences in all four scores were observed (Table 5).

Table 5: One-sample t test of differences between Azure- and participant-awarded scores.

Code	Adult Score			Racy Score			Gore Score			Event Description Score		
	A	R	p	A	R	p	A	R	p	A	R	p
A1	0.91	3	0.000*	1.18	2.11	0.000*	5.86	1.34	0.000*	8	3.79	0.000*
A2	9.34	3.46	0.000*	9.6	1.53	0.000*	8.85	3.54	0.000*	6.55	4.71	0.000*
A3	5.87	1.7	0.000*	6.03	6.91	0.000*	0.03	6.34	0.000*	3.71	2.65	0.000*
A4	10	1.83	0.000*	10	2.06	0.000*	3.36	1.63	0.000*	6.02	2.49	0.000*
A5	0.05	2.5	0.000*	0.1	1.37	0.000*	5.99	3.16	0.000*	6.7	3.17	0.000*
A6	9.03	1.67	0.000*	9.94	2.98	0.000*	3.68	2.73	0.000*	8.76	2.16	0.000*
A7	9.79	1.54	0.000*	9.97	1.49	0.000*	5	4.22	0.000*	9.09	6.26	0.000*
A8	9.86	3.45	0.000*	9.95	1.79	0.000*	2.78	1.81	0.000*	6.74	4.77	0.000*
A9	0.17	7.38	0.000*	0.2	3.49	0.000*	7.6	1.69	0.000*	7.93	4.76	0.000*

Whether participant gender affected image identification was also explored. The in-dependent samples t test was conducted to determine whether a significant gender difference existed in image identification. For most of the questions, no significant gender difference was noted. There were four questions for which a significant difference was found: Adult score for A5, Racy score for A9, Gore score for A9, and Event Description score for A8 (Table 6).

Table 6: Independent samples t test of score differences between genders.

Code	Adult		Racy		Gore		Event Description	
	p value	Significance	p value	Significance	p value	Significance	p value	Significance
A1	0.918	None	0.409	None	0.572	None	0.890	None
A2	0.698	None	0.817	None	0.856	None	0.645	None
A3	0.078	None	0.117	None	0.191	None	0.273	None
A4	0.352	None	0.993	None	0.206	None	0.052	None

A5	0.017*	Male > female	0.711	None	0.486	None	0.266	None
A6	0.318	None	0.479	None	0.180	None	0.574	None
A7	0.133	None	0.468	None	0.788	None	0.534	None
A8	0.130	None	0.785	None	0.260	None	0.009*	Male > female
A9	0.173	None	0.037*	Male > female	0.032*	Male > female	0.203	None

DISCUSSION AND CONCLUSIONS

This study explored the difference between artificial intelligence and human intelligence in image identification. Azure and human participants awarded significantly different Adult, Racy, Gore, and Event Description scores. Regarding the Adult scores, except for images A1, A5, and A9, Azure awarded higher scores than the participants. The three highest Azure scores were awarded for three artworks in the following order: A4 > A8 > A7. By contrast, the participants awarded the highest scores for three different artworks in the following order: A9 > A2 > A8. Regarding the Racy scores, except for A1, A3, A5, and A9, Azure awarded higher scores than the participants. In descending order, the highest Racy scores awarded by Azure were for A4, A7, and A8. By contrast, in descending order, the highest Racy scores awarded by the participants were for A3, A9 and A6. The results indicate considerable differences in judgment between artificial and human intelligence. Regarding the Gore scores, except for A3, Azure awarded higher scores than the participants. In descending order, the highest Gore scores awarded by Azure were for A2, A9, and A5. By contrast, in descending order, the highest Gore scores awarded by the participants were for A3, A7, and A2. Regarding the Event Description scores, Azure awarded higher scores than the participants for all images. In descending order, the highest Event Description scores awarded by Azure and the participants were for A7, A6, A1 and for A7, A8, and A9, respectively. Consensus was achieved for image A7.

A significant gender difference in image identification was observed for a few questions. Regarding the Adult scores, men awarded significantly higher scores for A5 than did women. Regarding the Racy scores, men awarded significantly higher scores for A9 than did women. Men also awarded significantly higher Gore scores for A9 and significantly higher Event Description scores for A8 than did women. In all the images for which a significant difference was obtained, men awarded higher scores. This may be attributed to men experiencing stronger feelings than women when viewing images with sexual content.

In certain real-world situations, judging the boundary between art and pornography is challenging. The introduction of artificial intelligence may help website administrators make judgments about images efficiently. However, it seems that the standard of artificial intelligence is more unique and stricter than that of humans. In the short term, the boundary between art and pornography may remain difficult to identify.

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