PEOPLE ARE POORLY EQUIPPED TO DETECT AI-POWERED VOICE CLONES

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ABSTRACT

As generative AI continues its ballistic trajectory, everything from text to audio, image, and video generation continues to improve in mimicking human-generated content. Through a series of perceptual studies, we report on the realism of AI-generated voices in terms of identity matching and naturalness. We find human participants cannot reliably identify short recordings (less than 20 seconds) of AI-generated voices. Specifically, participants mistook the identity of an AI-voice for its real counterpart 80% of the time, and correctly identified a voice as AI-generated only 60% of the time. In all cases, performance is independent of the demographics of the speaker or listener.

Keywords: Generative AI | Voice Cloning | Voice Identification

1 Introduction

In January 2024, in the lead up to the November US presidential election, an estimated tens of thousands of Democrat voters received a robocall in the voice of President Biden instructing them not to vote in the upcoming New Hampshire primaries. The voice was, of course, AI-generated.

The perpetrators of this attempted election interference were a political consultant Steven Kramer, a New Orleans-based street magician and hypnotist Paul Carpenter who was paid \$150 to create the fake audio, and a telecommunications company. Carpenter used ElevenLabs, a platform offering instant voice cloning for as little as \$5 a month. Kramer was fined \$6 million and subsequently charged with two dozen counts including impersonating a candidate and voter suppression, while the broadcaster, Lingo Telecom, received a \$1 million fine for transmitting the calls.

The ballistic rise of generative AI has super-charged all forms of frauds and scams from election interference, to disinformation campaigns [1], small-[2] and large-scale [3] fraud.

There is a large literature on distinguishing between real and manipulated content [4]. These techniques largely operate asynchronously and not as an audio or video call is unfolding in real time. The synchronous detection of fraudulent calls poses significant challenges. Until technology can monitor every landline, mobile device, and video call (raising privacy concerns), consumers are largely left to their own defenses to sort out the real from the fake.

Studies focusing on visual imagery have concluded that human participants are at chance at distinguishing head shots of real and AI-generated people [5, 6], while performance is only slightly better for video of people talking [7, 8].

On the audio front, Mai et al. [9] report that human participants were only able to accurately distinguish real from AI-generated voices with an accuracy of 70.4%. This study, however, only used a single English and a single Chinese speaker identity, and the spoken phrases consisted of a single sentence ranging in length from 2 to 11 seconds (by comparison the fake Biden robocall was 40 seconds in length). Müller et al. [10] report a similar accuracy of 80%. This second study has the advantage that it employed multiple speaker identities (107), but the spoken phrases were still relatively short at one to two sentences in length. For both of these studies, the AI-generated voices were not created using state-of-the-art, commercially available techniques, and both studies focused on the naturalness question (is the voice real or fake) and not on the identity question (who is speaking).

We expand on these previous studies by employing the state-of-the-art voice cloning of ElevenLabs (used in the Biden robocall), increasing the number of speakers to over 200, and considering how different tasks (identity and naturalness) impact our ability to distinguish AI-powered voices. This more diverse study reveals that people are poorly equipped to identify short recordings (less than 20 seconds) of AI-generated voices, both in terms of identity matching and naturalness. We do, however, find that performance improves for longer recordings.

2 Materials and Methods

2.1 Study Design

Our study consists of three parts that evaluate the naturalness and identity of AI-cloned voices. For the naturalness (#1 and #2), participants listened to one voice at a time and asked to classify it as real or AI-generated. For the identity (#3), participants listened to two voices back-to-back (saying something different) and were asked to specify if the voices are from the same identity.

For parts 1 and 3, participants were randomly assigned to one of 10 batches comprising a randomized set of 44 stimuli, 30 of which were scripted single-sentence responses, 10 of which were unscripted responses, and 4 attention checks. There was no stimuli overlap between batches. Part 2 of the naturalness task was added to disambiguate a result from part 1 in which there was a confound between scripted and unscripted responses with audio length. This part contained a new set of 25 additional audio clips with longer scripted responses.

For both naturalness parts, half of the audio clips were real and half were AI-generated. For the identity part, the paired audios were either both real, one real one fake, or both fake (Table 1). Participants were not told of these distributions.

2.2 Speaker Participants

Recordings of 220 speaking participants were collected through the Prolific research recruitment platform [11]. Speakers gave their consent for the use of their voice and likeness. Speakers were selected from a stratified sample ensuring equal distribution of gender; all participants were native English speakers and U.S. residents. Participants were paid \$7 for their time. Participant ages ranged from 18-75 (mean=38, sd=11.4), with 109 identifying as male, 107 female, and 4 non-binary. Racial identities included 158 White/Caucasian, 39 Black/African American, 26 Asian, 4 American Indian/Alaska Native, 2 Native Hawaiian/Other Pacific Islander, 5 other.

Each speaker was instructed to record themselves responding to 32 prompts. The first two prompts were used for voice-cloning (see below). The remaining prompts were divided into four categories: (1) standardized scripted responses in which each speaker read the same prompt extracted from transcripts of the TIMIT dataset [12]; (2) randomized scripted responses in which each speaker read a randomized prompt from TIMIT; (3) unscripted responses in which each speaker responded to four open-ended questions, and asked for a response that was close to 30 seconds in length; and (4) combined responses consisting of four open-ended unscripted questions in which each speaker read out loud a question and then answered the question.

Both audio and video were recorded using a custom-built web application. The audio/video recordings were converted from their initial .webm format to .mp4 at a bitrate of 192 kbps from which the audio was extracted as a .wav file. All real and fake audio files were converted to a .mp3 format with a sample rate of 44kHz, with an amplitude normalized between -1 and 1, and with silences at the start and end removed.

2.3 Speaker Voice Cloning and Matching

A voice clone of each of the 220 speakers was generated using the ElevenLabs' *Instant Voice Cloning* API. Transcripts of speakers' responses were used to create a cloned version of each original audio clip. For scripted responses, we assumed that the speaker correctly repeated the prompt; for unscripted responses, OpenAI's *Whisper* [13] was used to transcribe the audio.

For the identity study, participants heard two voices either of the same or different speaker identities. To make this task more challenging, for each speaker in our dataset, we determined another speaker with a perceptually similar voice. This matching was performed by first extracting a 192-D TitaNet embedding [14] of the same scripted sample. The closest matching voice was determined by finding the voice of another speaker (with replacement) with the maximal cosine similarity between extracted embeddings (the mean similarity was 0.6 in the range [-1, 1]).

2.4 Listener Participants

A total of 634 participants were recruited from the Prolific crowd-sourcing platform, split into two groups of 330 and 304 for the naturalness and identity studies. Listener ages ranged from 18-77 (mean=35, sd=11.7), with 308 male, 307 female, 12 non-binary and 7 not providing their gender. 428 listeners identified as White/Caucasian, 140 as Black/African American, 46 as Asian, 21 as American Indian/Alaska Native, 4 as Native Hawaiian/Other Pacific Islander, 32 as other and 6 preferred not to share.

Condition	N	Duration [sec]	Mean (SD) [%]	Sensitivity [%]	Specificity [%]
TO DO MANAGE.					
IDENTITY					
Overall	400	15.7	87.1 (14.9)	86.9	87.3
Real, same ID	89	15.2	92.0 (8.0)	92.0	-
Real, different ID	90	19.8	85.7 (17.3)	-	85.7
Mixed, same ID	88	16.3	79.8 (16.5)	79.8	-
Mixed, different ID	85	11.6	89.5 (11.3)	-	89.5
Fake, same ID	27	14.6	93.7 (18.2)	93.7	-
Fake, different ID	21	14.7	85.0 (15.8)	-	85.0
NATURALNESS					
Overall	425	8.1	63.9 (19.3)	67.4	60.2
Real	222	9.1	67.4 (20.5)	-	-
Fake	203	7.0	60.2 (17.1)	-	-
Scripted	313	4.4	59.3 (17.6)	60.6	57.8
Unscripted	107	17.9	76.7 (17.9)	85.5	66.3
Combined	5	28.2	80.7 (10.4)	85.0	77.8

Table 1: Summary statistics of accuracy on identity (top) and naturalness (bottom) tasks. Sensitivity denotes true positive rate (a real audio classified as real, and same speaker classified as same), and specificity denotes true negative rate (a fake audio classified as fake, and different speakers classified as different).

In all three parts of the study, participants were given an overview of the study and tested their hardware. For the naturalness experiments, participants were given two examples of real voices and two examples of AI-generated voices to set expectations as to the realism of the voices.

To ensure that participants were paying attention, four attention checks were randomly distributed throughout. These checks consisted of audios that clearly described the correct answer to be selected. Participants who failed any of these attention checks were removed from subsequent analysis. Participants could not progress without having listened to the entire audio(s). Participants were paid \$5 for their time.

3 Results

3.1 Identity

In the identity task, participants classified an AI-generated voice as having the same identity as a real voice 79.8% of the time (Table 1). By comparison, two real voices were correctly classified as the same identity 92.0% of the time. When the voices corresponded to different identities in these two conditions, participants were correct 89.5% and 85.7%, respectively. Chance performance is 50%. In other words, AI-cloned voices are not entirely convincing, but they are close. A Kruskal-Wallis test reveals a statistically significant effect of condition ($\chi^2(5) = 54.92$, p < 0.001). Speaker and listener demographics (age and gender) had no significant impact on accuracy.

Although not central to the question of realism, the *Fake*, *same ID* condition (penultimate row of Table 1), compared the identity of two samples of the same AI-generated voice. Participants

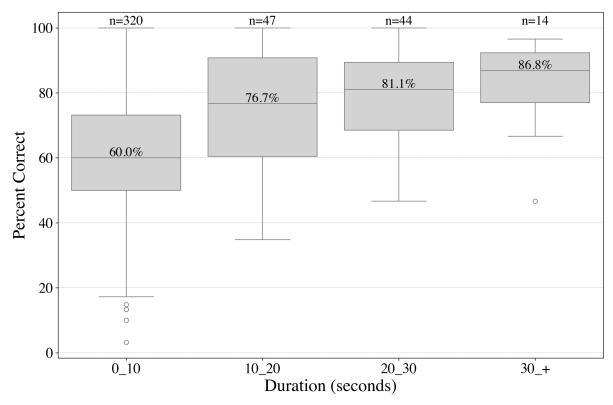


Figure 1: Accuracy on the naturalness task categorized by audio duration. Performance steadily increases with audio duration. Each box plot depicts the median (central line), 25% and 75% quartiles (gray box), 1.5 times the inter-quartile range (whiskers), and outliers (open circle).

correctly matched the voices at a rate of 93.7%. This result suggests a strong consistency between different generations of the same voice clone.

Although there is a 12 percentage point gap between identity matching of real and AI-generated voices, more often than not, the identity of AI-generated voices is convincing. We next wondered if participants could recognize a voice as AI-generated, regardless of identity.

3.2 Naturalness

In the naturalness task, for unscripted recordings (see Materials and Methods) with a mean length of 17.9 seconds (as compared to 15.8 seconds for the identity task), the mean accuracy on distinguishing a real from a fake voice was 76.7% (Table 1). This mean accuracy, however, is asymmetric where sensitivity (correctly classifying a real voice) is 85.5%, and specificity (correctly classifying a fake voice) is 66.3% (chance performance is 50%). That is, participants were unreliable at detecting AI-generated voices with a bias to reporting a voice is real.

For short scripted responses (less than 10 seconds in length), performance was also quite poor, with a mean accuracy of 59.3% and a sensitivity and specificity of 60.6% and 57.8%. The mean/median accuracy, however, increases to 82.7%/86.8% for audios longer than 30 seconds (Figure 1).

Both duration and the real condition exhibited significant effects (mixed-effects model coefficients 56.1 and 918.3, p-values 0.002 and 0.000, using a significance level of 0.05 and square-transform

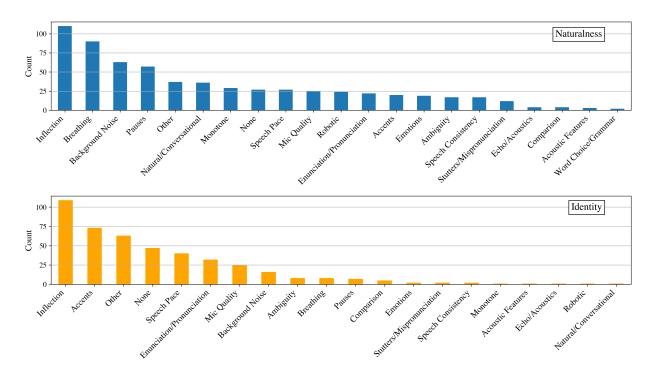


Figure 2: The 11 most frequent thematic codes as reported by participants in the naturalness (top) and identity (bottom) studies.

on the outcome variable), revealing that participants performed significantly higher on real and longer recordings. Speaker and listener demographics (age and gender) had no significant impact on accuracy.

Six audio recordings were correctly classified by all participants, all of which were real, and five of which were unscripted. We observed that these recordings contain audible background noise, opening mouth clicks, and several disfluencies (um, ah, etc.).

3.3 Qualitative Analysis

At the end of each study, participants were asked to share any tactics they used to differentiate between real/fake voice (330 responses) and same/different voice (304 responses). Keywords were extracted from their responses using a qualitative coding analysis and grouped into thematic codes. As shown in Figure 2, the top three most frequent codes in the identity task were "inflection," "breathing," and "background noise." For the naturalness task, these were "inflection," "acccent," and "other."

While some of these cues are almost certainly diagnostic, not all are. For example, "background noise" was mentioned 79 times across both studies, yet, upon analyzing the average background noise in both datasets, no significant effects on performance were found.

4 Discussion

Even in these early days of generative AI, synthesized voices have nearly passed through the uncanny valley in terms of naturalness and identity. Given the recent trajectory, there is good reason

to believe that AI-generated voices will soon be indistinguishable from reality. While this should be considered a triumph for those on the generative side, it raises real concerns for those of us on the safety side.

While modern forensic techniques [15] are better at distinguishing the real from the fake, these techniques typically operate asynchronously, making it difficult to protect consumers on phone/video calls. Our reporting of people's ability to detect AI-generated voices is almost certainly an upper bound since we drew their attention to a task that may not come naturally when they are on a call with a number or person they recognize.

One intervention that may prove useful (albeit not perfect) in mitigating the risk of AI-powered scams is the insertion of difficult to remove and easy to identify, imperceptible watermarks into AI-generated voices. With the appropriate software at the receiver, AI-generated voices can be easily identified. Another intervention, for now at least, is to keep the caller talking for more than 30 seconds at which point the chance of detecting an AI-generated voice increases.

5 Data Collection and Availability

Audio data is available at https://huggingface.co/datasets/faridlab/deepspeak_v1. Anonymized speaker and listener data is available at https://doi.org/10.5281/zenodo.13654688. This study was approved by the UC Berkeley Committee for Protection of Human Subjects (2023-09-16711). Participants provided informed consent prior to participation; data collection was performed in accordance with relevant guidelines and regulations.

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