

Characterizing the Impact of Audio Deepfakes in the Presence of Cochlear Implants

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DEEPFAKES





DEEPFAKES





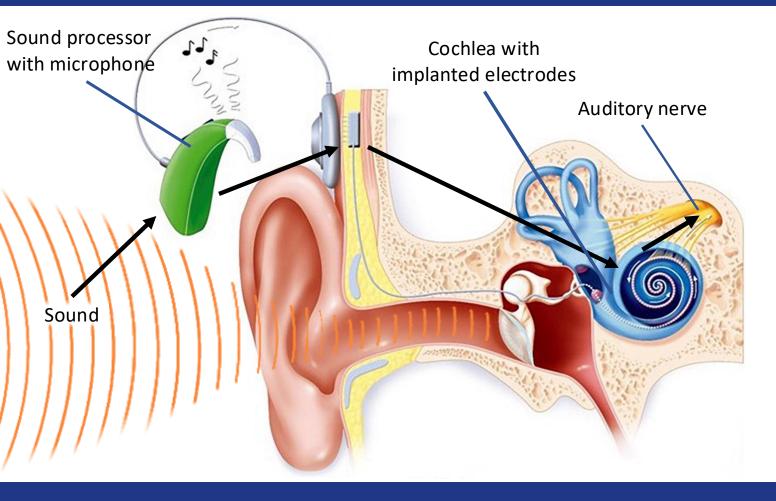
DEEPFAKES





Cochlear Implants (CIs)





Cochlear Implants (CIs)









RQ1. How susceptible are CI users to audio deepfake attacks?





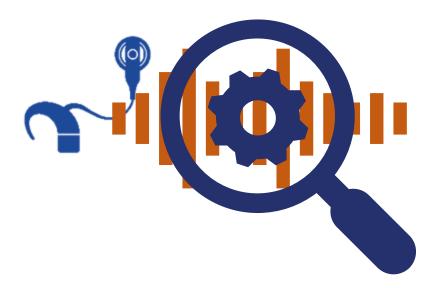
RQ1. How susceptible are CI users to audio deepfake attacks?







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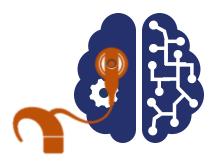
RQ2. How effective are automated





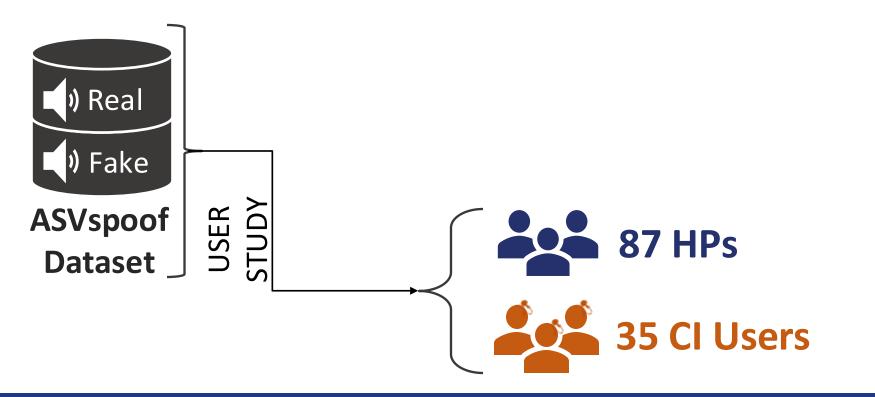
RQ1. How susceptible are CI users to audio deepfake attacks?

RQ2. How effective are automated

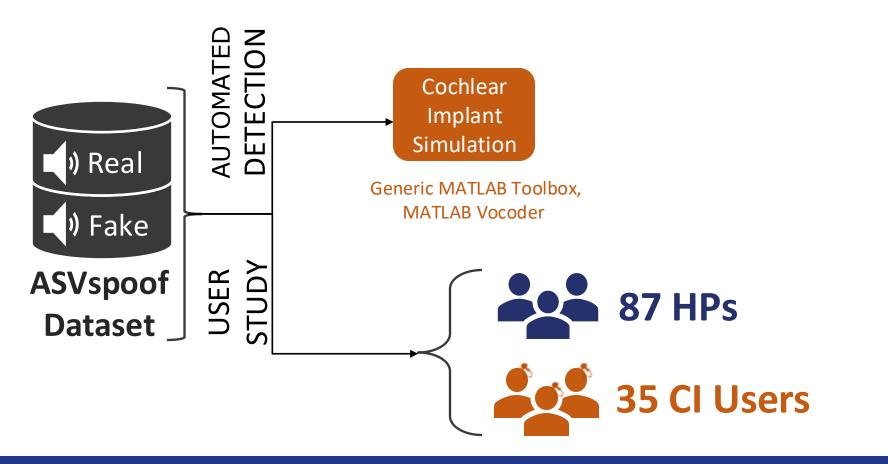


RQ3. Can these models be used as substitutes for CI users?

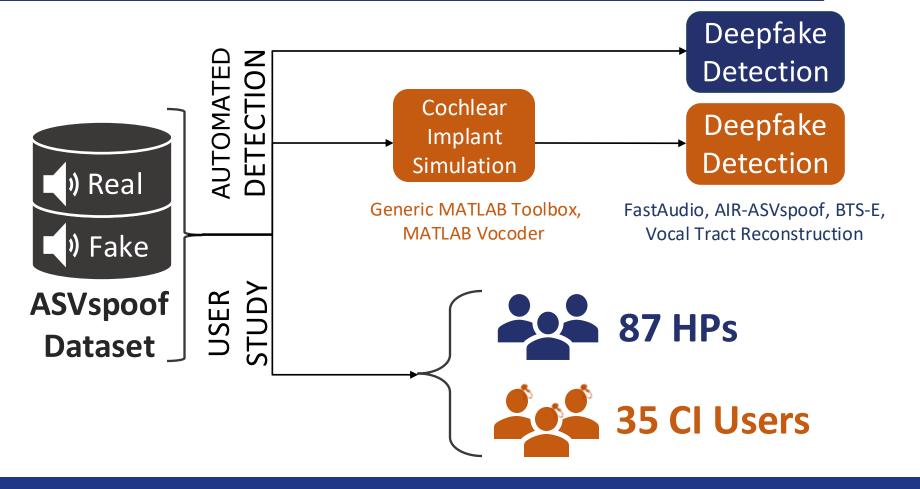










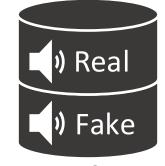






Automatic Speaker Verification spoofing detection





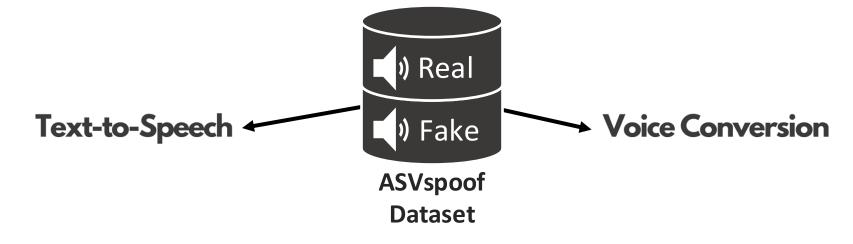
ASVspoof Dataset

Automatic Speaker Verification spoofing detection

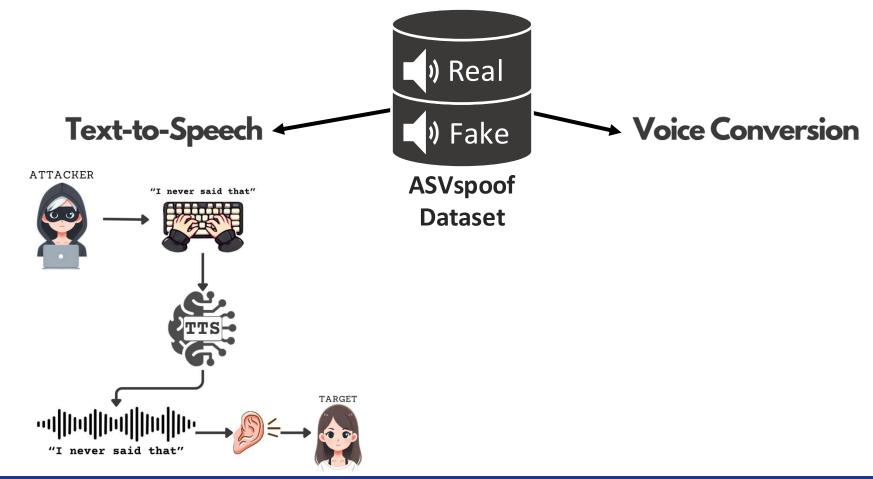
Speaker Verification

Spoofing Attack Detection

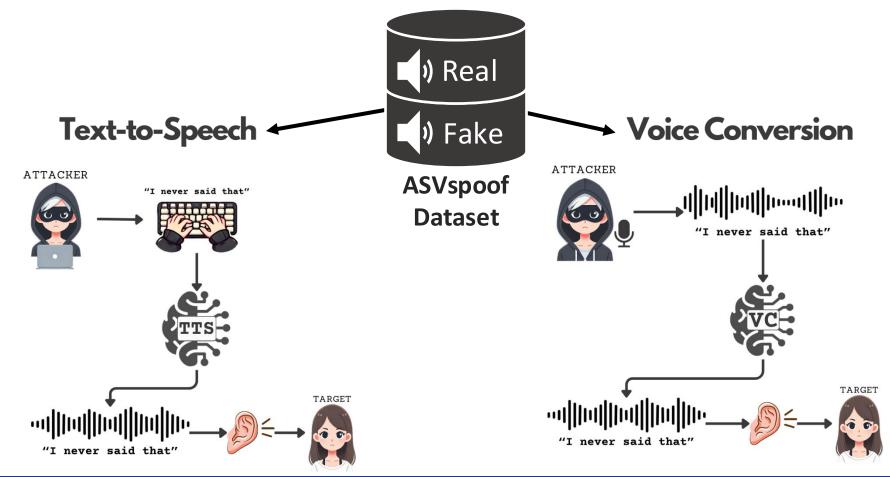










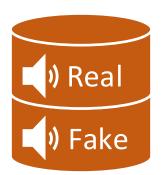


Automated Detection Results – RQ2

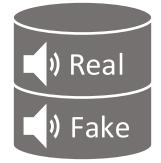




Original Dataset



CI-simulated (Generic MATLAB Toolbox) Dataset

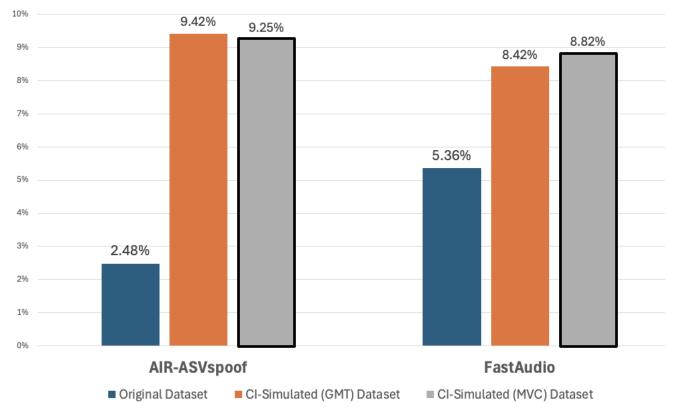


CI-simulated (MATLAB Vocoder) Dataset

Automated Detection Results – RQ2

UF

EERs



UF

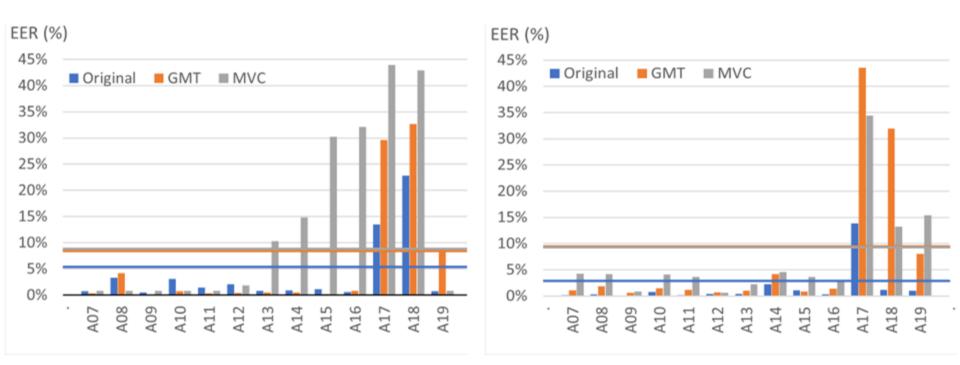
Spoofing attack systems and approaches in the ASVspoof2019 dataset

Attack	System	Approach
A01	TTS	neural waveform model
A02	TTS	vocoder
A03	TTS	vocoder
A04	TTS	waveform concatenation
A05	VC	vocoder
A06	VC	spectral filtering
A07	TTS	vocoder+GAN
A08	TTS	neural waveform
A09	TTS	vocoder
A10	TTS	neural waveform
A11	TTS	griffin lim
A12	TTS	neural waveform
A13	TTS&VC	waveform conc. & filt.
A14	TTS&VC	vocoder
A15	TTS&VC	neural waveform
A16	TTS	waveform concatenation
A17	VC	waveform filtering
A18	VC	vocoder
A19	VC	spectral filtering



FastAudio

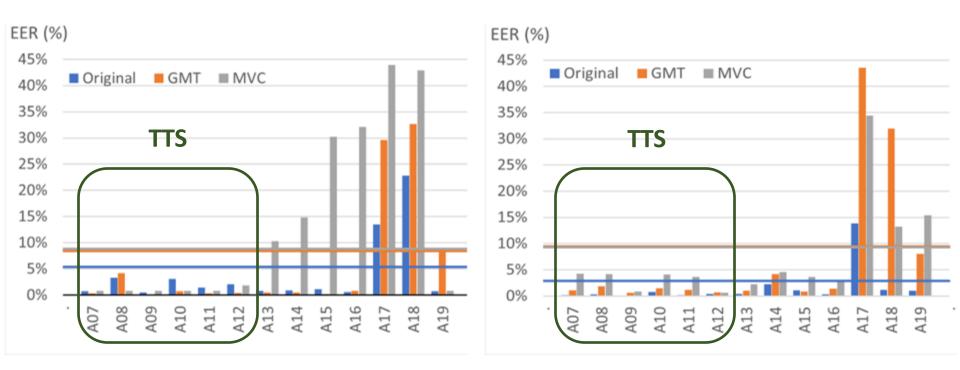
AIR-ASVspoof





FastAudio

AIR-ASVspoof

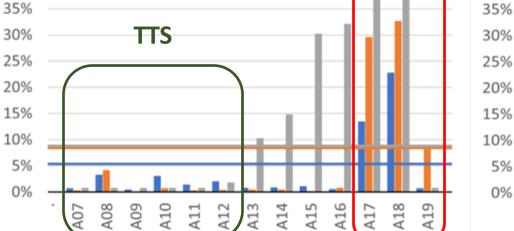


45%

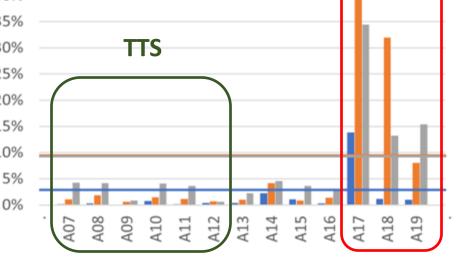
40%



FastAudio VC EER (%) EER (%) 45% Original ■ MVC Original GMT 40% 35% TTS 30% 25%

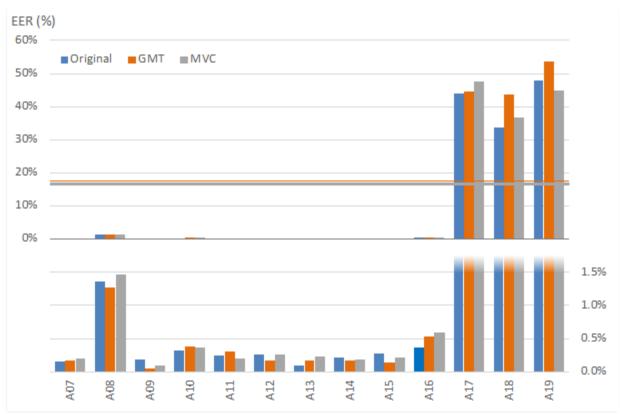


AIR-ASVspoof VC GMT MVC TTS



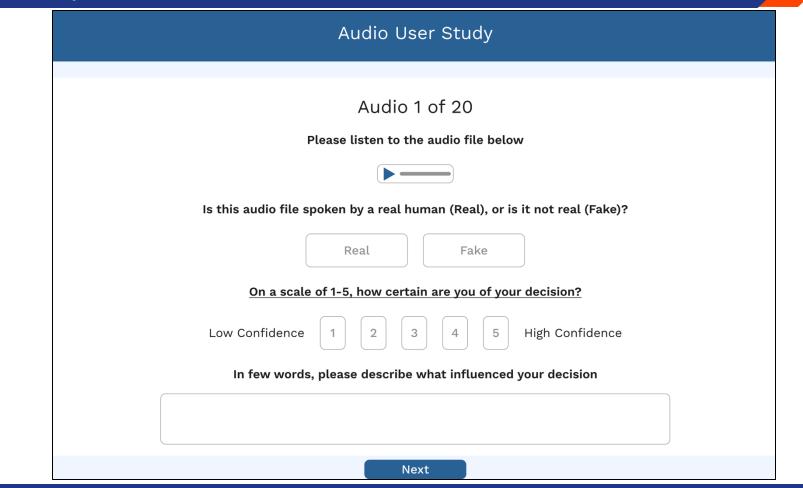


BTS-E



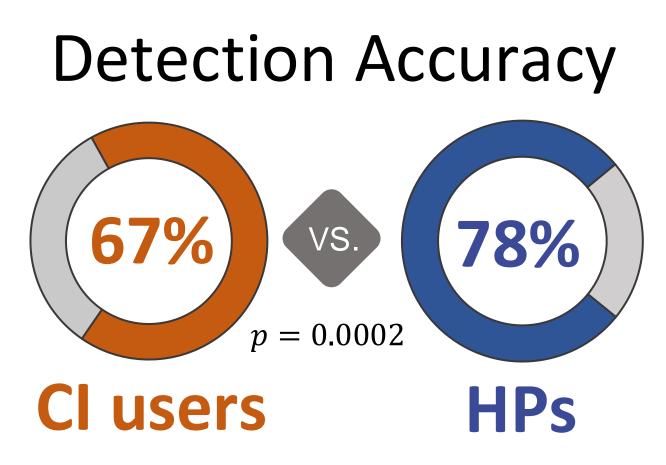
User Study – RQ1





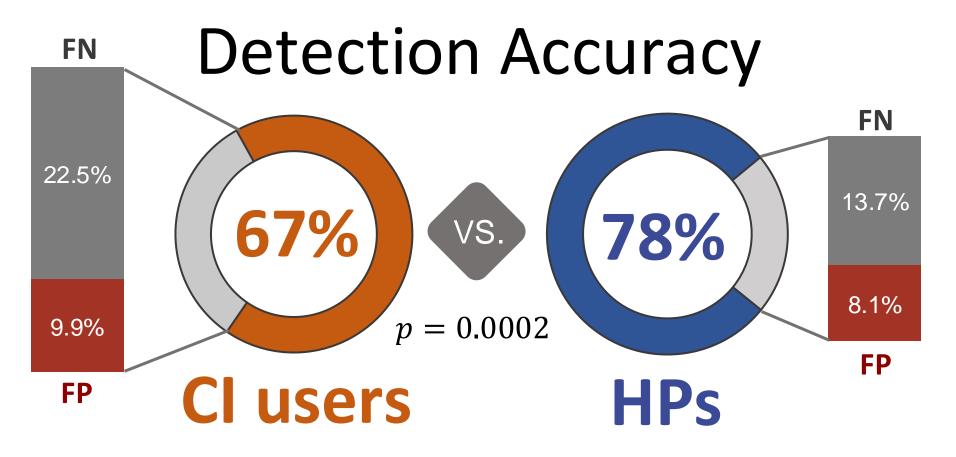
User Study Results – RQ1



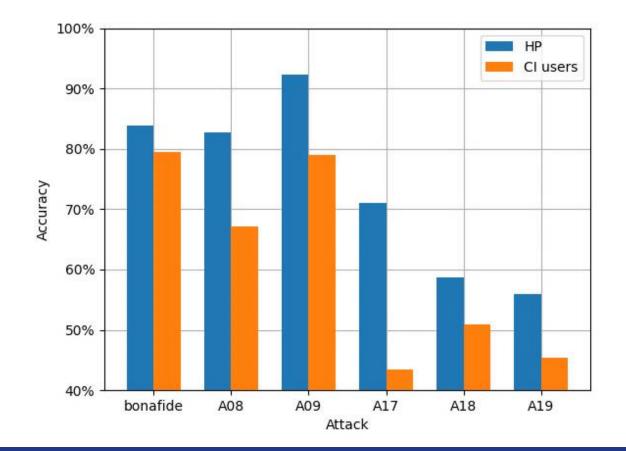


User Study Results – RQ1





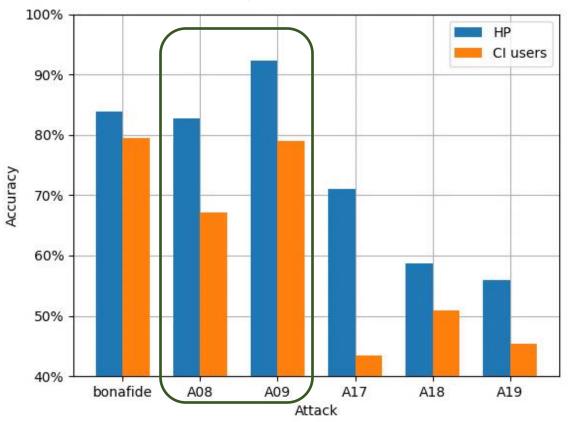




User Study Results – RQ1



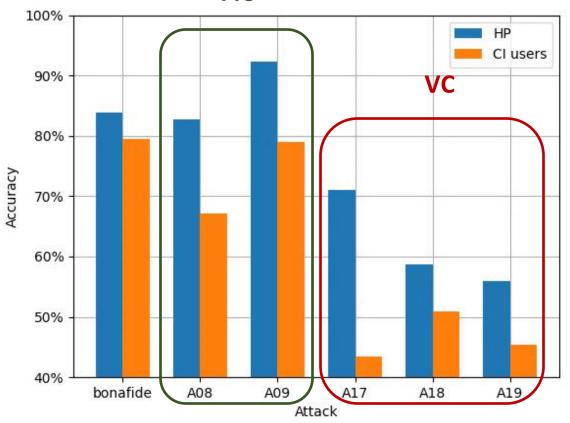
TTS



User Study Results – RQ1



TTS





WHY?

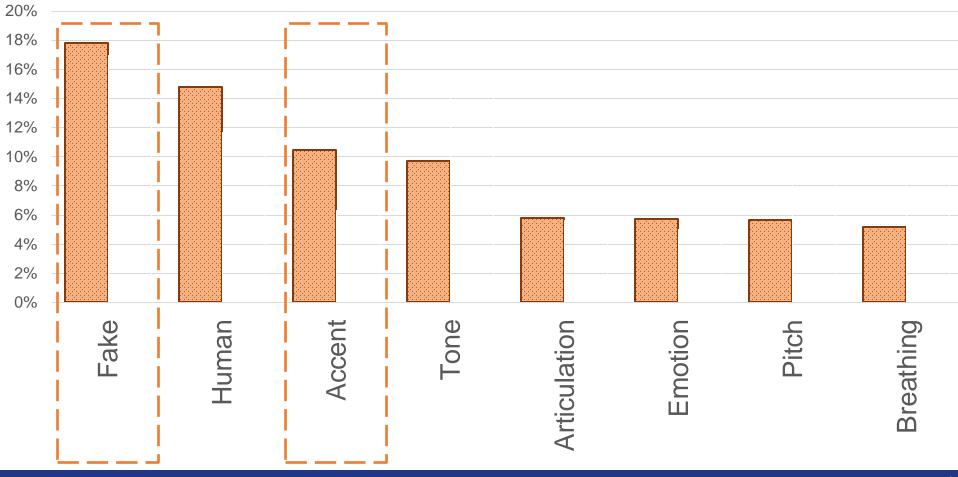


WHY?

Breathing Guess Fake Human Accent Tone Emotion Pitch Rhytm Recording Familiar Speed Pauses Mouth Articulation Background

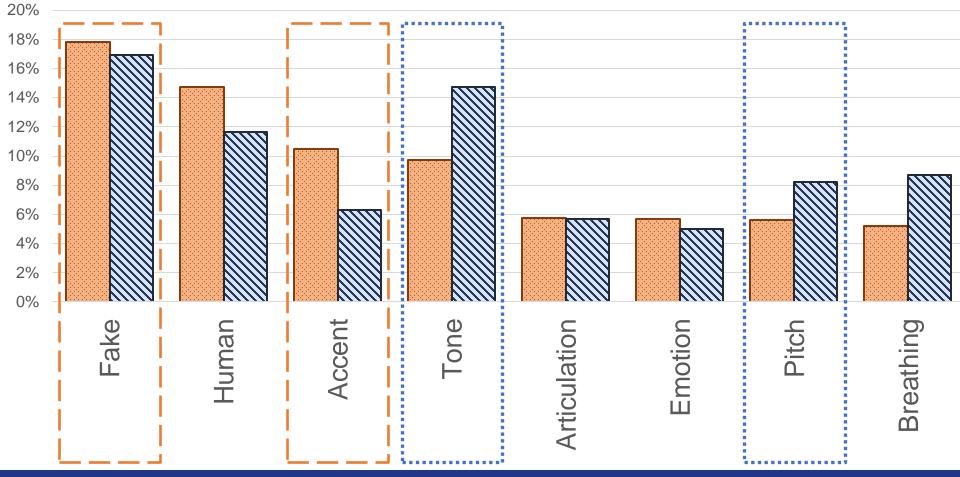
Cue Reliance – RQ1





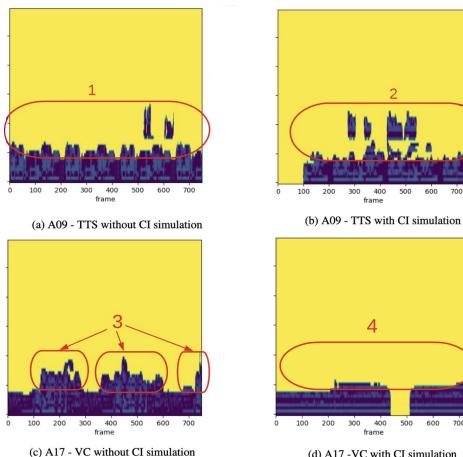
Cue Reliance – RQ1





Human vs. Model Evaluation – RQ3



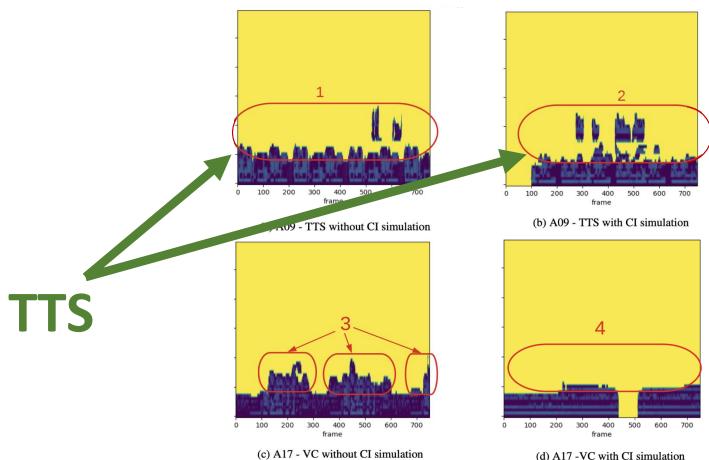


(d) A17 -VC with CI simulation

700

700

Human vs. Model Evaluation – RQ3

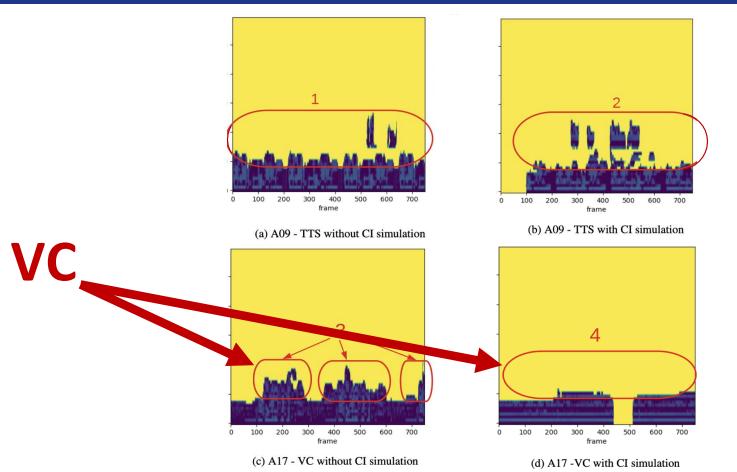


(d) A17 -VC with CI simulation

UF

FLORIDA

Human vs. Model Evaluation – RQ3



UF

FLORIDA







CI users are disproportionally vulnerable to VC deepfakes

Conclusions





CI users are disproportionally vulnerable to VC deepfakes



Improving the proxy will allow the enhancement of assistive deepfake detectors

Conclusions





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Improving the proxy will allow the enhancement of assistive deepfake detectors



Awareness & Education Programs

Conclusions





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Improving the proxy will allow the enhancement of assistive deepfake detectors



Awareness & Education Programs

Need for effective real-time assistive deepfake detection tools



Thank You

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