As Good As A Coin Toss

Human Detection of AI-Generated Images, Video, Audio, and Audiovisual Stimuli

Di Cooke*, Abigail Edwards, Sophia Barkoff, and Kathryn Kelly

International Security Program, Center for Strategic and International Studies, Washington D.C., USA

ABSTRACT

Currently, the principal defense against deceptive synthetic media relies on the ability of the human observer to visually and auditorily discern between real and fake. However, it remains unclear just how vulnerable people actually are to being misled by synthetic media in the course of their day to day lives. We conducted a perceptual survey series with 1276 participants to assess how accurate people were at distinguishing synthetic images, audio, video, and audiovisual stimuli from authentic. To reflect the circumstances under which people would likely encounter synthetic media 'in the wild', testing conditions and stimuli emulated a typical online platform interface, and all synthetic media used in the survey was sourced from generative AI technology accessible by the public. We find that overall, people struggled to meaningfully discern between synthetic and authentic content. We also find that detection performance worsens when the stimuli: contains synthetic content as compared to authentic content, images featuring human faces as compared to non-human face objects, a single modality as compared to being multimodal, mixedauthenticity audiovisual stimuli as compared to fully synthetic audiovisual stimuli, and foreign languages as compared to languages the observer is fluent in. Finally, we find that prior knowledge of synthetic media does not significantly impact detection performance, although age does, with older individuals performing worse than their younger counterparts. Collectively, our findings indicate that people are highly susceptible to deceptive synthetic media in their daily lives, and that human perceptual capabilities can no longer be relied upon as a useful defense. These results highlight the critical need for alternative robust countermeasures to effectively mitigate the potential and realized harms arising from synthetic media abuse.

ACKNOWLEDGEMENTS

We would like to thank Gamin Kim, Ike Barrash, and Daniel Pycock for their contributions in data analysis and formatting, as well as Alexis Day for her contributions to the survey's design and development.

1 Introduction

Advancements in generative AI technology have made it easier than ever for anyone to manufacture increasingly realistic synthetic media (colloquially known as 'deepfakes') at faster speeds, larger scales, and with more personalisation than ever before. [15] In turn,

this has led to synthetic media being increasingly employed for harmful purposes, including disinformation campaigns, nonconsensual pornography, financial fraud, child sexual abuse and exploitation activities, espionage, and more. [27] As of today, the principal defense to combat deceptive synthetic media depends nearly entirely on the human observer's perceptual detection capabilities or their ability to visually or auditorily identify AIgenerated content when they encounter it. [15] Yet the growing realism of synthetic media impedes this ability, heightening people's vulnerability to being misled by synthetic content. Moreover, it has been found that people overestimate how capable they are at identifying synthetic media, further exacerbating the problem. [13] As a result, an accurate measure of people's perceptual ability to differentiate between the real and fake is critical to effectively combat the potential and realised harms arising from synthetic media. While there are rising efforts to develop and implement alternative technical solutions, such as machine detection, watermarking, or content provenance, these methods either currently lack robustness or are not yet sufficiently widespread enough to be effective. [12, 15, 36] Similarly, despite widespread calls to deploy educational interventions such as digital media literacy campaigns, formalized efforts have been relatively limited in practice.

We conducted a study to measure the human perceptual detection capabilities for distinguishing between human-authored and AIgenerated digital content, requiring participants to classify synthetic and authentic images, audio-only, video-only, and audiovisual stimuli. Our study analyzes detection performance overall and by media type, as well as investigating the individual impacts of specific stimuli content characteristics on human perceptual detection capabilities. These characteristics include the stimuli's authenticity, image subject matter, modality, and language familiarity on detection accuracy rates. In addition, it assesses how people's prior self-reported knowledgeability of synthetic media as well as their age impacts their detection performance. To ensure that study results are reflective of human detection performance as it would be 'in the wild', or how they are likely to engage with synthetic media over the course of their daily lives, our survey design sought to emulate typical online platform environmental conditions. Discussed in greater detail in our 'Methods' section, this included structuring the survey format to mimic typical online platform features such as sequentially shown content and vertical scrolling, as well as providing signposts for participants to progress through the survey at a pace reflective of average web browsing speeds. The stimuli content was also selected to be representative of the most commonly featured digital content in major online platforms. Moreover, participants were not provided with any feedback, nor were they advised what the proportion of synthetic to authentic content there would be. Finally, synthetic stimuli were solely sourced from generative AI tools and services accessible to members of the public, either commercially or via open-source software, to accurately reflect the quality of synthetic content that people are already encountering online today.

To the best of the authors' knowledge, this is the first study to test human perceptual detection performance of most of these synthetic media types under such conditions. While Josephs et al's 2023 study examined the impact of real world web browsing conditions on human detection performance on video-only stimuli, [8] the majority of research thus far has assessed detection performance under conditions not necessarily reflective of the circumstances of how people would likely encounter and determine the presence of synthetic media in their regular lives, such as requiring twoalternative forced choice methods, providing instant feedback or unlimited testing time, as well as informing participants what the percentage of synthetic versus authentic media will be. [6, 7, 14, 16, 21] As far as the authors are aware, this is also the first study to test human detection capabilities on images which didn't feature human faces, examines the role of language in detecting synthetic video-only and audiovisual stimuli, compare accuracy rates between mixed-synthetic and fully synthetic audiovisual stimuli, and examine the impact of prior knowledgeability of synthetic media on participant performance.

Our results find that participants' overall accuracy rates for identifying synthetic content are close to a chance level performance of 50% with minimal variation between media types, suggesting that people's visual and auditory perceptual capabilities are inadequate for reliably identifying synthetic media encountered in online platforms today. Our results also find that detection accuracy rates worsen when people are presented with stimuli featuring synthetic content as compared to authentic content, images of human faces as compared to non-human face objects, stimuli containing a single modality as compared to multimodal stimuli, mixed-authentic as compared to fully synthetic audiovisual stimuli, and stimuli featuring foreign languages as compared to featuring languages participants are fluent speakers in. This indicates that individual content characteristics present within the stimuli affect certain visual and auditory perceptual processes such as object, speech, and language recognition, providing potentially novel observations to not only synthetic media detection research but the human perception field as well. We also find that age plays a role in perceptual detection capabilities, with older participants performing worse than younger ones - particularly in identifying audio and audiovisual stimuli. This indicates that older individuals are more susceptible to being deceived by synthetic media than their younger counterparts, especially in regards to synthetic media containing audio content. Finally, we find that people's prior

knowledge of synthetic media does not impact detection performance, with people who reported being unfamiliar, semi-familiar or highly familiar with synthetic media prior to taking the survey all performing similarly. This suggests either that current public knowledge of synthetic media even at higher degrees is insufficient for meaningfully improving detection performance, or that synthetic media has become convincingly realistic enough that perceptual-based educational interventions are inadequate.

Collectively, these results demonstrate that depending on people's perceptual detection capabilities to discern the real from the take is no longer a viable bulwark against the threats posed by synthetic media. While our findings provide useful insights on how to reduce people's susceptibility to certain digital content characteristics, such as stimuli featuring a foreign language or in a single modality, it is expected that the benefits will be short term. Rather, it is expected that continued advancements in generative AI technology will eventually lead to any detection performance differences resulting from these characteristics to become negligible, and that human detection performance overall will plateau. Ultimately, it reveals the critical need for alternative robust countermeasures to be developed and deployed to combat the potential and realised harms arising from synthetic media, whether this be technical, educational, or otherwise.

2 Results

We conducted a pre-registered perceptual survey series, requiring 1276 participants to classify authentic and synthetic media stimuli presented to them under typical online platform environmental conditions. To assess the impact of individual stimuli characteristics and prior knowledgeability of synthetic media on detection performance, we conducted a binomial logistic regression along with a series of ANOVA and t-tests. The p-value was adjusted to p=0.0031 (α /16) using Bonferroni correction to reduce the risk of type 1 error.

Predictor	β	SE	Wald's	df	р	β CI (95%)
Intercept	0.924	0.022	1767.698	1	<0.001	[0.97, 0.88]
Authenticity [Authentic Media] +						
Synthetic Media	-1.140	0.012	8300.303	1	<0.001	[-1.06, -1.07]]
Image Subject [Non-Human Face Objects]						
Human Face	-0.269	0.016	265.364	1	< 0.001	[-0.24, -0.30]
Language [Fluent in Language]						
Foreign Language	-0.158	0.020	59.707	1	< 0.001	[-0.12, -0.20]
Deepfakes Familiarity [Unfamiliar]						
Highly Familiar	-0.035	0.022	2.332	1	0.115	[0.08, -0.01]
Semi-Familiar	-0.005	0.015	0.095	1	0.758	[0.02, -0.03]
Likelihood ratio test = X ² (6) = 9142.5, p<0.001						
Nagelkerke R2 = 0.095						

Note: † Reference categories for the independent variables are bracketed

Table 1. Logistic Regression Analysis of Synthetic Media Detection Performance

2.1 Media Type & Authenticity

Mean detection performance across all stimuli was found to be 51.2%, close to a random chance performance of 50%. As shown in Figure 1, participants were the least accurate at classifying image stimuli with a 49.4% accuracy rate. Comparatively, mean detection accuracy was higher for video-only stimuli at 50.7% and audio-only stimuli at 53.7%, with participants being the most accurate at correctly classifying audiovisual stimuli at a 54.5% accuracy rate.

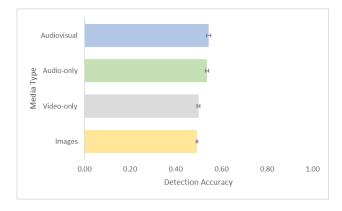


Figure 1. Average detection accuracy by media type, with error bars representing 95% confidence intervals.

It was also found that the stimuli's authenticity was a meaningful predictor for detection performance, as shown in Table 1. Participants were significantly better at correctly identifying fully authentic stimuli (M=64.6%) as compared to stimuli which contained synthetic media (M=38.8%). Participants were also significantly more accurate [t(9861)=6.3, p<0.001; d=0.11] in classifying audiovisual stimuli containing both synthetic audio and video (M=49%) as compared to audiovisual stimuli containing synthetic video and authentic audio (M=43.4%).

2.2 Single Versus Multimodal Stimuli

Detection accuracy was found to be significantly higher [t(49004)=5.18, p<0.001; d=0.4] for participants classifying multimodal audiovisual stimuli in comparison their single modality counterparts, audio-only and video-only stimuli (M=52.2%). Post hoc analysis of the 30 video stimuli which were presented in an audiovisual format, either fully authentic or mixed synthetic (synthetic video and authentic audio), in one of the surveys and in a video-only format in the other survey found that participants were significantly more accurate in identifying the stimuli [t(37517)=10.15, p<0.001; d=0.1] when the audio was included (M=55.9%) than when the stimuli was presented in a video-only format (M=50.7%).

2.3 Human Face vs. Non-Human Face Images

Participants were also found to be significantly less accurate (see Table 1) when classifying images featuring human faces (M=46.6%) as compared to images featuring non-human face

objects such as animals (M=51.7%), food (M=49.9%), and landscapes (M=54.7%). Post hoc analysis confirmed this difference in detection performance remained present even when controlling for model type [t(12201)=-13.83, p<0.001; d=0.21].



Figure 2. The top row are synthetic images from each subject matter category which were most often *misclassified* as authentic, while the bottom row are synthetic images which were most often *correctly identified* as synthetic. Beneath each image is its corresponding mean accuracy rate.

2.4 Language Familiarity

Participants were found to be significantly more accurate (see Table 1) in classifying stimuli when presented with visual and auditory content featuring a language they reported being fluent speakers (M=54.5%) of as opposed to those featuring foreign languages (M=51.3%), as shown in Figure 3. Regarding audioonly stimuli, post hoc analysis found that participants were significantly more accurate [t(17696)=3.947, p<0.001; d=0.06] discerning between synthetic and authentic audio-only stimuli featuring a known language (M=55.3%) as opposed to a foreign language (M=52.3%). Further analysis also revealed that participants were significantly better at respectively identifying audiovisual stimuli [t(22640)=6.864, p<0.001; d=0.09] featuring known languages (M=56.5%) compared to those featuring foreign languages (M=52%). This was also found to be the case for videoonly stimuli, with participants being significantly more accurate [t(19278)=2.83, p<0.001; d=0.04] at detecting known language video-only stimuli (M=52%) versus foreign language stimuli (M=49.5%).

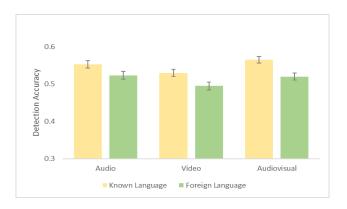


Figure 3. Mean detection accuracy by language familiarity and media type, with error bars representing 95% confidence intervals.

When examining the 30 video stimuli presented in either a videoonly and audiovisual format depending on the survey, post hoc analysis found that the inclusion of audio featuring known languages significantly improved detection performance [t(23035)=9.17, p<0.001; d=0.12] by 5.5 percentage points (see Figure 4). For videos featuring foreign languages, detection performance also significantly improved [t(16966)=5.63, p<0.001; d=0.09] but to a lesser degree by 4.3 percentage points.

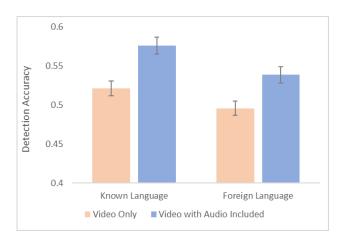


Figure 4. Mean detection accuracy by language familiarity between video-only clips and their audiovisual counterparts, with error bars representing 95% confidence intervals.

2.5 Prior Knowledgeability

No significant difference in detection performance was found (see Table 1) between participants who self-reported being previously unfamiliar with synthetic media (M=51.1%) and those who reported having prior knowledge of synthetic media, either semifamiliar (M=51%) or highly familiar (M=51.9%). A post hoc oneway ANOVA also did not find any significant difference in detection performance between the three groups [F(2,124185)=1.4,

p=0.25; $\eta 2 < 0.01$], with Tukey's HSD test confirming no significant difference between their means.

2.6 Age

Post hoc linear regression analysis found age to be a significant predictor of detection performance, [β =-56.64, p<0.001] with older participants being significantly less accurate in classifying stimuli as compared to younger participants. [R^2 =0.04, F(1,1274)=55.63, p<0.001] When examined by media type, it was found that detection performance by age decreased the greatest amount for audiovisual and audio-only stimuli, with less of a decrease for image and video-only stimuli.

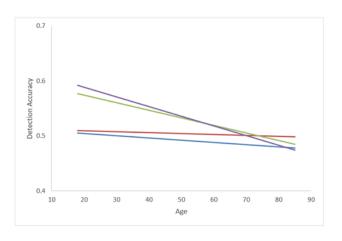


Figure 5: Mean detection accuracy by age, with each trendline showing detection accuracy by media type: video (red), image (blue), audio (green), and audiovisual (purple)

3 Limitations

This study is not without limitations. Firstly, as all synthetic media items used in this survey were collected or produced prior to 2023, current human detection performance of synthetic media at this moment may be lower than reported in this study, as further advancements in generative AI technology have continued to advance the realism of synthetic content. Furthermore, while this study's design sought to mimic online platform environmental conditions to replicate the manner in which individuals would probably encounter synthetic media in their day to day lives, it is unlikely that individuals will solely encounter synthetic media in an online platform without any accompanying contextual information such as added text, comments, or source information, which may further inhibit or facilitate the their ability to determine the legitimacy of the digital content. Another limitation to be considered is that participants self-reported their degree of preexisting synthetic media knowledge and fluency in languages, wherein participants may have over or underestimated their capabilities in comparison with other participants.

4 Discussion

4.1 'In the Wild' Detection Performance

Multiple implications can be drawn from the results of this study. First, people struggled to meaningfully distinguish synthetic images, audio, video, and audiovisual stimuli from their authentic counterparts, with overall detection accuracy rates being close to a chance level performance. This is congruent with existing research to some degree, as some prior studies have recorded similar detection accuracy rates for synthetic images, [21, 31] yet studies on video, audio, and audiovisual stimuli have typically found higher detection accuracy rates. [3, 6, 7, 14, 16, 23, 26] Although study differences bar a more detailed comparison, it is hypothesized that the overall divergence in detection performance is due to the differing environmental testing conditions - which suggests that people's detection performance is constrained when they encounter synthetic media under online platform environmental conditions. This divergence in performance is consistent with Josephs et al 2023's study, which similarly found that online platform environmental factors, including divided attention, exposure length, amongst others, also had inhibitory effects on people's detection capabilities. [8] Further research might be conducted on how these and other environmental factors may also impact detection performance, both individually and cumulatively. Having a better understanding of what these environmental factors are and their effects on detection performance will provide a clearer picture of how vulnerable people may be to deceptively employ synthetic media 'in the wild'. For instance, despite the smartphone's growing popularity as people's primary device to access online information, it has been found that people employ lower amounts of cognitive resources when consuming digital content via smartphones. [4, 33] As a consequence, widespread smartphone use may further hinder people's abilities to detect deceptive synthetic media when consuming current event and news content via their online platform news feeds.

4.2 Stimuli Content Characteristics

Detection performance is also found to be sensitive to certain stimuli content characteristics, which suggests that these individual characteristics may affect people's detection capabilities because of how they impact their cognitive perceptual processes.

Authenticity: People are more accurate at identifying authentic as compared to synthetic content, revealing a bias towards classifying all digital content as being real. This is consistent with previous research which also found people had a similar inclination to classify video-only stimuli as being authentic. [8, 13].

Modality: People are also less accurate at detecting synthetic audio-only and video-only stimuli as compared to audiovisual, which suggests the inclusion of additional modalities to stimuli improves people's perceptual ability to distinguish between authentic and synthetic media. This is consistent with existing research such as Groh et al 2023's study, which found the addition

of audio to videos of real and fake political speeches improved detection performance. [7] This may be due to the multimodal nature of speech perception, as speech perception research has found that people rely on both visual and auditory perceptual cues to comprehend spoken words. [25] Therefore, synthetic audiovisual stimuli may be less difficult to detect than its monomodal counterparts because people are able to leverage both the auditory and visual information present to better identify observable AIgenerated artifacts present in the stimuli. In addition, detection accuracy is found to be higher when identifying fully synthetic audiovisual stimuli, as compared to mixed synthetic audiovisual stimuli where the video contains synthetic content while the audio is authentic. This suggests that people may be better at identifying fully synthetic audiovisual stimuli than mixed synthetic due to the higher potential presence of observable artifacts in both the audio and visual modalities which they are able to leverage to determine authenticity, as opposed to potential observable artifacts only being present in only one modality as would be the case with mixed synthetic audiovisual stimuli.

Image Content: Meanwhile, people are worse at detecting synthetic images featuring human faces as compared to synthetic images featuring animals, food, and landscapes, indicating they found synthetic images featuring human faces to be more convincing than similarly realistic looking images featuring nonhuman face images. This may be due to the specialized human visual perceptual process which occurs when people observe faces as opposed to non-face objects. Visual perception research has established that whereas humans recognize faces as a perceptual whole, non-face objects are conversely identified by their distinct individual components. [11, 30] Therefore, the more gestalt face recognition process which takes place once an image is recognised to feature a face may lead people to be less sensitive towards identifying observable AI-generated artifacts than they would if employing the more fragmented object recognition process which occurs when observing non-face objects.

Language: People are also more accurate in detecting synthetic audio-only, video-only, and audiovisual stimuli featuring languages the observer is a fluent speaker of compared to stimuli featuring foreign languages, suggesting that language familiarity plays a significant role in people's visual and auditory perceptual detection capabilities. This is consistent with existing synthetic audio detection research such as Müller et al's 2023 study, which found native English speakers to be better at detecting English synthetic audio clips than non-native speakers. [16] Detection performance may be higher when known languages are present in visual and auditory stimuli due to the observer being more familiar with the visual and auditory language information available. making them more sensitive to observable artifacts. [19] In addition, when comparing detection performance of video-only stimuli as compared to their audiovisual counterparts (the same video clips but with the audio included) it was found that people's detection accuracy improved to a greater degree between videoonly and audiovisual stimuli featuring known languages versus those featuring foreign languages. This suggests that people are more sensitive to auditory perceptual cues in audiovisual stimuli featuring familiar language as opposed to foreign ones. This is congruent with established language perception research, which has found that people weigh auditory information more highly when observing known languages being spoken, while they rely on visual perceptual cues to a greater degree when observing foreign languages. [28, 34] Therefore, it may be that the inclusion of audio facilitated people's sensitivity to synthetic visual content to a greater degree for stimuli featuring familiar languages than foreign languages because of the greater weight given to auditory perceptual cues when observing familiar languages as part of the language perceptual process.

Understanding how individual stimuli characteristics such as the ones examined in this study may inhibit or facilitate people's perceptual detection capabilities is valuable as it provides more accurate predictions of how susceptible people potential are to different types of synthetic content they may be exposed to. In addition, it identifies demographics that may be more vulnerable to being duped by synthetic media than others, such as monolingual speakers potentially being less sensitive to visual and auditory AIgenerated artifacts presented in foreign languages than multilingual speakers. In turn, these insights can inform the development of more effective countermeasures to better mitigate people's susceptibility to synthetic media, such as specific content moderation tactics. For instance, although the default for many social media platforms is to have audiovisual stimuli muted when being played, detection performance of synthetic media is likely to be improved if the audio is not muted when the video automatically plays. Therefore, a useful content moderation policy to adopt may be to not automatically mute videos deemed to be at higher risk of containing deceptive synthetic content, such those featuring political content in the run up to government elections. Future research would be useful to identify additional actionable countermeasures as well as further explore the effects of these and other stimuli characteristics on detection performance, such as determining whether the difference in detection performance between faces and non-face objects is also found in identifying synthetic video and audiovisual stimuli. Regardless, as generative AI technology continues to improve, periodic reassessment of these stimuli content characteristics would be beneficial to determine whether they continue to have the same effect.

4.3 Prior Knowledgeability

People's prior knowledgeability of synthetic media did not affect detection performance, with people who reported being highly familiar with synthetic media performing similarly to those who reported being less familiar or unfamiliar. As this study did not test participants on their synthetic media knowledge, rather asked them to self-report, this suggests one of two possible causes. The first is that synthetic media has become convincingly realistic to the degree where increased familiarity with synthetic media does not

meaningfully improve people's perceptual detection capabilities. Alternatively, it may be that current public knowledge of synthetic media, even at comparatively higher levels, does not sufficiently educate people on effective perception-based detection methods. Existing research suggests the truth is currently somewhere in the middle, as some studies have found that increased exposure to synthetic content and providing immediate feedback or prior training has improved detection performance, while others have found that not to be the case. [6, 7, 14, 16, 21] However, as synthetic media continues to improve in realism, it expected that eventually perceptual-based educational interventions will become less effective. Nonetheless, further work to clarify in what contexts perceptual-based interventions are able to improve detection performance will be beneficial for developing more effective educational interventions to reduce people's current vulnerability to deceptive synthetic content. In addition, research into the impact of non-perception based educational interventions, such teaching critical analysis skills like fact-checking or cross-referencing, on detection performance would also be valuable.

4.4 Age

People's age significantly affected detection performance, with older people being less accurate in identifying synthetic media than younger people across all media types. The relationship between age and detection performance is consistent with previous research, which similarly found older people to be less accurate in classifying audiovisual and audio stimuli, respectively. [3, 16] This suggests that as people age, they become less sensitive to perceptual cues such as observable artifacts present within synthetic media. We speculate that this may be due to the widespread visual and auditory perceptual degradation which occurs with aging. [5] Detection performance in relation to older age declined the most for stimuli containing audio components, which may be a result of hearing loss being more prevalent than visual impairment in older demographics, along with the lower frequency of people actually using treatments for improving their hearing in comparison to their sight. [5, 18] Audiovisual stimuli, which younger people were the most accurate at classifying, was the media type least often correctly classified by older people. This may be due to how agerelated auditory and visual degradation impacts the multisensory perceptual process. Existing speech perception research finds that older individuals depend more on multisensory information to compensate for degradation of unisensory perception, such as relying more on adjacent visual cues to improve their comprehension of auditory information. [22] This higher reliance on the integration of perceptual information has led to older individuals being more likely to be susceptible to illusionary effects, such as purposefully mismatched visual and auditory information, than their younger counterparts.[22] Similarly, this may mean older individuals are less sensitive to artifacts present in audiovisual stimuli because they are more reliant on utilizing their multisensory perception capabilities than unisensory when observing audiovisual content.

Altogether, this indicates that age increases susceptibility to being misled by synthetic media, with a greater vulnerability to audio and audiovisual synthetic content than visual. This insight suggests the potential need for age-related content moderation policies to better improve older digital consumer's resilience against being tricked by deceptive synthetic media, or for the heighted need of educational interventions tailored to this higher risk demographic. This is especially important considering older individuals are increasingly becoming the targets of synthetic media enhanced scams. [37] Future research on how age-related limitations may be mitigated would be useful, such assessing whether corrective devices such as glasses or hearing aids meaningfully improve perceptual detection performance.

5 Conclusion

The results of our study demonstrate that people's perceptual detection capabilities are no longer a suitable defense against deceptive synthetic media. The ability to create synthetic content which is convincingly realistic has now become available for any member of the public to use, including those with harmful intent. Our findings underscore the critical importance of developing and deploying robust countermeasures which are not reliant on human perceptual detection capabilities. This includes increasing investment and research for technical solutions such as machine detection, watermarking or cryptographic signatures, as well as the wider adoption of other techniques like content provenance or hashing databases. It also highlights the need to pursue widespread educational interventions such as digital media literacy campaigns to better equip people with the skills and knowledge to identify false content in other ways, such as critical analysis techniques like cross-referencing and fact checking.

Importantly, our study also identifies several stimuli content characteristics that have inhibitory or facilitatory effects on peoples' perceptual detection capabilities. These findings provide actionable useful insights for informing immediate countermeasures which could be taken in the short term to reduce people's vulnerability to more convincingly deceptive content, such as specific content moderation policies for online platforms. Nevertheless, as synthetic media outputs continue to progress realism, it is anticipated that perceptual-based countermeasures will eventually plateau, requiring alternative solutions over the long term. Regardless, further work in this space is vital to improve our understanding of and monitor the limitations of human perceptual deception capabilities to better identify and improve societal resilience against the potential and realised dangers posed by synthetic media.

6 Methods

6.1 Design

Our pre-registered mixed design study was divided across two online surveys, with participants only able to take one of the two

surveys. This was done to reduce the risk of participant exhaustion and to eliminate carryover effects. All participants gave fully informed consent prior to taking part in the study. Participants were required to use a computer to take the survey and were provided with an introduction to the study's purpose and explanation of synthetic media. Participants were then asked to report on their fluency of non-English languages, and to select their level of preexisting knowledge of synthetic media as being either: 1) Highly Familiar ("I have a comprehensive understanding what kind of deepfakes can be made, and have encountered many examples before"), 2) Semi-Familiar ("I have a general understanding of deepfakes, and have encountered a couple of examples before"), or 3) Unfamiliar ("I've never heard of deepfakes before, or I recognise the term but don't know much about them, and have not encountered examples yet that I can recall.")

Participants were asked to classify the stimuli as either being authentic or as containing synthetic media. The stimuli were presented sequentially in randomized order and participants progressed through the survey by scrolling vertically, emulating the experience of browsing through an online platform news feed. Audio, video, and audiovisual clips were all replayable. Participants were asked to progress through the survey at a pace reflective of how they would browse through an online platform's newsfeed. While there was no hard time restraint and participants had the freedom to decide how much time they spent on each question, signposts reminding them to take the survey at their typical browsing speed appeared when participants completed 25%, 50%, and 75% of the survey. A self-regulated approach to pacing was decided to be appropriate for this study, as imposing hard time limits would risk insufficiently accounting for the variety of factors which existing research has shown to affect browsing speed, including media type, subject matter, emotional valence, and personality. [17, 32, 35]

Two attention checks each were presented at random within Survey 1 subsections 1 and 2, while two attention checks were presented at random in Survey 2. Participants who failed to pass both attention checks within each Survey 1 subsection or within Survey 2 had their results removed from that section respectively. Participants who dropped out part way through a section or reported having issues with playing the audio, video, or audiovisual clips, had their results removed from those sections as well.

In subsection 1 of Survey 1, 663 participants classified 96 image stimuli and passed both attention checks. Image stimuli were presented in a separate subsection from the other media types so that if participants had difficulties playing the audio, video, and audiovisual clips, requiring their results being removed, this would not also require removing their image stimuli results as well. In subsection 2 of Survey 1, 604 participants from the same group of participants classified 48 stimuli including 14 audio-only, 16 video-only, and 18 audiovisual clips, passing both attention checks. In Survey 2, 614 novel participants classified a different set of 16 audio-only, 14 video-only, and 18 audiovisual stimuli, passing both

attention checks. The video-only stimuli presented in Survey 2 contained the same visual content as the audiovisual stimuli from Survey 1 but with the audio content removed, with the reverse for the Survey 1 video-only and Survey 2 audiovisual stimuli.

6.2 Participants

A total of 124187 observations were collected and retained from 1276 participants for this pre-registered study. All participants were fluent English speakers and were North American residents. The sex and age demographic distribution was representative of US demographics: Survey 1 being 45% Female, 8% Unreported; 19% 18-29 years old, 62% 30-64 years old, 19% 65+ years old and Survey 2 being 49% Female, 2% Unreported; 19% 18-29 years old, 61% 30-64 years old, 20% 65+ years old. Participants were recruited from the research survey platform Prolific, and paid a pro rata rate of \$11.4 per hour.

6.3 Stimuli

A total of 194 stimuli were presented to participants across both surveys, consisting of authentic and synthetic images, audio-only, video-only, and audiovisual clips. Image, audio-only, and videoonly stimuli were each 50% synthetic and 50% authentic. Of the audiovisual stimuli, 15 clips were fully authentic, 15 contained synthetic video and authentic audio, and 8 were fully synthetic. The stimuli content and subject matter was representative of popular digital content found on online platforms, containing predominantly human-featured content including images, user generated social media videos, film scenes, news segments, music videos, vlogs, podcasts and audiobooks clips, and radio segments. [2] Image stimuli also contained other subject matters commonly featured on online platforms, including food, landscapes, and animals. In all synthetic stimuli, AI-generated content was prominently featured. Audio content included many of the most widely spoken languages online, including English, Mandarin, Spanish, Hindi, Turkish, Russian, Portuguese, French, German, Hebrew, Swedish, Japanese, and Korean. [24]

To ensure participants relied predominantly on their perceptual detection capabilities, extraneous cues within the content were minimized or excluded, such as unique backgrounds or memorable contextual information. However, as contextual content could not be fully removed from all stimuli, diverse subject matters were ensured to further reduce possible participant reliance on contextual cues for detection.

So that the synthetic stimuli in the study reflected the quality of synthetic content being published in online platforms, all synthetic content sourced from commercially available generative AI products and services or open-source software and was generated

prior to 2023. Synthetic stimuli were either produced for the purposes of this study or were collected from previously published digital content. Authentic stimuli were collected from commensurate publicly digital content on multiple online platforms and manually curated to match the synthetic stimuli in terms of subject matter, content types, and quality. Synthetic stimuli collected from pre-existing digital content was verified by confirming the source content contained observable AI-generated artifacts. The legitimacy of authentic stimuli was verified by being published as human-created content by a credible source.

Images: 96 images each containing single subject matter were used, with of them prominently and separately featuring 48 human faces, 26 animals, 12 landscapes, and 10 of food. Synthetic images of human faces were sourced from multiple publicly available general adversarial network (GAN) datasets and were manually curated to be diverse across sex, race, and age (Male-presenting, Female-presenting; Caucasian, Black, East Asian, Southeast Asian; Child, Young Adult, Middle Aged Adult, Elderly Adult). [1, 9, 10] Authentic human faces were sourced from the FFHQ dataset and were matched against the synthetic dataset in terms of race, sex, and age. [10] Synthetic non-face images were sourced from open source or publicly available GAN and latent diffusion (LD) datasets or directly from models.² [9, 10, 29] **Audio-Only**: 30 audio stimuli consisting of 5- to 6-second-long clips were used, each featuring a human voice speaking clearly in a single language. Synthetic audio clips were specifically generated for this study or collected from pre-existing outputs.3 While exact model information was not available for all stimuli, audio manipulation techniques employed to produce the clips included text-to-voice (TTV), voice cloning, and voice masking. [12] Audiovisual & Video-Only: 38 audiovisual and 30 video stimuli in both vertical and horizontal formats were used. Each clip was between 5 to 6 seconds long and featured a human speaking clearly in a single language. In all the stimuli the human speaking features prominently and their face is fully visible the entire clip. Synthetic stimuli were sourced from published outputs produced from open-source⁴ and commercially available⁵ generative AI software and services. While exact model information was not available for all stimuli, video manipulation techniques employed to produce the clips included face swapping, head generation, and lip syncing, as well as audio manipulation techniques such as voice cloning, TTV, and voice masking. [20]

7 Data

The study pre-registration can be found at https://osf.io/fnhr3. Study datasets are not yet publicly available but can be made available upon request in support of reviewing this submission.

We declare no competing interests.

¹ Sources which requested biography citation specifically have been listed as such in the references. Additional stimuli sources include: Generated Media, Inc., and This Person Does Not Exist

² Sources which requested biography citation specifically have been listed as such. Additional sources include: Nyx.AI, Stability AI 2.1, DALL-E 2

³ Synthesia, Yepic, Respeecher, Play.ht, Well Said Labs, Google Aloud

⁴ DeepfaceLab, DeepfaceLive, FaceSwap, SimSwap

Synthesia, Yepic, Canny AI, Flawless, Mac Guff, DOB Studies, Pulse9, Metaphysic.ai, Adapt Entertainment, DeepBrain AI

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