Gender Biases in Digital Audio Coding: Impacts on Female Vocal Representation and Listener Perception

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Elizabeth J. Recktenwald

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Advisor
Bryn E. Seabrook, Department of Engineering and Society

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Introduction; Who Isn't Heard?

Have you ever had a choir or band class over Zoom or Microsoft Teams and think, "That sounded awful"? Well, this is actually a common thought amongst many. Digital audio algorithms use frequency cutoffs to "optimize" audio transmission, but these optimizations are not always neutral. Research suggests that audio compression disproportionately affects female voices, as higher-frequency components—more common in female speech—are often lost or distorted during coding processes (Herre & Dick, 2019; Moore & Tan, 2003). Psychoacoustic models used in perceptual audio coding were primarily designed around male vocal characteristics, leading to an imbalance in how voices are processed (Herre & Dick, 2019).

Digital audio technology plays a crucial role in how we communicate, experience entertainment, and engage with artistic expression. However, biased audio processing has tangible consequences, influencing how female voices are perceived in professional settings, music production, and AI-driven voice applications (Gallardo & Sanchez-Iborra, 2019). Research indicates that when female voices are compressed using certain algorithms, they are often perceived as less warm and engaging, which can contribute to their subconscious devaluation (Gallardo & Sanchez-Iborra, 2019). Additionally, the underrepresentation of women in audio technology development exacerbates this issue, as design decisions often reflect the perspectives of a male-dominated industry (Mathew et al., 2016).

This paper investigates how digital audio coding biases affect female vocal representation and listener perception. Using the Social Construction of Technology (SCOT) framework (Pinch & Bijker, 1984) and the concept of Technological Momentum (Hughes, 1969), this analysis explores how social and cultural factors influence the development of digital audio technology and why biased systems, once widely adopted, are resistant to change. By examining existing research, this study highlights both the structural and perceptual consequences of biased audio coding and its broader gender implications in digital media.

Methods

This study investigates how digital audio coding algorithms contribute to gender bias by disproportionately distorting high-frequency vocal characteristics. Female voices, which typically exhibit higher fundamental frequencies compared to male voices, are particularly affected by this degradation. The research specifically explores whether such distortion influences listener perception, potentially fostering a subconscious preference for male voices in music and media.

This research adopts a literature review methodology, synthesizing existing studies on digital audio compression, gender bias, and voice recognition technologies. Data was gathered from peer-reviewed articles, industry reports, and relevant case studies, with a focus on the impacts of compression algorithms on female vocal clarity and their broader social implications. Key terms guiding this research include codec, gender bias, vocal perception, and audio compression artifacts.

The paper is structured as follows: The Results section presents findings on how digital audio codecs affect different vocal frequencies and listener perception. The Discussion section contextualizes these findings within STS frameworks, particularly Social Construction of Technology (SCOT) and Technological Momentum, to analyze how gender biases persist in digital audio processing. Finally, the paper addresses limitations and suggests future research directions.

Background: Why is this Issue Important?

Digital audio coding is the process of compressing audio files to reduce their size while trying to maintain sound quality. Platforms like Zoom and Microsoft Teams rely on these compression techniques to make real-time communication possible. However, perceptual audio coding—the method used to determine which sounds can be removed without noticeable loss—does not work equally well for all voices because it prioritizes certain frequency ranges over others. Since these algorithms have traditionally been optimized for average male vocal characteristics, they tend to preserve lower frequencies more effectively while unintentionally distorting or degrading higher frequencies, which are more prominent in female voices.

Historically, early audio compression standards, such as the MP3 format developed in the 1980s and 1990s, were designed based on psychoacoustic models tested primarily on male voices (Brandenburg & Bosi, 1997). The research teams developing these codecs relied on listening tests conducted predominantly with male participants, leading to optimization decisions that prioritized male vocal characteristics. These early choices have had a lasting impact, as many modern compression algorithms build upon the same foundational psychoacoustic principles.

One of the core principles of audio coding is psychoacoustic masking, where certain sounds become imperceptible when louder sounds at nearby frequencies dominate. Research by Herre and Dick (2019) highlights how psychoacoustic models are essential in audio compression, but they often fail to fully capture the range of female vocal frequencies. Since lower-frequency sounds—more common in male voices—are preserved more effectively, higher-frequency components in female voices tend to get lost in compression (Moore & Tan, 2003). This leads to a degradation in clarity and warmth, making female voices sound thinner or more artificial, which can impact how they are perceived in both professional and entertainment settings.

The issue is worsened by a lack of diversity in the development of audio technology. Audio engineering and algorithm design have historically been male-dominated fields, meaning that decisions about what aspects of sound quality are prioritized have largely been shaped by male perspectives (Mathew et al., 2016). As a result, female vocal characteristics have often been overlooked—not necessarily by intention, but due to the absence of diverse representation in technical teams developing the codec algorithms.

Bias in audio compression also affects how listeners perceive female voices. Studies on spectral distortion show that when female voices are compressed using algorithms that do not adequately preserve their frequency range, they are often perceived as less engaging, warm, or natural (Gallardo & Sanchez-Iborra, 2019). Since emotional connection plays a large role in communication and media, this could have significant consequences, from professional settings to entertainment, reinforcing subtle biases against female speakers. Understanding these technical and social factors is crucial to analyzing how digital audio coding impacts gendered voice perception, which this paper explores using STS frameworks.

STS Framework Applicaiton

The Social Construction of Technology (SCOT) framework provides a useful perspective for understanding how digital audio coding algorithms have developed in a way that disadvantages female voices. SCOT, introduced by Pinch and Bijker (1984), challenges the idea that technology develops purely through scientific and technical progress, arguing instead that it is shaped by social, cultural, and institutional factors. In this view, technology evolves based on the priorities, values, and decisions of the people and industries that create it.

The Social Construction of Technology (SCOT) has been widely used in analyzing how societal values shape technological development, particularly in areas like information technology (Bijker, 1995) and medical technology (Hughes, 1994). SCOT emphasizes how technologies reflect the interests of the groups that create and control them. Similarly, Technological Momentum, introduced by Hughes (2004), has been applied to understand how established technologies resist change due to their deep integration into societal infrastructure, such as in the case of the automobile industry and power grid systems. These frameworks are critical in understanding how gender bias in digital audio compression is a product of both historical decisions and institutional inertia.

A key concept in SCOT is "relevant social groups," referring to the different stakeholders that influence technological innovation. In the case of digital audio coding, these groups include audio engineers, software developers, musicians, media professionals, and consumers. Since male researchers and developers have historically dominated the field, their perspectives have largely shaped how audio algorithms are designed. As a result, compression algorithms were optimized for male vocal frequencies, often at the unintentional expense of female voices. However, some scholars argue that this bias is not a result of gendered decision-making but rather a byproduct of engineering efficiency—designers optimize for the most common user profiles, which happen to be male-dominated. This debate highlights a key tension in SCOT: whether technological outcomes are actively shaped by social bias or whether they emerge passively through technical decision-making processes.

Another key SCOT concept, interpretative flexibility, suggests that technologies can be designed in multiple ways depending on the priorities of their creators. Digital audio coding could have been developed with greater sensitivity to female vocal characteristics, but because the dominant voices in the field were male, algorithmic optimization reflected their experiences. Over time, these initial design choices became ingrained in industry standards, reinforcing the bias rather than correcting it.

Recently, researchers and audio engineers have begun addressing these issues by developing machine learning models that adapt compression algorithms to individual vocal profiles rather than applying a one-size-fits-all approach (Ngueajio & Washington, 2022). Some companies, such as Dolby and Fraunhofer IIS, have started refining their codecs to improve frequency preservation for higher-pitched voices. Additionally, diversity initiatives within audio engineering aim to include more women in codec development teams, ensuring that future algorithms account for a broader range of vocal characteristics.

To explain why these biases persist, this paper also draws on Technological Momentum (Hughes, 1969), which suggests that once a technology becomes widely adopted, it gains resistance to change. Digital audio compression algorithms have been embedded in global communication platforms, streaming services, and AI-driven voice applications, making them difficult to modify. Even as awareness of gender bias in audio coding grows, economic pressures, industry standards, and the widespread reliance on existing algorithms make it challenging to implement fundamental changes.

Results

The findings of this research reveal a troubling imbalance in the way digital audio compression affects male and female voices. Digital audio compression reduces the size of audio files by removing less essential sound components, often relying on psychoacoustic models to decide which data can be discarded (Keller, n.d.). Multiple studies have shown that commonly used compression algorithms, such as MP3 and AAC, tend to degrade high-frequency components, which are more prominent in female speech (Chung, 2014; Keller, n.d.). This degradation is not simply a technical issue—it has profound consequences on how voices are perceived, with significant implications in media, music, and voice-based technologies.

1. Degradation of High-Frequency Data and Its Impact on Listener Perception

Each time an audio file undergoes compression, it loses some of its original data, with the impact compounding over multiple compressions. Research shows that higher-frequency vocal elements—often key to clarity and emotional expressiveness in speech—are more vulnerable to this degradation (Chung, 2014). When high-frequency overtones are removed or distorted, voices lose warmth and richness, sometimes sounding thin or unnatural.

Schweobel (2020) presents datasets used in gender bias detection for voice recognition models, illustrating how machine learning struggles with higher-pitched voices. Similarly, Bailey and Plumbley (2020) found that gender bias in audio-based AI models—such as those used for depression detection—often stems from the way speech features are processed, further demonstrating that these issues extend beyond entertainment media into AI-driven fields. Ween, R., & Ransom (2009) and discussions from r/audioengineering (theraccoonbear, 2023) corroborate these findings, highlighting that repeated compression disproportionately reduces the clarity of high-frequency sounds. As Chung (2014) explains, removing high-frequency data diminishes a voice’s natural timbre, which is particularly harmful to female voices due to their naturally higher fundamental frequencies.

The effects of this distortion extend beyond technical loss, influencing perception on a larger scale. When this phenomenon occurs across major streaming platforms, digital assistants, and compressed media files, it can contribute to a broader bias where female voices are perceived as less clear, less engaging, or even less professional (Tatman, 2020; Seldon, 2025).

This bias is not just a limitation of current technology but also a perceptual issue: listeners often associate vocal clarity with authority, warmth, and professionalism. The evidence gathered from existing literature demonstrates that digital audio compression disproportionately impacts female voices due to their higher-frequency components, which are more susceptible to distortion in compression algorithms. This aligns with the research question by showing how these biases are not merely technical flaws but reflect broader societal patterns of gender inequality in technology. The findings suggest that male-dominated fields, such as audio engineering, have historically shaped these technologies in ways that disadvantage female vocal frequencies. Consequently, this research answers the question of how digital audio compression affects gendered voices, revealing a persistent bias that affects both the perception and representation of female voices in digital media. If compression algorithms consistently degrade female voices more than male voices, the technology itself may be reinforcing societal biases rather than reflecting objective differences in vocal quality.

Reddit discussions from r/audioengineering (2014) highlight growing concerns among audio professionals about whether MP3 compression sufficiently preserves high-frequency markers. Their concerns align with findings by Tatman (2020), who showed that Google's speech recognition system systematically underperforms for female voices. This bias can have wide-ranging consequences, particularly in AI-driven communication tools and professional environments where voice clarity affects how individuals are perceived. If digital assistants, automated transcription services, and other voice-based technologies fail to recognize or properly process female voices, this may reinforce gender disparities in workplace interactions, accessibility, and digital communication.

Currey & Hsu (2024) provide further evidence that gender bias is not unique to audio compression; their research on machine translation models found that biases in AI-driven language processing reflect broader systemic inequalities in computational models. This suggests that the biases observed in digital audio compression are part of a larger pattern in which algorithmic decision-making reinforces existing societal structures rather than mitigating them.

2. Perceptual Effects of Frequency Loss

The distortion of high-frequency data has more than a technical impact; it also affects how listeners emotionally and cognitively engage with female voices in music and media. Research by Koelsch (2014) and Blood & Zatorre (2001) highlights the importance of tonal clarity and spectral balance in shaping emotional and cognitive responses to sound. Li, Cheng, & Tsai (2023) extend this by showing that music and auditory stimuli activate the brain's hypothalamus, brainstem, and cerebellum, all of which play key roles in emotional processing. If frequency degradation weakens these responses, female voices may elicit less emotional engagement simply due to compression artifacts, further reinforcing their underrepresentation in digital media.

This phenomenon may help explain why certain female artists struggle for recognition compared to male counterparts on platforms like Spotify and YouTube. Algorithms that prioritize engagement may inadvertently favor male voices because their frequencies remain clearer in compressed formats, contributing to the male-dominated landscape of popular music (Tatman, 2020; Seldon, 2025).

Additionally, cognitive load theory suggests that listeners experience mental fatigue when processing degraded speech (Bailey & Plumbley, 2020). If compression artifacts make female voices harder to understand, listeners may disengage more quickly, unconsciously developing a preference for male voices that are less affected by these distortions. This has broader implications for female representation in the music industry, voice-over work, and even AI-generated voices in digital communication.

These findings emphasize the need for greater awareness of gender bias in digital audio processing and suggest that industry standards must evolve to ensure vocal parity in both compression algorithms and machine-learning-based speech recognition systems.

Discussion

The evidence suggests that digital audio compression does not affect all voices equally, with female voices disproportionately impacted. This can be further understood through the Social Construction of Technology (SCOT) and Technological Momentum frameworks, which highlight the societal forces that shape and sustain these biases.

SCOT and the Gendered Development of Audio Technology

SCOT posits that technological artifacts are shaped by the values and priorities of the social groups that design them. In the case of digital audio compression, male-dominated fields like electrical engineering and computer science historically dictated how these algorithms were developed. Early compression models optimized for vocal frequencies most familiar to these engineers—those of male speakers—resulting in systemic oversight regarding the preservation of high-frequency sounds (Seldon, 2025).

The persistence of this bias is further explained by Alexis, Hilmar, & Duval (2017), who describe how audio signals are divided into sub bands when compressed. Since high frequencies contain less perceived loudness than low and mid frequencies, compression algorithms often prioritize preserving lower frequencies. This process, while efficient, inherently disadvantages voices that rely on high-frequency clarity—namely, female voices.

The gender imbalance within technical fields has also contributed to the longevity of these biases. With men continuing to dominate audio engineering and software development, the social group shaping these technologies has remained relatively homogenous, limiting the likelihood that concerns about female voice degradation would be addressed. This dynamic is amplified by AI-based systems trained on biased datasets, reinforcing disparities that extend beyond audio compression into other domains of digital processing (Seldon, 2025; Currey & Hsu, 2024).

Technological Momentum and Resistance to Change

The concept of Technological Momentum, as outlined by Hughes (2004), explains how the persistence of gender bias in digital audio compression is driven by the inertia of widely adopted technologies. Once MP3 and AAC became industry standards, changing their design to correct for gender bias became increasingly difficult. The deep integration of these technologies into the infrastructure of streaming platforms, telecommunications, and digital media means that altering their design would require widespread, coordinated effort across industries. This means that companies might care about money more than equity when it comes to mass recalling audio processing algorithms. The recall, fixing, and then mass re-deployment of many common algorithms and codecs means countless hours of labor and millions of dollars.

As a result, the adoption of new standards to address gender bias in digital audio compression faces significant resistance. This resistance is not only due to economic factors but also due to the technological trade-offs involved. Altering the compression algorithms to preserve high-frequency sounds may result in larger file sizes, reducing the efficiency that makes these formats so widely used. Developers and companies are often unwilling to make such changes unless there is substantial pressure from external forces, such as economic incentives or regulatory changes (Vaj, 2024).

Implications for Music Representation and Future Research

The biases embedded in digital audio compression have profound implications for female vocalists and voice assistants. Because compression algorithms disproportionately degrade high-frequency components—most prominent in female voices—this can lead to systematic disadvantages in the music industry. Engagement algorithms that prioritize vocal clarity may unintentionally favor male voices in streaming platforms, voice search results, and content recommendations, reinforcing existing industry biases (Tatman, 2020). Over time, this effect could contribute to the underrepresentation of female artists and professionals in audio-driven fields, subtly shaping audience preferences and industry opportunities.

A real-world example of this issue can be seen in the popular streaming platform Spotify. The use of lossy audio formats such as MP3 and AAC, which rely on compression algorithms, has been linked to a shift in listener preferences toward male-dominated vocal frequencies (Spotify Community, 2019). The streaming industry's push for higher-quality streaming services such as Spotify HiFi suggests a growing recognition of these biases, as well as a potential shift toward more equitable representation of all vocal types, including female voices (Spotify Newsroom, 2021). By addressing the limitations of existing audio compression technologies, it is possible to create more inclusive platforms that better represent diverse vocal types in digital media.

To address these disparities, future research should focus on developing compression algorithms that maintain a more balanced preservation of vocal frequencies. AI-driven adaptive compression models, which dynamically adjust based on speaker characteristics rather than applying uniform psychoacoustic assumptions, could offer a promising solution. Additionally, industry leaders and policymakers should consider implementing gender-fair audio encoding standards, akin to regulations addressing bias in machine learning and digital accessibility (Seldon, 2025). Without intervention, these biases will likely persist, continuing to influence how voices are perceived, valued, and represented across digital platforms.

However, addressing this issue is not without challenges. One major limitation is the infrastructure cost associated with expanding digital bandwidth to accommodate a broader range of vocal frequencies. High-frequency sound preservation requires increased data storage and transmission capacity, which can significantly raise energy consumption in data centers. Research suggests that improving compression efficiency without exacerbating environmental and operational costs is a complex trade-off, particularly for large-scale streaming services and cloud-based audio processing. As companies weigh the economic and sustainability implications of such changes, the urgency of mitigating gender bias in digital audio may compete with broader industry priorities.

These findings show the importance of considering both technical and social dimensions when designing audio technologies. Without targeted interventions, digital audio processing will continue to reinforce implicit gender biases, subtly shaping public perception of vocal clarity, authority, and engagement. Future research should not only refine technical solutions but also explore the sociotechnical feedback loop that sustains these disparities, ensuring a more equitable digital soundscape.

Conclusion

This research highlights a significant and persistent gender bias in digital audio processing, demonstrating how compression algorithms disproportionately degrade female voices. By applying SCOT, this study reveals that these biases stem from early industry decisions that prioritized male vocal frequencies. Technological Momentum explains why these biases persist, as entrenched audio standards resist change due to economic and infrastructural constraints.

The findings emphasize the broader implications of gendered audio degradation, particularly in professional and entertainment settings where voice clarity affects perception, engagement, and opportunities for female speakers and artists. Addressing these biases requires collaboration across multiple fields, including audio engineering, AI ethics, and digital policy. Future research should explore solutions such as adaptive compression algorithms that account for vocal diversity, as well as energy-efficient methods to support high-frequency retention in large-scale audio processing.

Until such changes are implemented, the digital audio landscape will continue to reinforce gender disparities, shaping how voices are heard and valued in modern media. If left unchecked, these biases may perpetuate a cycle of underrepresentation, with female voices relegated to the margins of media, communication, and technology. The time has come for the industry to confront this issue head-on and create a more inclusive, equitable soundscape for all voices.

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