International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Comparative Analysis of Human and AI Generated Voice Using Pitch, Frequency and Intensity for Threat Detection.

Mahima Rani Maddela

Department of Forensic Science, Msc in Forensic Science Garden City University, Bangalore, Karnataka, India

ABSTRACT:

Human voice is the most significant mode of communication, embodying various unique acoustic qualities such as pitch, frequency, and intensity. But, with artificial intelligence steadily becoming part and parcel of daily living, those AI-generated voices are getting increasingly sophisticated, leading to great concerns regarding their actual and possible abuse in identity fraud, misinformation, and other security threats. The research distinguishes between human and AI voices, focusing on variations in pitch, frequency, and intensity. Descriptive statistical methods were then used to compare 200 paired samples of male and female voices from 18 to 26 years old. Significant differences were found for all three parameters with respect to the voice samples, which indicate that AI voices bear specific differential patterns compared to organic human speech. This study contributes an actual proof of concept toward voice forensics or danger assessment, thus providing valuable insight for developing much more effective detection systems for AI-generated voice identification.

Keywords: *AI voice changing, Pitch, Praat software, Intensity, Frequency, Threat analysis*

1. Introduction

The voice is vital for vocal communication, which makes it crucial for social interactions as well. Moreover, a person's vocal traits contribute to their identity. Given that the male voice has a lower frequency than the female voice, voice frequency is the primary trait that is frequently used to distinguish gender. The pitch of the vocal voice fluctuates as a result of changes in an individual's vocal cords [1] Human voice pitch is a variable perceptual correlate of the fundamental frequency. Men without vocal training can relax their cricothyroid and thyroarytenoid muscles to decrease their pitch. Even while it's just momentary, this change may cause other people to view masculine speakers as more aggressive, more powerful, and scary. discovered that, both with and without adjusting for the speakers' assessed fighting prowess, male speakers' perceived violent intent dramatically increased when their pitch was lowered as opposed to raised[2]. Pitch reduction, on the other hand, did not improve the perceived fighting abilities of male speakers once their perceived violent intent was statistically controlled. These results imply that, at least in men, pitch lowering serves as a warning indicator of aggression.

During infancy and early childhood, there is a presence of high pitch with a fundamental frequency range of 250-400 Hz. From childhood to adolescence, male and female voice cords gradually lengthen and thicken, resulting in a pitch of roughly 250Hz. The pitch drops significantly throughout puberty as the larynx and voice cords expand. Males' typical pitch after puberty ranges from 85 to 185 Hz, whereas girls' average pitch is 200 to 300 Hz. In maturity, the typical pitch range for males is roughly 85-180 Hz, whereas females vary from 165-255 Hz. Male pitch rises in the vocal cords as they age owing to lack of flexibility, whereas female pitch drops after menopause due to hormonal changes. The typical old male pitch varies from 110 to 130 Hz, whereas female pitches vary from 180 to 220 Hz. The selection of this sexual dimorphism in voice pitch was probably caused by male intrasexual rivalry and female preference. Men who naturally or artificially lower their voices are viewed by women as more attractive and by men as more likely to win fistfights, supporting both processes. The impact of pitch on men's perceived dominance, however, is greater than five times that of pitch on men's perceived beauty. It is advantageous for both signallers and receivers to utilize dominance signals. Men who communicate authority with lower-pitched voices are subordinate men's means of avoiding physical harm, and dominant men's means of obtaining resources without engaging in combat[3].

As the media landscape changes constantly, artificial intelligence (AI) is beginning to be integrated into our routine data usage. Artificial intelligence voice assistants, which are common in gadgets like smart speakers and smartphone integrations, are now widely used for audio-based content. These voice assistants use advanced speech synthesis, voice recognition, and natural language processing technologies to meet a variety of user needs, such as playing music, making calls, answering questions, making purchases, sharing information, and controlling other smart devices[4].

Along with the humanities, artificial intelligence has been utilized in numerous fields. Natural language processing (NLP) enables artificial intelligence to analyze massive text corpora such as books, articles, and historical records to find themes, subjects, and ideas, as well as how they change over time. AI assistants answer inquiries from digitized archives and recommend related resources, therefore disseminating humanities knowledge and facilitating humanities study. AI enables the digitization and analysis of visual materials such as ancient images, paintings, manuscripts, and schematics, allowing for better access and preservation of humanities resources. Artificial intelligence (AI) has grown significantly in recent years innovative technology with deep learning algorithms and microphones that can change a speaker's voice in real time. With the advancement of consumer-level computing technology, it is now feasible to clone a person's speech and utilize it for a phone call or online conversation. While there may be entertainment value to this technology, there is a serious security risk associated with its advances. Humans frequently pass judgment on others based only on their voice recognition in social contexts [5].

Another notable aspect of AI's visual characteristics is that its generative models generate new texts, pictures, and music in the styles of historical periods or specific artists, extending creative works and enhancing cultural study. Furthermore, AI is employed in sentiment analysis and emotion recognition by analyzing literary texts such as novels, poetry, and plays to better understand how authors represent and provoke different emotions across time. AI not only gives insights into cultural and historical patterns, but it also investigates viewers' emotional responses to artworks such as paintings, sculptures, performances, and films to better comprehend human experiences and cultural influences throughout periods. Voice analysis has been one of the most important fields of study in linguistics, psychology, and speech processing ever since time immemorial. The human voice is an acoustic signal shaped by the trinity of physiology, neurology, and emotion. Among the many aspects influencing speech production, pitch of voice plays a major role since it determines the-frequency of the vibration of vocal folds. Apart from communication, pitch variation is highly significant for speech recognition and identification verification [6]. The development in different voice research areas made it interesting and valid to study exact voice properties. Nowadays digital tools make pitch analysis, modulation, and forensic identification of voice interesting, thereby making an analysis of realization of speech by a human that much easier in both natural and artificial conditions.

2. Methodology

The materials which were used for conducting the research were:

1. Ease US Voice Wave software
2. Praat software
3. Audacity software
4. Smartphone
5. Human voices

The data acquired is empirical, and the sampling method employed is convenient sampling.

Data Collection

1. The speech recordings or the voice samples were obtained from 200 individuals where it was consisting of 100 Males and 100 Females of age ranging from 18 to 26.
2. Each individual belonged to a different region in India and each individual was given a specific sentence to speak for 10 seconds and recorded in two different recorders. The normal human voice was recorded by smartphone and the AI voice was by laptop using a mic.
3. The AI voice was bought by using a Voicemod software installed in the laptop which had changed the voice configuration of the laptop into AI voices based on gender.
4. The Voicemod software converted the normal voice into AI voice when an individual speaks on the laptop using a mic and the AI voice was recorded using the Audacity software on the laptop.
5. The normal human voice and AI voice of each individual were been recorded in the format of an MP3 audio file.

Analysis

1. The Praat software was utilized to evaluate the voice recordings of every participant.
2. Open the Praat software and import the audio files individually by specifying the normal voice and AI voice in the objects table. Click on the voice sample file individually to analyze the speech characters of each individual's normal and AI voice.
3. The audio spectrograph was selected and played for listening to the sentences and words. Pay attention to the speech character such as pitch, frequency, and intensity of the voice. This same method has been individually followed for the normal and AI voice samples.

4. The speech characters of the selected sentence in the voice sample showed specific numerical values which were been noted separately in the Excel sheet for the normal and AI voice of every individual.

5. Based on the values observed in normal and AI voice samples the differences between the AI and normal voices in their pitch, frequency, and intensity were been calculated separately.

6. The statistical analysis of Correlation was done individually for the speech characters that is pitch, frequency, and intensity of AI voice and normal voice.

3. Result and Discussion

This study was carried out to suggest and clarify the relationship between the typical human voice and the AI voice. Some specific acoustic parameters were taken for the analysis of both voices: pitch, frequency, and intensity. This aimed to analyzed the comparison and the difference in the voice samples of both male and female participants. Our sample consisted of 200 pairs of voice samples, comprising 100 males and 100 females. Each voice sample was meticulously analyzed, and there were notable differences in pitch, frequency, and intensity between both genders. These findings were clearly illustrated in the following graph to facilitate understanding and highlight the differences in the normal and AI voices.
The figures below show the details of each individual's pitch, frequency, and intensity values in the form of chart, where we can observe a wide difference in pitch and frequency and less difference in intensity between normal and AI voices.

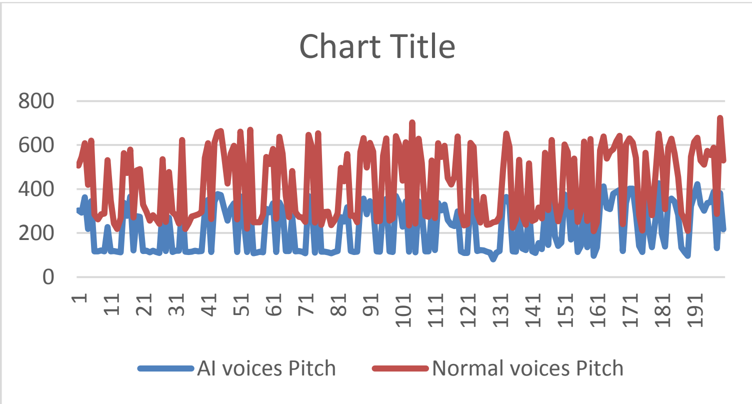

Fig 1: Pitch values of normal and AI voices in humans.

The figure 1 shows the values of the pitch in normal and AI voices in humans. The orange line in graph shows the normal voice and the blue line indicates the AI voices. The image depicts about the how the normal and AI voices are having a great difference where normal voice is having greater pitch than the AI voice.

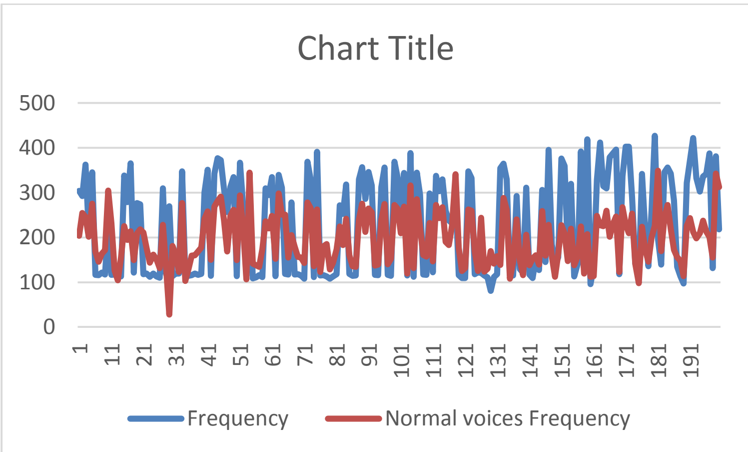

Fig 2: Frequency values of normal and AI voices in humans.

The figure 2 show that values of frequency of normal and AI voices in humans. The image depicts the frequency between the normal and AI voice has been having an overlap between the samples. Based on the figure 1 and 2 of pitch and frequency, the analysis has revealed an difference of approximately 112.79Hz between the male and female human voices. This aligns with the biological expectations where the female vocal folds vibrate faster due to small size and the structure than the male. While the AI generated voice has a broad pitch gap which demonstrated an narrower intra group variability. The AI voice remain tightly constrained which reflects both model smoothing and the absence of natural physiological variation which makes the AI speech sound more uniform.

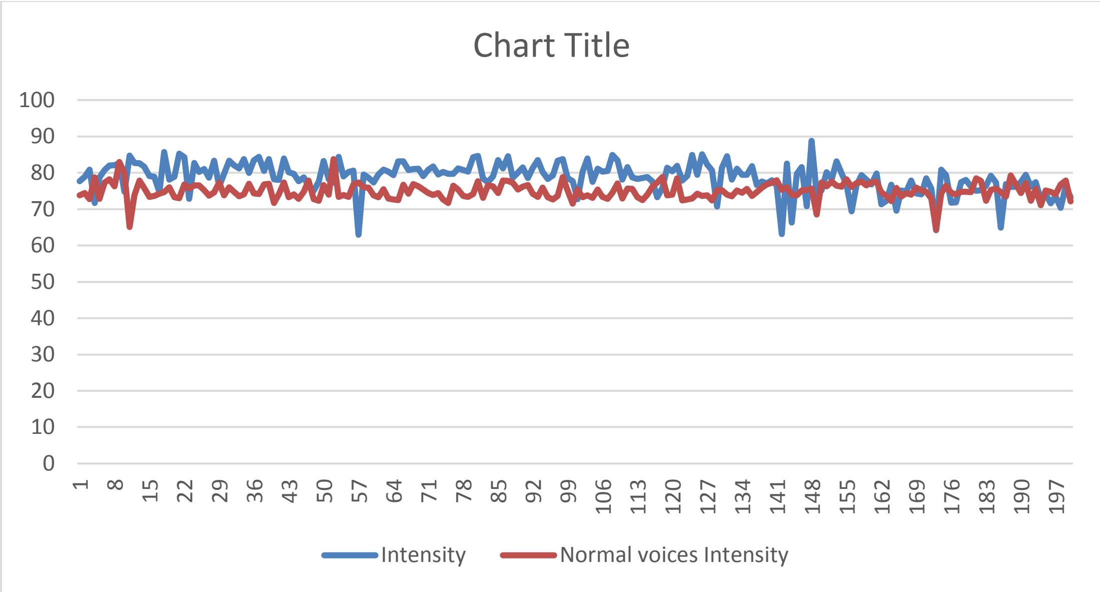

Fig 3: Intensity values of normal and AI voices in humans.

The figure 3 show that values of intensity of normal and AI voices in humans. The image depicts the intensity between the normal and AI voice has been ranging between 70-90 Hz in the samples. The intensity shows an minimal divergence between male and female voice which implies that intensity is not alone a strong predictor for speaker identity or the voice type. But in AI generated voices the voices produce via them tend to produce mire louder outputs dues the standardised volume setting during the speech synthesis which makes them appear more acoustically prominent but not natural.

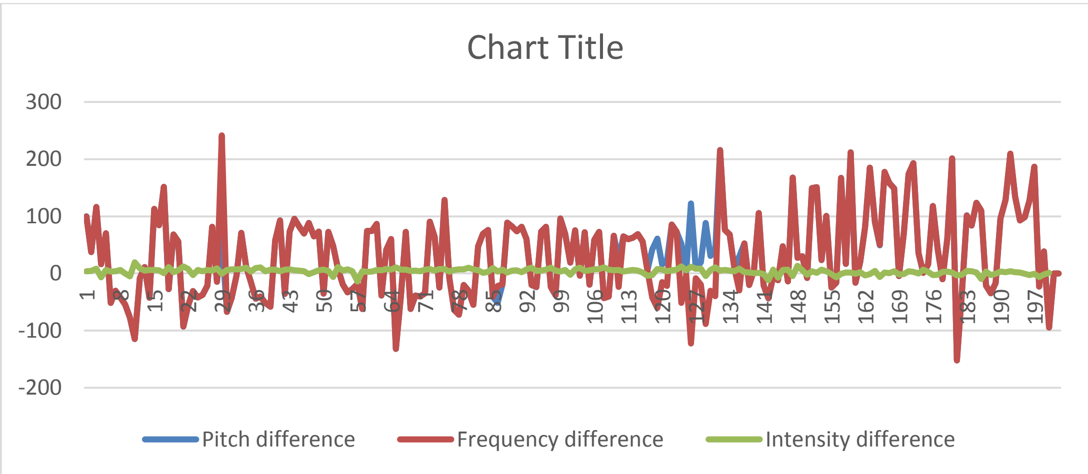

Fig 4: Overall differences in pitch, frequency, and intensity.

The below figure 4 demonstrates the overall differences in pitch, frequency, and intensity between normal and AI voices, with the pitch and frequency overlapping in the maximum range and the bottom showing the intensity level.

Samples	AI voices			Normal voices					
	Pitch	Frequency	Intensity	Pitch	Frequency	Intensity	Pitch difference (AI-Normal)	Frequency difference (AI-Normal)	Intensity difference (AI-Normal)
Samples 1	303.54	303.5	77.68	203.8	203.8	73.85	99.74	99.7	3.83
Samples 2	292.13	292.1	78.92	254.67	254.7	74.47	37.46	37.4	4.45
Samples 3	362.16	362.2	80.87	246.11	246.1	72.76	116.05	116.1	8.11
Samples 4	217.85	217.9	71.69	201.58	201.6	78.72	16.27	16.3	-7.03
Samples 5	345.26	345.3	78.75	275.24	275.2	72.83	70.02	70.1	5.92
Samples 15	337.87	337.9	79.12	225.11	225.1	73.36	112.76	112.8	5.76
Samples 16	278.78	278.8	78.89	194.54	194.5	73.68	84.24	84.3	5.21
Samples 17	365.15	365.2	74.69	213.85	213.9	74.23	151.3	151.3	0.46
Samples 19	276.41	276.4	78.16	208.46	208.5	76.02	67.95	67.9	2.14
Samples 20	273.62	273.6	78.9	217.71	217.7	73.32	55.91	55.9	5.58
Samples 27	309.11	309.1	78.64	227.45	227.8	73.71	81.66	81.3	4.93
Samples 29	269.56	269.6	76.32	207.9	27.9	77.3	61.66	241.7	-0.98
Samples 33	347.23	347.2	81.21	276.45	276.5	73.54	70.78	70.7	7.67
Samples 40	299.98	300	78.23	241.72	241.7	71.74	58.26	58.3	6.49
Samples 41	350.96	351	78.06	258.106	258.1	74.11	92.854	92.9	3.95
Samples 43	342.31	342.3	80.2	268.96	269	73.31	73.35	73.3	6.89
Samples 44	376.76	376.8	79.74	281.04	281	74.05	95.72	95.8	5.69
Samples 45	372.64	372.6	77.71	290.8	290.8	72.87	81.84	81.8	4.84

Fig 5: The values of the pitch, frequency, and intensity and their differences in the females.

Samples	AI voices			Normal voices					
	Pitch	Frequency	Intensity	Pitch	Frequency	Intensity	Pitch difference (AI-Normal)	Frequency difference (AI-Normal)	Intensity difference (AI-Normal)
Samples 6	116.2	116.2	80.8	167.65	167.7	77.32	-51.45	-51.5	3.48
Samples 7	116	115.96	82.01	146.09	146.1	78.182	-30.09	-30.14	3.828
Samples 8	121.58	121.6	82.11	163.75	163.8	76.32	-42.17	-42.2	5.79
Samples 9	117.28	117.3	82.71	171.59	171.6	83	-54.31	-54.3	-0.29
Samples 10	226.91	226.9	74.8	304.42	304.4	79.94	-77.51	-77.5	-5.14
Samples 11	116.82	116.8	84.71	231.52	231.5	65.1	-114.7	-114.7	19.61
Samples 12	117.47	117.5	82.68	125.72	125.7	73.77	-8.25	-8.2	8.91
Samples 13	115.22	115.2	82.65	104.01	104	77.89	11.21	11.2	4.76
Samples 14	112.74	112.7	81.7	155.19	155.2	75.76	-42.45	-42.5	5.94
Samples 18	121.62	121.6	85.69	149.33	149.3	74.68	-27.71	-27.7	11.01
Samples 21	117.69	117.7	85.3	210.93	210.9	73.06	-93.24	-93.2	12.24
Samples 22	119.54	119.5	84.34	175.84	175.8	76.84	-56.3	-56.3	7.5
Samples 23	112.31	112.3	72.85	143.39	143.4	75.67	-31.08	-31.1	-2.82
Samples 24	119.17	119.2	82.72	161.49	161.5	76.56	-42.32	-42.3	6.16
Samples 25	113.06	113.1	80.26	150.97	151	76.56	-37.91	-37.9	3.7
Samples 26	109.93	109.9	81.04	131.23	131.2	75.25	-21.3	-21.3	5.79
Samples 28	117.97	118	83.33	132.74	132.7	74.64	-14.77	-14.7	8.69
Samples 30	113.59	113.6	79.68	180.89	180.9	73.78	-67.3	-67.3	5.9

Fig 6: The values of the pitch, frequency, and intensity and their differences in the males.

The above figure (5, 6) shows the values of pitch, frequency, and intensity that were obtained while analyzing normal and AI voice samples in Praat software, and their differences were analyzed in Excel.

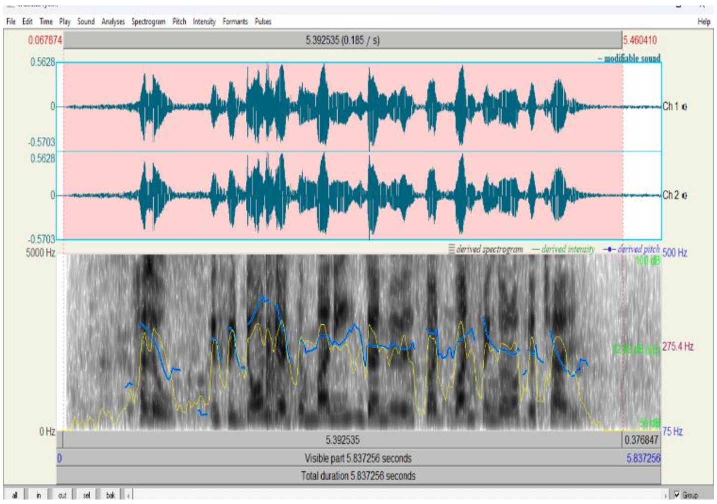

Fig 7: The pitch, frequency, and intensity are shown for the normal voice sample.

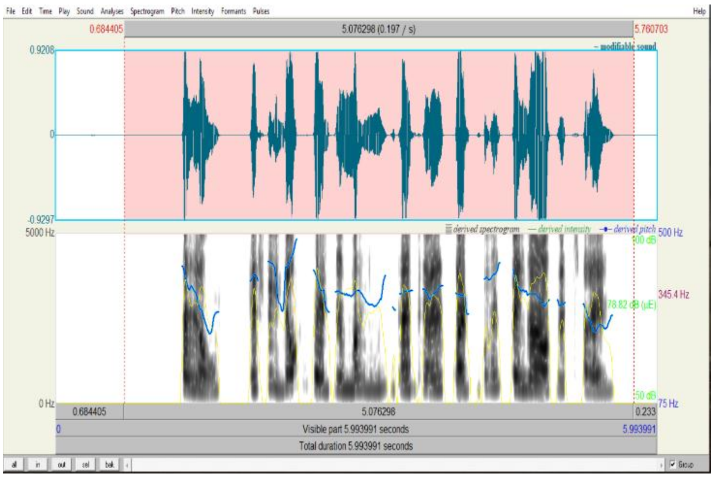

Fig 8: The pitch, frequency, and intensity are shown for the AI voice sample.

The figures (7,8) show the normal voice and AI voice spectrograph which was analyzed by the Praat software. This blue in this is indicating about the pitch of the voice sample and the yellow line is indicating about the intensity of the voice. The side value 275.4Hz in normal voice and 345.4 Hz is indicating the overall frequency of the sample.

Gender-specific difference patterns of the pitch, frequency, and differences in intensity of participants were unfolded through analysis as follows:

Pitch Differences: For females, the maximum range for pitch differences existed between 67.32 Hz and 89.63 Hz, found with 27 female participants. Comparatively, among males, the maximum pitch differences range existed between –55.27 Hz and 9.73 Hz with 36 male participants.

Frequency Differences: The greatest range of frequency differences in 40 women was 56.79 Hz to 86.93 Hz. The frequency difference range in 34 men was significantly smaller, ranging from -65.8 Hz to -29.6 Hz.

Intensity Differences: The greatest intensity difference in 33 men was 4.12 dB to 7.82 dB. The intensity differences for 28 women, however, ranged from 3.71 dB to 6.39 dB.

The analysis of pitch, frequency, and intensity variations revealed notable trends that differentiate male and female voice characteristics in both human and AI-generated samples. Female participants demonstrated broader pitch shifts, indicating greater tonal variability and possibly richer vocal dynamics in both natural and synthetic forms. Males, however, showed a wider distribution skewed toward lower pitch differences, suggesting a flatter tonal pattern, particularly among AI-generated voices.

Frequency differences among female voices were also substantially higher, peaking close to 94 Hz, further underscoring the variability and modulation typically present in female speech patterns. Male frequency ranges, by contrast, showed consistently negative deltas, implying a shift or compression effect in AI replication of male voices.

In terms of intensity, both genders exhibited comparable ranges, though males slightly surpassed females in both average and maximum intensity variance. This could indicate less dynamic amplitude modulation in female AI models or greater loudness normalization in female recordings. These findings contribute to the broader understanding of how voice synthesis systems preserve or distort natural acoustic traits, and provide insight for improving realism in gender-specific AI voices. Pearson correlation coefficient was calculated for intensity, pitch, and frequency in AI and normal voice (1 = positive co-relation, -1 = negative co-relation). The positive value greater than 0.5 and the negative value less than -0.5 show a perfect co-relation. When the co-relation was taken for the total participants, the values observed for all three parameters were pitch ($r_p = 0.7894$), frequency ($r_f = 0.7677$), and intensity ($r_i = -0.00433$), where we can observe the perfect negative co-relation in intensity.

When the co-relation of the parameters was taken separately for males and females, the females had the co-relation values observed for pitch ($r_p = 0.42472$), frequency ($r_f = 0.1326$), and intensity ($r_i = -0.00130$) and the males had the co-relation values observed for pitch ($r_p = 0.5492$), frequency ($r_f = 0.1568$), and intensity ($r_i = -0.0522$) where both males and females showed perfect negative co-relation in their intensity. It was also found out that the intensity showed inverse correlation between AI and normal voices.

4. Conclusion

The study focuses on the potential of Artificial Intelligence (AI) in voice synthesis, highlighting the importance of human voice analysis in assessing threats. The findings suggest a perfect correlation between AI-generated voice and the normal human voice for a parameter, indicating that AI voice closely matches the human voice in this aspect. Among the important findings was the high positive correlation between pitch and frequency for men and women, which indicates that while AI voices closely approximate some natural vocal parameters, they still have recognizable differences when closely scrutinized by way of overall acoustic analysis. The intensity parameter was particularly enlightening, showing a weak or even negative correlation, which indicates that AI synthesis continues to have trouble approximating the dynamic vocal energy and emotional expressiveness that are inherent in human speech. This difference can conceivably be a valuable discriminator in forensic audio authentication and threat assessment. Against the backdrop of alarming abilities of AI-powered voice technology–demonstrated by deepfakes and voice impersonation in cyber-attacks–the study underlines not just the sophisticated quality of artificial voices but also the corresponding security risks. The risks increase the need for robust detection systems and protocols that provide privacy-preserving voice verification. The biological markers ingrained in speech are highlighted by the notable pitch difference between human male and female voices. The decreased intensity variation indicates a limited emotional range, which is crucial for human-like voice synthesis, even though AI-generated voices mimic these patterns. These results offer a starting point for upcoming advancements in AI voice technology. But the study acknowledges its own sample size and diversity limitations and attempts to emphasize the necessity of large-scale research to confirm and extend these results. Future studies could be improved by the use of a more diverse population, more voice parameters, and machine learning-based classifiers to further facilitate AI voice identification. In summary, as AI voice synthesis developments are progressing at a fast pace, this research offers a useful point of reference in comprehending its acoustic limitations and associated security considerations. It emphasizes the paramount importance of pitch and frequency as distinguishing factors in the discipline of voice forensics and advocates ongoing caution and ingenuity in protecting human auditory identity against synthetic media proliferation.

REFERENCES:

1. L. S. Boogers, B. S. J. Chen, M. J. Coerts, R. N. P. M. Rinkel, and S. E. Hannema, “Mobile phone applications Voice Tools and Voice Pitch Analyzer validated with LingWAVES to measure voice frequency,” J. Voice, Nov. 2022.
2. J. Zhang, B.-B. Chen, C. Hodges-Simeon, G. Albert, S. J. C. Gaulin, and S. A. Reid, “Elevated recognition accuracy for low-pitched male voices in men with higher threat potential: Further evidence for the retaliation-cost model in humans,” Evol. Hum. Behav., vol. 42, no. 2, pp. 148–156, Mar. 2021.
3. J. Zhang and S. A. Reid, “Aggression in young men high in threat potential increases after hearing low-pitched male voices: two tests of the retaliation-cost model,” Evol. Hum. Behav., vol. 38, no. 4, pp. 513–521, Jul. 2017.
4. T. Tsourakas, G. Terzopoulos, and S. Goumas, “Educational use of Voice Assistants and Smart Speakers,” J. Eng. Sci. Technol. Rev., vol. 14, no. 4, pp. 1–9, 2021.
5. J. J. Bird and A. Lotfi, “Real-time detection of AI-generated speech for DeepFake Voice Conversion,” arXiv [cs.SD], 24-Aug-2023.
6. P. K. Sharma et al., “Eminent method of voice identification by applying pitch, intensity and pulse,” in RECENT TRENDS IN SCIENCE AND ENGINEERING, Krishnagiri, India, 2022.
7. H. White, J. Penney, A. Gibson, A. Szakay, and F. Cox, “Influence of pitch and speaker gender on perception of creaky voice,” J. Phon., vol. 102, no. 101293, p. 101293, Jan. 2024.
8. R. S. Gisladottir et al., “Sequence variants affecting voice pitch in humans,” Sci. Adv., vol. 9, no. 23, p. eabq2969, Jun. 2023.
9. C. J. Chen and D. A. Miller, “Pitch-synchronous analysis of human voice,” J. Voice, vol. 34, no. 4, pp. 494–502, Jul. 2020.
10. D. K. Singh, G. P. Prajapati, and H. A. Patil, “Voice Privacy Using Time-Scale and Pitch Modification,” SN Computer Science, vol. 5, no. 2, p. 243, Jan. 2024.
11. C. Krumpholz, C. Quigley, K. Ameen, C. Reuter, L. Fusani, and H. Leder, “The effects of pitch manipulation on male ratings of female speakers and their voices,” Front. Psychol., vol. 13, p. 911854, Jul. 2022.
12. A. B. Baskoro, N. Cahyani, and A. G. Putrada, "Analysis of voice changes in anti-forensic activities case study: Voice changer with telephone effect," Int. J. Inf. Commun. Technol. (IJoICT), vol. 6, no. 2, pp. 64–77, Oct. 2020.
13. G. Cho, J. Choi, H. Kim, S. Hyun, and J. Ryoo, “Threat modeling and analysis of voice assistant applications,” in Information Security Applications, Cham: Springer International Publishing, 2019, pp. 197–209.
14. H. Kawahara, K. Yatabe, K.-I. Sakakibara, T. Kitamura, H. Banno, and M. Morise, “Objective measurement of pitch extractors’ responses to frequency modulated sounds and two reference pitch extraction methods for analyzing voice pitch responses to auditory stimulation,” arXiv [cs.SD], 05-Nov-2021.
15. V. U. Aithal, R. Bellur, S. John, C. Varghese, and V. Guddattu, “Acoustic analysis of voice in normal and high pitch phonation: a comparative study,” Folia Phoniatr. Logop., vol. 64, no. 1, pp. 48–53, 2012.
16. Y. Dai, J. Lee, and J. W. Kim, “AI vs. Human Voices: How Delivery Source and Narrative Format Influence the Effectiveness of Persuasion Messages,” International Journal of Human-Computer Interaction, pp. 1–15.
17. M. Aliaskar, T. Mazakov, A. Mazakova, S. Jomartova, and T. Shormanov, “Human voice identification based on the detection of fundamental harmonics,” in 2022 IEEE 7th International Energy Conference (ENERGYCON), Riga, Latvia, 2022.
18. A. J. S. S. Jha, “Analysis of Human Voice for Speaker Recognition: Concepts and Advancement,” Journal of Electrical Systems, vol. 20, no. 1s, pp. 582–599, Mar. 2024.
19. L. Bakkouche, S. Cooper, X. Luo, M. Rees, and E. Lau, "Finding the Human Voice in AI: Insights on the Perception of AI-Voice Clones from MUSHRA and Similarity Tests," Cambridge University Press, 2024.
20. J. J. Bird and A. Lotfi, "Real-time Detection of AI-Generated Speech for DeepFake Voice Conversion," arXiv preprint arXiv:2308.12734, 2023.
21. H. A. Hamid, "What Happens When Students Have Artificial Intelligence Do Their Assignments for Them," Asian Journal of Distance Learning, 2023.
22. C. Mamahit, A. Wauran, F. Manoppo, and F. Seke, "Smart Home with Voice Control Lights Using Arduino Uno R3," JURNAL EDUNITRO, 2023.
23. A. Boutadjine, F. Harrag, and K. Shaalan, "Human vs. Machine: A Comparative Study on the Detection of AI-Generated Content," ACM Transactions on Asian and Low-Resource Language Information Processing, vol. 2025.
24. J. Brusseau, "AI human impact: Toward a model for ethical investing in AI-intensive companies," Journal of Sustainable Finance & Investment, 2023.

25. G. G. Genelza, "A Systematic Literature Review on AI Voice Cloning Generator: A Game-changer or a Threat?" Journal of Emerging Technologies, 2024.
26. K. Warren, D. Olszewski, S. Layton, and K. Butler, "Pitch Imperfect: Detecting Audio Deepfakes Through Acoustic Prosodic Analysis," arXiv preprint arXiv:2502.14726, 2025.
27. K. Kumari, M. Abbasihafshejani, A. Pegoraro, and P. Rieger, "VoiceRadar: Voice Deepfake Detection using Micro-Frequency and Compositional Analysis," NDSS Symposium, 2025.
28. L. Bradshaw, V. Perepelytsia, and V. Dellwo, "Vocal effort in human interactions with voice-AI," Proceedings of the International Speech Communication Association, 2023.