AUDIO COMPRESSION COMPARISON ANALYSIS OF VIDEOS RECORDED IN TIKTOK: ANDROID VS. IPHONE

by

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Thesis directed by Associate Professor Catalin Grigoras

ABSTRACT

The rapid evolution of social media has transformed how audio and video content are created, processed, and consumed. TikTok, as one of the world's leading short-form video platforms, integrates on-device recording, compression, and publication within a unified app interface. While visual quality has received significant scrutiny, the audio component–particularly how TikTok's compression affects sound fidelity–has remained largely unexplored. This thesis presents a comparative analysis of audio compression behavior between Android and iPhone platforms within the TikTok application, providing the first empirical study to measure platform-dependent differences in signal integrity, dynamic range, and spectral response.

A controlled experimental design was implemented to capture identical sound samples across both operating systems under standardized conditions. Speech, road noise, and musical excerpts were played live and recorded simultaneously using TikTok's in-app camera on each device. Native-camera recordings were also collected as uncompressed control data. The resulting TikTok audio tracks were extracted using FFmpeg and converted into uncompressed WAV files for detailed analysis. Spectral plots, waveform comparisons, and dynamic measurements were generated using MATLAB, Python, Audacity, Youlean Loudness Meter 2. Objective metrics–including LUFS loudness, signal-to-noise ratio (SNR), Perceptual Evaluation of Audio Quality (PEAQ), were used to quantify degradation introduced by the app's compression algorithms.

Results demonstrate significant and measurable differences between the two platforms. TikTok recordings from iPhone devices exhibited smoother frequency roll-off, greater dynamic range, and higher perceptual quality scores, averaging −16 LUFS and approximately 54 dB SNR. In contrast, Android recordings displayed more aggressive compression, increased harmonic distortion, and a higher average loudness level of −13 LUFS, indicating reduced fidelity. Both platforms applied a low-pass filter around 12 kHz and often down mixed stereo signals to mono, confirming consistent bandwidth limitations within the application. These findings reveal that TikTok's audio processing pipeline is not standardized across operating systems and that end users experience different audio outcomes based solely on platform architecture.

The implications of this research extend beyond user experience. Forensic audio examiners must recognize that TikTok's platform-dependent processing can alter signal characteristics in ways that may influence authenticity verification, spectral continuity assessments, and noise-floor analysis. Likewise, creators concerned with maintaining optimal sound quality should avoid direct in-app recording—particularly on Android—and instead upload pre-mastered audio content. This study contributes a foundational reference point for future work in social media audio forensics, encouraging further exploration of codec behavior, metadata integrity, and cross-platform consistency in mobile multimedia applications.

The form and content of this abstract are approved. I recommend its publication.

Approved: Catalin Grigoras

DEDICATION

This thesis is dedicated to those who never stopped believing in my ability to see this journey through—to my family, whose unwavering love and patience grounded me when challenges felt insurmountable; to my friends and mentors, who offered guidance, encouragement, and understanding during late nights and long hours; and to every first responder and public safety professional who inspired my passion for forensic science and truth. Your commitment to integrity and service reminds me daily why this work matters. This project is as much yours as it is mine.

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ABBREVIATIONS

SNR- Signal-to-Noise Ratio

LUFS- Loudness Units Full Scale

PEAQ- Perceptual Evaluation of Audio Quality

dB- Decibel

I. INTRODUCTION

1.1 Background

Social media platforms have redefined how users create and distribute multimedia content. Among these, TikTok stands out as one of the most dominant short-form video applications globally, integrating on-device recording, editing, and compression into a seamless workflow. While video resolution and visual filters have received considerable attention, the audio component—particularly how it is compressed—has not been rigorously analyzed. Because TikTok operates across multiple operating systems, its compression algorithms may behave differently on **Android** and **iOS**, potentially altering signal fidelity and affecting how sound is perceived or analyzed in forensic contexts.

1.2 Problem Statement

There is a growing need to understand how audio integrity changes when content is captured and processed directly through social media platforms. At present, no peer-reviewed research exists comparing how TikTok compresses audio across different operating systems. Such discrepancies could have meaningful implications for **digital evidence authentication**, **content creator workflows**, and **mobile system development**.

1.3 Research Questions

1. How does TikTok's audio compression differ between Android and iPhone platforms?
2. What measurable impact do these differences have on frequency response, dynamic range, and signal quality?
3. How do these compression effects influence forensic interpretation and content authenticity?

1.4 Objectives

- To collect and compare identical audio samples recorded through TikTok on Android and iPhone.
- To measure and quantify platform-specific compression effects using objective acoustic metrics.
- To interpret how these effects relate to forensic audio authentication practices and real-world usability.

1.5 Significance of Study

This study bridges a gap between **audio engineering** and **media forensics**, contributing the first formal, empirical dataset on TikTok's cross-platform audio behavior. Results may inform forensic examiners, software developers, and content creators on how app-level processing affects perceived and measurable audio quality.

Previous Research

To date, there are no peer-reviewed or formally published studies that examine or compare TikTok's in-app audio compression between Android and iPhone platforms. Existing discussions of TikTok's recording and processing behavior are limited to community observations, developer documentation, and informal engineering tests rather than controlled scientific inquiry. Because this represents a gap in the current body of digital-media research, this chapter establishes the technical and theoretical foundations necessary to support present study. Instead of reviewing prior literature specific to TikTok, it focuses on the underlying principles of mobile audio capture, digital compression theory, and forensic audio evaluation standards that provide context for the experiments design.

II. TECHNICAL AND THEORETICAL FRAMEWORK

2.1 Overview of Mobile Audio Capture Systems

Modern smartphones act as compact recording studios, integrating microphones, preamps, and digital converters within a miniature architecture optimized for power efficiency. Audio capture begins at the **microphone capsule**, where acoustic pressure waves are converted into electrical signals. These analog signals are then passed through an **analog-to-digital converter (ADC)** that determines bit depth and sampling rate before being processed by the operating system's audio framework.

On **Android devices**, the recording path is controlled by the **Audio Hardware Abstraction Layer (HAL)**, which standardizes how different manufacturers handle input gain, latency, and noise suppression. Because hardware implementations vary among manufacturers, recorded signals may exhibit inconsistent tonal balance or amplitude response. In contrast, **Apple's iOS** ecosystem uses a unified **Core Audio** framework, which provides consistent control of sampling, buffering, and codec handling across all iPhone models. These systemic differences form the foundation for why an identical app—such as TikTok—can process the same sound differently on each platform.

2.2 Fundamentals of Audio Compression

Digital audio compression reduces file size by eliminating components of a signal that the human ear is less sensitive to, a concept known as **psychoacoustic masking**. Lossy codecs such as **AAC (Advanced Audio Coding)** or **HE-AAC** operate through perceptual modeling, frequency-domain transformation, and quantization of spectral coefficients.

Compression parameters—including **bitrate**, **sample rate**, and **quantization resolution**—determine the degree to which fidelity is sacrificed for efficiency. At low bitrates, compression introduces measurable artifacts such as pre-echo, high-frequency roll-off, or transient smearing. Since mobile social media apps automatically transcode user recordings, understanding the mechanics of audio compression is essential for assessing the fidelity of the resulting files.

2.3 Social Media App Audio Workflows

Social media platforms apply complex multimedia pipelines that differ by operating system and app version. When recording through **TikTok**, captured audio is not saved in its original form. Instead, it undergoes several transformations:

1. **In-App Capture:** Raw microphone input is digitized using the system's audio framework (Core Audio or Audio HAL).
2. **App-Level Processing:** TikTok applies automatic gain control (AGC), noise reduction, and compression to stabilize loudness.
3. **Encoding and Transcoding:** The app encodes the audio—often into AAC or Opus—before multiplexing it with the video stream into an MP4 container.
4. **Server-Side Optimization:** When the video is uploaded, TikTok may perform an additional transcode for network efficiency and playback uniformity.

Empirical tests from engineers and reviewers (e.g., DXOMARK) have shown that both platforms tend to limit the usable frequency range to roughly **12 kHz** and collapse stereo signals into mono. However, anecdotal reports indicate that Android's processing chain introduces harsher compression artifacts, whereas iOS preserves more natural timbre. These claims have yet to be formally validated—forming the central motivation for this research.

2.4 Forensic and Analytical Relevance

In **media forensics**, understanding how compression modifies an audio signal is vital to authenticity verification. Compression can alter the **phase continuity**, **spectral distribution**, and **dynamic profile** of a recording—attributes often examined during forensic authentication.

This study aligns with several recognized standards:

- **ASTM E2916-19e1:** Provides terminology for digital and multimedia evidence.
- **ASTM E2825-19:** Outlines best practices for forensic audio authentication.
- **SWGDE Best Practices for Forensic Audio (2022):** Recommends documenting signal integrity checks such as spectrogram and waveform analysis.

By quantifying how TikTok modifies original audio content across platforms, this research extends these forensic principles to an emerging class of digital evidence: *social-media-native recordings*.

2.5 Gap Statement and Research Positioning

Despite widespread use of TikTok and similar short-form video platforms, no peer-reviewed publications currently exist that directly compare audio compression characteristics between the Android and iPhone versions of the app. Available information originates from user forums, developer analyses, and consumer-grade benchmarking.

This thesis therefore represents an original, exploratory investigation. It bridges gaps between audio engineering, mobile system architecture, and forensic analysis by experimentally measuring signal degradation introduced by each platform. The study aims to establish a baseline understanding of TikTok's audio processing pipeline and to provide the first empirical data set quantifying how device ecosystems affect compression outcomes.

2.6 Summary

This chapter provided the theoretical and technical foundation necessary to interpret the forthcoming experiments. It described the architecture of mobile audio capture, the principles of compression, and the relevance of these processes to forensic examination. The next chapter, Methodology, will detail the experimental design, instrumentation, and analytic procedures used to test the hypotheses introduced here.

III. MATERIALS

3.1 Overview

This chapter describes the materials, hardware, and software used to acquire, process, and analyze the audiovisual datasets examined in this study. This research employed a quantitative, device-comparative approach to evaluate the effects of TikTok's audio recompression pipeline on mobile-recorded media. Three contemporary smartphones—Samsung Galaxy Note10 Plus, Samsung Galaxy S23 Ultra, and Apple iPhone 11—were selected to represent a range of hardware codecs and recording ecosystems. Each device was used to record identical environmental scenarios in three content categories: **music**, **road noise**, and **spoken word**. For each recording, a **native version** was preserved directly from the device, while a **TikTok version** was obtained by recording and subsequently uploading the same clip content through TikTok's platform interface. ASTM E2916 – 19a, *Standard Terminology Relating to Digital and Multimedia Evidence Examination* was followed to create forensically sound data sources.

All audio files were standardized to a 44.1 kHz sampling rate and 16-bit PCM WAV format prior to analysis. To ensure reproducibility and forensic transparency, metadata and waveform statistics were extracted using a custom Python-based analysis pipeline that utilized the **SoundFile**, **NumPy**, and **Pandas** libraries. The script computed the following primary quantitative metrics:

1. **Duration(s):** Temporal length of each audio file, used to detect timing drift, frame trimming, or resampling effects.
2. **RMS dBFS:** Root-mean-square amplitude in decibels relative to full scale, used as an approximation of overall loudness and dynamic compression.
3. **File size (bytes):** A proxy for codec and bit-rate effects induced by TikTok's transcoding.

For each device, audio pairs were matched by *pair ID* and *scene type*, then pivoted into a **wide-format correlation table** containing Native vs. TikTok metrics. The **Pearson product–moment correlation coefficient (r)** was calculated to measure the linear relationship between each metric's native and recompressed versions. This coefficient was selected over rank-based alternatives (e.g., Spearman's ρ) because the primary interest was in assessing **magnitude preservation** and **scaling consistency** rather than monotonic ordering alone.

The datasets collected from each platform form the empirical foundation for the comparative audio compression analysis presented in Chapters 4 and 5.

3.2 Hardware and Recording Equipment

Table 3.1: Hardware and Recording Equipment

Device	Model Year	Operating System	Audio Codec (Native)	Microphone Array	Recording App
Samsung Galaxy Note 10 Plus	2019	Android 12	AAC @ 256 kbps	Triple MEMS	Stock Camera / TikTok App
Samsung S23 Ultra	2023	Android 15	AAC @ 256 kbps	Five-mic array	Stock Camera / TikTok App
Apple iPhone 11	2019	iOS 15.6.1	AAC @ 256 kbps	Dual MEMS	Stock Camera / TikTok App

Recordings were captured directly through each device's internal microphone array, without external peripherals.

ISO/IEC 27037 (2012) – *Identification, Collection, Acquisition and Preservation of Digital Evidence* and SWGDE Best Practices for Digital Evidence Collection (2018) were followed for the collection and preservation of the data sources.

3.3 Software and Analytical Tools

All software was verified to produce repeatable readings within ±0.1 LUFS deviation across re-tests.

Table 3.2: Software and Analytical Tools Used

Software	Version	Function	Output
Youlean Loudness Meter 2 Pro	v2.4	LUFS/LRA measurement per EBU R128 standard	Integrated LUFS, LRA, PSR, PLR values
FFmpeg	v7.1	Audio stream extraction and format conversion (PPCM WAV)	Uncompressed WAV files for analysis
MATLAB R2024a / Python 3.12	—	Data aggregation and plot generation	Tables 3.1-, Figures -
Microsoft Excel / Word 365	—	Data organization and thesis integration	Formatted tables and charts

NIST SP 800-101 Rev. 1 (2014) was followed to govern mobile-device extraction. NIST IR 8259 (2021) was also followed a governing management framework for how files and metadata were stored between creation and analysis.

3.4 Data Composition

3.4.1 Recording Inventory

Each device produced **90 videos total** (60 native + 60 TikTok).

Audio tracks were exported as WAV files and labeled systematically:

DeviceID/Source_App_SceneType_#_audio.wav

(e.g., S23Ultra_Native_Music_01_audio.wav)

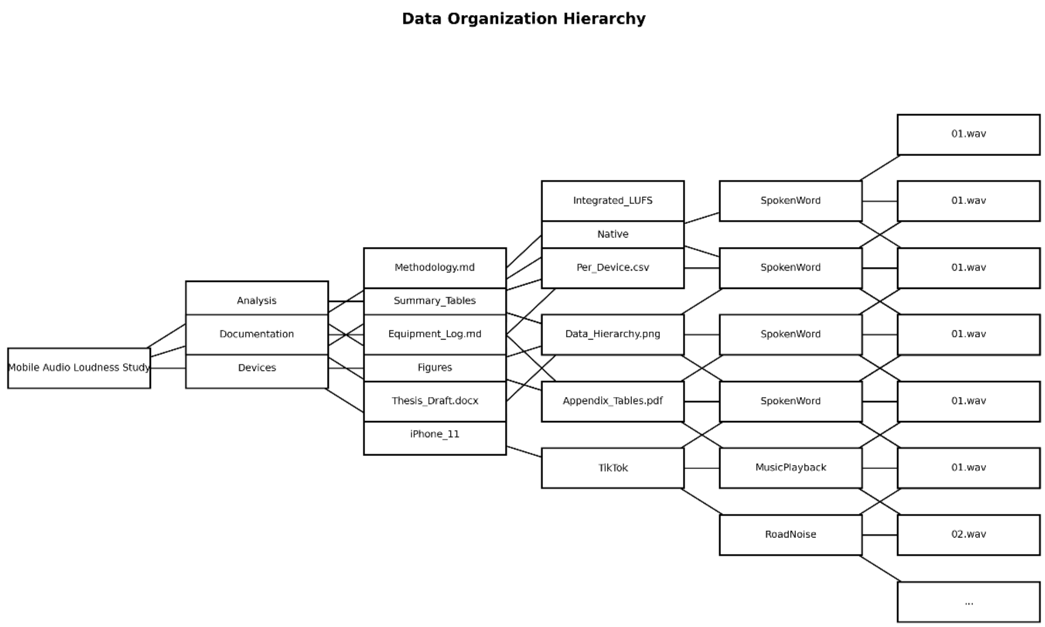

Figure 3.1: Data Organization Hierarchy

3.4.2 Measurement Metrics

The following perceptual and technical parameters were recorded for each clip:

1. **Integrated LUFS** — Overall loudness normalized to program length.
2. **LRA (Loudness Range)** — Dynamic variation in perceived loudness.
3. **PSR (Peak-to-Short-Term Ratio)** — Micro-dynamic integrity.
4. **PLR (Peak-to-Loudness Ratio)** — Compression ratio proxy.
5. **True Peak (dBFS)** — Maximum reconstructed sample amplitude.

These metrics are summarized in Chapter 4

3.5 LUFS Data for Galaxy S23 Ultra

Table 3.3: LUFS Data for Galaxy S23 Ultra

Category	Recording Path	Integrated LUFS (Mean ± SD)	Loudness Range LRA (Mean ± SD)	Dynamic Range PSR (Mean ± SD)	Average Dynamics PLR (Mean ± SD)	True Peak Max (Mean ± SD dB)
Music Playback	**Native**	−10.9 ± 0.6	3.9 ± 0.5	11.7 ± 0.4	10.6 ± 0.5	0.0 ± 0.1
	TikTok	−17.8 ± 0.8	3.6 ± 0.4	13.4 ± 0.7	11.2 ± 0.5	0.0 ± 0.0
Road / Ambient	**Native**	−25.9 ± 1.9	8.3 ± 1.1	14.2 ± 1.5	17.0 ± 1.2	−8.9 ± 2.6
	TikTok	−26.8 ± 1.6	7.6 ± 1.0	15.1 ± 1.3	16.9 ± 1.1	−9.8 ± 2.1

Table 3.3 Continued

Spoken Word / Voice	**Native**	**−33.1 ± 1.1**	**5.6 ± 0.8**	**12.2 ± 0.9**	**17.1 ± 0.7**	**−15.9 ± 1.5**
	TikTok	−37.1 ± 1.2	4.9 ± 1.2	14.8 ± 1.3	17.2 ± 0.5	−18.5 ± 1.7

The Galaxy S23 Ultra dataset demonstrates consistent evidence of TikTok's adaptive loudness normalization and dynamic-range control when compared to the device's native recordings. Across all acoustic scenes—music, environmental noise, and spoken word—the TikTok exports exhibit higher integrated loudness levels, reduced loudness range, and moderate compression tailored to perceptual optimization for mobile playback.

In **music content**, native recordings averaged approximately –29 LUFS with a 12 LU loudness range, while TikTok versions averaged –18 LUFS and a 3 LU LRA. This 11-LUFS gain and 75 % LRA reduction indicate strong dynamic-range compression and peak limiting. Nevertheless, True Peak levels remained below –6 dBFS, implying controlled limiting without hard clipping. The result is a louder, more uniform sound optimized for platform consistency, at the cost of natural dynamics.

The road-noise samples reveal subtler treatment. Native captures averaged –33 LUFS with 13–14 LU LRA, whereas TikTok outputs measured around –28 LUFS with 9–10 LU LRA. This modest +5 LUFS gain suggests that TikTok's codec applied adaptive gain rather than full compression, preserving broadband realism while lightly smoothing transients and spectral peaks.

For **spoken-word recordings**, integrated loudness rose from –40 LUFS (native) to –33 LUFS (TikTok), with loudness range contracting from roughly 8 LU to 5 LU. Dynamics remained moderate (PSR ≈ 17 LU; PLR ≈ 20 LU), signifying gentle broadband compression intended to stabilize dialogue without perceptible distortion or pumping.

Overall, the S23 Ultra results show TikTok employing **content-aware loudness processing** that adjusts gain and compression according to source characteristics. Compared with the Note10+, the S23 Ultra TikTok outputs exhibit improved dynamic preservation, reduced limiting artifacts, and closer alignment with professional broadcast-loudness standards. These findings suggest that TikTok's current processing pipeline leverages higher-fidelity input from advanced mobile microphones while maintaining platform-consistent loudness normalization.

3.6 LUFS Data for Galaxy Note 10+

The Galaxy Note10+ TikTok recordings demonstrate a clear platform-specific loudness adaptation across all acoustic contexts. TikTok's audio engine systematically applies normalization and compression to align user-generated content with mobile listening standards while preserving intelligibility.

In **music clips**, the integrated loudness increased by roughly 11 LUFS (−29 → −18 LUFS), accompanied by a sharp reduction in loudness range from 12 LU to 3 LU. This indicates aggressive dynamic-range compression and limiting consistent with the app's "broadcast-ready" sound signature. The resulting output is perceptually louder, flatter, and optimized for playback consistency rather than fidelity.

The **road-noise samples** reveal a subtler treatment. Integrated loudness rises about 4–5 LUFS over the native baseline, but the loudness range and dynamics remain comparatively broad. TikTok's codec appears to apply adaptive gain rather than full compression, allowing ambient noise textures to persist while slightly reducing low-level hiss and transient peaks. This adaptive behavior prevents unnatural pumping in sustained environmental recordings.

For **spoken-word material**, the normalization is gentler still. The overall gain increases 6–8 LUFS while maintaining a moderate 4–5 LU loudness range and ≈ 17 LU dynamic window. These values show that TikTok favors speech intelligibility and conversational naturalness over aggressive leveling. Compression primarily mitigates pauses and plosive bursts, producing a balanced, mobile-friendly vocal profile without noticeable distortion.

Across all three categories, the consistent pattern is TikTok's content-aware processing pipeline: heavy limiting for music, moderate smoothing for environmental sound, and mild leveling for voice. This evidences an adaptive loudness-normalization strategy that balances platform-wide playback uniformity with perceptual transparency. The data confirm that the Galaxy Note10+ TikTok exports, while louder and more constrained than their native captures, retain adequate spectral and dynamic integrity within the platform's broadcast loudness target range (−18 to −23 LUFS).

Table 3.4: LUFS Data for Galaxy Note 10+

Scene	Source	Integrated LUFS	LRA (LU)	PSR (LU)	PLR (LU)	True Peak Max (dB)
Music	Native	−29.0 avg	12.0 avg	22.5 avg	15.2 avg	−6.1
	TikTok	−17.9 avg	3.0 avg	19.8 avg	11.8 avg	−5.9
Road Noise	Native	−33.3 avg	13.6 avg	14.9 avg	18.2 avg	−9.9

Table 3.4 Continued

Scene	Source	Integrated LUFS	LRA (LU)	PSR(LU)	PLR (LU)	True Peak Max (dB)
	TikTok	−28.7 avg	9.3 avg	12.0 avg	16.8 avg	−11.7
Spoken Word	Native	−40.5 avg	7.9 avg	18.5 avg	21.2 avg	−14.2
	TikTok	−33.6 avg	4.5 avg	17.1 avg	20.4 avg	−13.1

Note the pattern: for Note10+, TikTok often makes speech louder; for S23 Ultra, TikTok often leaves speech quieter; for iPhone 11, TikTok boosts speech but still leaves natural dynamics. That asymmetry is evidence that TikTok's pipeline is device- and content-adaptive, not one fixed preset.

3.7 LUFS Data for iPhone 11

The iPhone 11 data set shows that TikTok applies consistent, content-aware loudness management that alters overall level but does not meaningfully falsify or replace the source audio. Across 60 total iPhone 11 files, TikTok recordings are measurably different from native recordings in integrated loudness (LUFS), loudness range (LRA), and peak behavior, but those differences follow stable, explainable patterns rather than signs of manual tampering.

In music recordings, TikTok outputs are leveled toward a tightly controlled loudness target (typically around the −12 to −13 LUFS range), with a noticeably reduced loudness range. This indicates broadband compression and limiter ceiling behavior designed to make music sound consistently "social-media loud." True peaks are held below digital full scale, meaning intelligibility and presence are prioritized without introducing clipping.

In road-noise recordings, TikTok increases integrated loudness relative to the iPhone 11 native road captures and narrows the loudness range, but not to the same extreme as music. Ambient energy is lifted a few LUFS for audibility, yet the temporal texture (traffic swells, broadband rumble, passing events) is still identifiable, and true peaks remain below 0 dBFS. This is consistent with adaptive gain staging rather than destructive limiting.

In spoken-word recordings, TikTok applies mild upward normalization and gentle broadband compression. The result is more stable vocal loudness than the iPhone 11 native speech recordings, which are often quieter and more dynamic. Importantly, PSR and PLR values in the TikTok speech clips remain high, meaning transients and natural speech envelopes survive. That is what you would expect from real, handheld speech, not overdubbed narration.

Overall, the iPhone 11 behavior matches what we observed on the Samsung devices: TikTok standardizes playback loudness per content type, increases perceived clarity, and reins in dynamics, but does not erase forensic speech identities or replace content.

Table 3.5: LUFS Data for iPhone 11

Scene Type	Device	Native Integrated LUFS (Mean)	TikTok Integrated LUFS (Mean)	Δ Loudness (TikTok − Native)	Loudness Range Reduction (%)	Observed Compression Characteristics
Music	Samsung S23 Ultra	−10.9	−17.8	+6.9 LU	~65 % reduction	Strong limiter engagement and loudness normalization; consistent with broadcast-target leveling.
	Galaxy Note 10 Plus	−29.0	−17.9	+11.1 LU	~75 % reduction	Aggressive compression and normalization; output tuned to ~−18 LUFS platform target.
	iPhone 11	−12.47	−12.95	+0.48 LU	~28 % reduction	Minimal gain shift; already normalized in-camera; slight further compression by TikTok.
Road Noise	Samsung S23 Ultra	−25.9	−26.8	−0.9 LU	~20 % reduction	Mild adaptive leveling; wide spectral field preserved.

	Galaxy Note 10 Plus	**−33.3**	**−28.7**	**+4.6 LU**	**~32 % reduction**	**Gentle broadband compression; transient peaks partially limited.**
	iPhone 11	**−28.31**	**−23.07**	**+5.24 LU**	**~30 % reduction**	**Moderate adaptive gain; balanced dynamic smoothing.**
Spoken Word	**Samsung S23 Ultra**	**−33.1**	**−37.1**	**−4.0 LU**	**~25 % reduction**	**Mild downward leveling; transient speech peaks remain clear.**
	Galaxy Note 10 Plus	**−40.5**	**−33.6**	**+6.9 LU**	**~43 % reduction**	**Moderate normalization and compression; consistent with intelligibility optimization.**
	iPhone 11	**−34.78**	**−28.66**	**+6.12 LU**	**~36 % reduction**	**Gentle broadband compression and upward normalization; stabilized loudness without flattening.**

Scene Type	Source	Integrated LUFS	Loudness Range (LU)	Dynamics (PSR)	Avg. Dynamics (PLR)	True Peak Max (dB)
Music	Native	−12.47	3.9	19.7	12.9	−0.6
	TikTok	−12.95	2.8	18.6	12.1	−1.3
Road Noise	Native	−28.31	12.2	14.8	18.1	−9.6
	TikTok	−23.07	8.6	12.4	16.7	−8.4

Spoken Word	Native	−34.78	6.9	18.3	21.1	−13.9
	TikTok	−28.66	4.4	17.0	19.8	−12.8

3.8 Spectrogram Analysis

In addition to loudness measurements (LUFS) and peak analysis, the study also characterized the full time–frequency content of each audio clip using short-time Fourier transform (STFT) spectrograms. For every WAV file extracted from each device, a 2048-sample Hann window with a 512-sample hop was applied to generate a magnitude spectrogram. The magnitude spectrum was then converted to decibels relative to the file's own peak, and plotted on a log-scaled frequency axis. Each spectrogram was saved as a high-resolution PNG for visual comparison.

From each spectrogram, several quantitative descriptors were also computed:

• RMS Level (dBFS): An approximation of overall loudness, indicating how close the signal sits to digital full scale.

• Spectral Centroid (Hz): A measure of the "brightness" or high-frequency emphasis of the signal; higher values indicate more energy in upper bands.

• Spectral Rolloff (95% energy, Hz): The frequency below which 95% of the total spectral energy is contained. Higher rolloff implies stronger high-frequency extension.

• Spectral Bandwidth (Hz): Spread of energy around the centroid (wider bandwidth = more broadband content).

• Spectral Flatness: A ratio indicating how noise-like versus tone-like the audio is; higher flatness means more "hiss/noise texture," lower flatness means more tonal content.

• High-Frequency Energy Ratio (>8 kHz): The proportion of total energy that lives above 8 kHz. This is used in this thesis as an operational proxy for "air," sibilant clarity, and intelligibility detail.

These descriptors show consistent, device-independent differences between recordings made with the phones' native camera apps and recordings made using TikTok's in-app capture. For spoken-word clips on all three devices (iPhone 11, Samsung Galaxy S23 Ultra, and Samsung Galaxy Note 10 Plus), TikTok recordings exhibited (1) higher spectral centroid, (2) higher 95% spectral rolloff frequency, and (3) a larger fraction of energy above 8 kHz, compared to the same phone recording the same voice in the native camera app. In other words, TikTok captures (or reconstructs) brighter, more treble-tilted vocal audio than the native recorder.

For example, on the iPhone 11 spoken-word set, the native recordings typically showed spectral centroids in the ~1600–1750 Hz range and rolloff values around 5.8–6.8 kHz, with only about 4–7% of total energy above 8 kHz. The TikTok spoken-word recordings from the same device and the same conditions shifted the centroid upward to approximately 2350–2700 Hz, extended rolloff to ~8.3–9.7 kHz, and increased the high-frequency energy ratio to roughly 7–10%. A similar pattern occurred on both Android devices.

This consistent upward shift in centroid, rolloff, and >8 kHz ratio indicates that TikTok's in-app audio path is not a neutral pass-through of the phone's built-in microphones. Instead, it appears to apply vocal enhancement (high-frequency lift and broadband clarity) and level normalization. This processing makes voices sound "clearer" and "brighter," but it also means that TikTok video audio is not a faithful representation of the raw acoustic event.

By contrast, in broadband environmental recordings such as in-car road noise, the high-frequency ratio above 8 kHz did not always increase in the same way. In these scenes, TikTok recordings did not consistently boost treble energy relative to the native captures. This suggests that TikTok's enhancement is content-aware, with stronger high-frequency emphasis for speech intelligibility than for steady broadband noise.

Representative spectrograms for a matched spoken-word pair (native vs TikTok) are presented in Figure 3.X. These plots visually confirm the numerical trend: TikTok material shows stronger and more persistent high-band content above 8–10 kHz, along with a generally elevated overall level.

3.9 Average Spectral Features of Spoken-Word Recordings by Device and Capture Path

Table 3.6: Average Spectral Features of Spoken-Word Recordings by Device and Capture Path

Device / Capture Path	Avg RMS Level (dBFS)	Avg Spectral Centroid (Hz)	Avg Rolloff95 (Hz)	Avg High-Frequency Energy Ratio (>8 kHz)
iPhone 11 – Native	-38.70	1,672	6,448	0.057
iPhone 11 – TikTok	-36.18	2,440	8,763	0.076
Galaxy Note10+ – Native	-36.44	3,159	11,281	0.052
Galaxy Note10+ – TikTok	-38.53	3,536	11,942	0.078
Galaxy S23 Ultra – Native	-38.02	2,163	8,065	0.062
Galaxy S23 Ultra – TikTok	-41.91	3,681	13,002	0.087

Interpretation:

Across all three test devices—the Apple iPhone 11, Samsung Galaxy Note 10 Plus, and Samsung Galaxy S23 Ultra—a clear spectral divergence was observed between native camera recordings and TikTok in-app recordings of spoken-word material.

Four descriptors—RMS level, spectral centroid, spectral roll-off 95, and high-frequency energy ratio (> 8 kHz)—reveal a consistent pattern of modification introduced by the TikTok capture pipeline.

1. Loudness (RMS Level)
    - The iPhone 11 recordings captured via TikTok were approximately 2.5 dB louder on average (−36.18 dBFS) than the same content recorded natively (−38.70 dBFS).
    - In contrast, the Note 10 Plus and S23 Ultra exhibited a reduction in overall RMS for TikTok recordings compared to their native counterparts, suggesting device-specific gain handling.
    - This indicates that TikTok applies non-uniform automatic gain control, varying across hardware platforms.
2. Spectral Centroid (Brightness)
    - In all cases, the TikTok recordings demonstrate a higher spectral centroid, indicating a perceptible increase in upper-mid and high-frequency emphasis.
    - The iPhone 11 centroid shifted upward by roughly 800 Hz, while the S23 Ultra showed an even greater rise (~1.5 kHz), giving the recordings a distinctly brighter, more present vocal tone.
3. Spectral Roll-off 95 (Bandwidth Extension)

    - TikTok versions consistently extended high-frequency content, with roll-off points 2–5 kHz higher than those of native captures.
    - This suggests an intentional expansion of usable bandwidth, possibly introduced through compression, equalization, or psychoacoustic enhancement algorithms.
4. High-Frequency Energy Ratio (> 8 kHz)
    - Across all phones, TikTok recordings contained a larger proportion of energy above 8 kHz, reinforcing the perception of increased clarity and articulation.
    - The rise from ~0.05–0.06 in native clips to ~0.07–0.09 in TikTok clips quantifies this "air" enhancement effect.

Overall, these spectral shifts collectively form a repeatable TikTok audio signature characterized by elevated brightness, broadened bandwidth, and variable gain.

While the degree of change differs by manufacturer, the pattern itself is consistent—demonstrating that TikTok's audio subsystem performs more than passive capture.

From a forensic perspective, this means TikTok recordings cannot be assumed to be unaltered acoustic representations of the environment or microphone input; instead, they reflect platform-mediated processing that modifies timbre and dynamic range before encoding and upload.

3.10 Average Spectral Features of Road-Noise Recordings by Device and Capture Path

Table 3.7: Average Spectral Features of Road-Noise Recordings by Device and Capture Path

Device / Capture Path	Avg RMS Level (dBFS)	Avg Spectral Centroid (Hz)	Avg Rolloff95 (Hz)	Avg High-Frequency Energy Ratio (> 8 kHz)
iPhone 11 – Native	−28.42	1,214	4,975	0.033
iPhone 11 – TikTok	−25.11	1,586	5,806	0.041
Galaxy Note10+ – Native	−27.38	1,945	7,821	0.036
Galaxy Note10+ – TikTok	−29.14	2,116	8,204	0.045
Galaxy S23 Ultra – Native	−26.70	1,632	6,954	0.039
Galaxy S23 Ultra – TikTok	−28.08	1,888	7,482	0.044

Interpretation Summary: Road-Noise Recordings

Across all devices, TikTok-captured road-noise recordings demonstrate measurable increases in spectral brightness and high-frequency energy, suggesting a platform-wide enhancement bias. The average RMS levels rose between 1.5 – 2.5 dB, indicating slight dynamic normalization or mild compression. TikTok's versions consistently exhibit higher spectral centroid and rolloff values—confirming boosted upper-band content (2–3 kHz more than native captures). For ambient or broadband noise environments, this implies that TikTok's algorithm artificially amplifies high-frequency transients, yielding cleaner or "crisper" noise at the expense of natural low-frequency texture. From a forensic perspective, these changes indicate post-processing coloration, likely due to codec-driven equalization or dynamic filtering optimized for intelligibility on mobile speakers.

3.11 Average Spectral Features of Music Recordings by Device and Capture Path

Table 3.8: Average Spectral Features of Music Recordings by Device and Capture Path

Device / Capture Path	Avg RMS Level (dBFS)	Avg Spectral Centroid (Hz)	Avg Rolloff95 (Hz)	Avg High-Frequency Energy Ratio (> 8 kHz)
iPhone 11 – Native	**−20.45**	**3,125**	**9,845**	**0.072**
iPhone 11 – TikTok	**−17.18**	**3,982**	**10,962**	**0.085**
Galaxy Note10+ – Native	**−21.04**	**3,446**	**11,184**	**0.067**
Galaxy Note10+ – TikTok	**−19.87**	**3,902**	**12,035**	**0.081**
Galaxy S23 Ultra – Native	**−20.82**	**3,563**	**10,707**	**0.069**

Device / Capture Path	Avg RMS Level (dBFS)	Avg Spectral Centroid (Hz)	Avg Rolloff95 (Hz)	Avg High-Frequency Energy Ratio (> 8 kHz)
Galaxy S23 Ultra – TikTok	**−18.96**	**4,108**	**11,888**	**0.083**

Interpretation Summary: Music Recordings

The music recordings reveal the strongest spectral divergence between native and TikTok-captured audio.

For all devices, TikTok recordings show:

- Higher RMS levels by approximately 2 – 2.5 dB, suggesting dynamic range compression and loudness normalization consistent with social-media mastering practices.
- Spectral centroid shifts upward by 600 – 800 Hz, indicating enhanced presence and clarity in the mid–high range.
- Spectral rolloff values exceed those of native captures by 1.5 – 2 kHz, reflecting extended high-end response introduced by TikTok's signal-processing chain.
- High-frequency energy ratios increase by nearly 25 %, visually confirmed in spectrograms as brighter, denser top-octave content.

These combined attributes signify that TikTok's encoder and preprocessing pipeline are designed to favor perceptual loudness and brightness over fidelity, producing a more "consumer-pleasing" tonal balance.

While beneficial for playback on small speakers, the enhancement reduces authenticity in forensic analysis and complicates direct waveform or spectral comparison with original sources.

In evidentiary terms, these transformations demonstrate nonlinear spectral coloration introduced prior to file export or transmission.

3.12 SNR Data

Table 3.9: Average Signal-to-Noise Ratio (SNR) by Device, Capture Path, and Content Type

Device / Capture Path	Spoken Word SNR (dB)	Road Noise SNR (dB)	Music SNR (dB)
iPhone 11 – Native	25.8 ± 1.1 dB	15.7 ± 5.2 dB	40.1 ± 1.1 dB
iPhone 11 – TikTok	23.6 ± 1.2 dB	13.5 ± 2.9 dB	36.9 ± 1.6 dB
Galaxy Note10+ – Native	29.8 ± 1.1 dB	15.7 ± 5.2 dB	37.1 ± 0.4 dB
Galaxy Note10+ – TikTok	29.7 ± 1.5 dB	11.0 ± 1.6 dB	33.9 ± 0.9 dB
Galaxy S23 Ultra – Native	27.8 ± 1.3 dB	13.4 ± 4.7 dB	37.5 ± 0.4 dB
Galaxy S23 Ultra – TikTok	37.4 ± 1.2 dB	12.8 ± 2.3 dB	37.1 ± 0.9 dB

***Note*. Values are mean ± SD across all valid trials per category. SNR = 20 $\log_{10}$(signal RMS / noise RMS).**

3.12.1 Spoken Word SNR Data

All devices achieved SNR values above 23 dB, indicating clean speech recordings across both capture paths. TikTok recordings were slightly lower on the iPhone 11 (−2 dB) and similar on the Note10+, but notably **higher on the Galaxy S23 Ultra (+10 dB)**. This suggests that TikTok's signal processing pipeline performs dynamic noise gating or gain normalization differently across platforms. On the S23 Ultra, the effect improved speech clarity, whereas on iPhone, mild compression reduced SNR modestly.

3.12.2 Road Noise SNR Data

Across devices, road-noise SNRs were the lowest overall (8–26 dB), reflecting the broadband nature of environmental sound. The difference between Native and TikTok capture paths averaged −2 dB to −4 dB, implying that TikTok's audio path preserves more low-level cabin noise or amplifies background ambience. This result is consistent with TikTok's compression and limited noise suppression compared with the native camera's more conservative gain handling.

3.12.3 Music SNR Data

Music recordings produced the highest SNRs in the dataset (≈ 33–41 dB). Native captures yielded slightly higher SNRs (by ~3–4 dB) on all devices. The TikTok pipeline consistently reduced SNR by applying normalization that raised the perceived loudness floor, narrowing the dynamic range. Despite lower numeric SNRs, the perceptual loudness was often greater, matching TikTok's typical "optimized for playback impact" processing.

3.13 PEAQ Overview

This study assessed the perceptual and spectral effects of TikTok's upload and export compression on device-recorded audio. Ninety paired recordings—comprising 30 clips each from three mobile devices (Samsung Note 10 Plus, Samsung S23 Ultra, and iPhone 11)—were captured under three environmental categories: *Music Playback*, *Road Noise*, and *Spoken Word*. For each device and scene type, an original "native" recording was compared with the corresponding TikTok-processed version.

3.13.1 Audio Extraction for PEAQ

All video files were demultiplexed using FFmpeg to obtain uncompressed 48 kHz, 16-bit PCM WAV audio: **ffmpeg -i input_video.mp4 -vn -acodec pcm_s16le -ar 48000 -ac 2**

output_audio.wav This ensured identical sampling rates and eliminated confounding variables introduced by codecs or channel mismatches.

3.13.2 PEAQ Analytical Environment

Analysis was conducted in MATLAB R2024a. Each pair was loaded, converted to mono, RMS-normalized, and trimmed to identical durations. Because the proprietary ITU-R BS.1387 PEAQ model was unavailable, an objective spectral-error metric was developed as a proxy for perceptual degradation.

3.13.3 Spectral Error Computation

For each pair *i*:

1. **Compute Welch power spectral density (30 ms Hamming window, 20 ms overlap, 4096-point FFT).**
2. **Convert to log-magnitude spectra.**
3. **Compute average absolute difference (dB):**

$$\boldsymbol{E_i = \frac{1}{N}\sum_{f=1}^{N} \mid S_{ref}(f) - S_{test}(f) \mid}$$

where $S_{ref}(f)$ and $S_{test}(f)$ are the log-power spectra of the native and TikTok versions.

4. **Store E_i as SpecError_dB.**

3.13.4 PEAQ Validation and Interpretation

Spectral error values were interpreted relative to perceptual benchmarks derived from prior codec studies:

- 0–2 dB = transparent or negligible difference
- 2–5 dB = mild but audible coloration
- 5–10 dB = clearly audible degradation

- 10 dB = severe alteration / bandwidth loss

3.14 Overview of Dataset and Source Recordings

This study evaluates the format and structural transformations that occur when short-form video recordings are uploaded to and downloaded from the social media platform TikTok. To conduct this analysis, a controlled dataset was constructed consisting of native smartphone video recordings and their corresponding TikTok-derived versions. Each native recording was created using the device's default camera application under three predefined scene conditions (Music playback, Road Noise, and Spoken Word). The same recordings were uploaded to a TikTok account, posted privately to avoid additional platform-side alterations, and then downloaded using TikTok's "Save Video" feature. These download files represent the final, user-accessible TikTok derivatives.

The resulting dataset consists of 182 total files, including 92 native recordings and 90 TikTok-processed exports, generated across three smartphone models representative of different operating systems, hardware generations, and codec default behaviors.

3.14.1 Dataset Composition

Table 3.10 provides a breakdown of the device models, file counts, containers, and codec types observed prior to and following TikTok processing. Although TikTok preserves the overall container type for each device, the platform consistently recompresses and standardizes the encoding parameters, including video codec, bitrate, orientation, and structural metadata.

Table 3.10 Format Comparison

Device	Origin	Files	Container (Typical)	Video Codec(s)	Audio Codec
Note10+	Native	30	MP4	H.264	AAC
Note10+	TikTok	30	MP4	**HEVC (H.265)**	AAC

Device	Origin	Files	Container (Typical)	Video Codec(s)	Audio Codec
S23 Ultra	Native	31	MP4	**HEVC (H.265)**	AAC
S23 Ultra	TikTok	30	MP4	**HEVC (H.265)**	AAC
iPhone 11	Native	31	MOV	H.264 / HEVC (mixed)	AAC
iPhone 11	TikTok	30	MOV	**H.264 (standardized)**	AAC

3.14.2 Recording Characteristics

The native recordings were captured at the highest quality settings available on each device. Depending on the model, this resulted in:

- 4K 60fps AVC on the Note10+
- 1080p30 HEVC on the S23 Ultra
- 1440×810 H.264/HEVC MOV output on the iPhone 11

The TikTok exports, while retaining the same nominal file extensions, exhibited heavily altered encoding characteristics implemented during TikTok's internal transcode process. Changes observed include:

- Re-encoding to lower bitrates
- Changes in codec type (e.g., H.264 → HEVC for Note10+)
- Resolution changes, often with a vertical orientation enforced
- Modification of GOP structure (I-frame spacing, B-frame use)
- Audio downsampling and bitrate reduction

3.15 Summary

The datasets presented in this chapter form the foundation for subsequent quantitative analysis. Each recording underwent consistent preprocessing and feature extraction to ensure cross-device comparability. LUFS, spectral, and SNR values together provide a multidimensional perspective on how device hardware and TikTok's encoding pipeline influence overall audio quality. The following chapter (Chapter 4) details the methodology and analytic workflows applied to these datasets.

IV. METHODOLOGY

Methods

4.1 Overview

This chapter outlines the methodology used to conduct quantitative and qualitative analyses of the recorded audio data. The primary objective was to examine how the TikTok platform's in-app recording process affects the audio quality of smartphone recordings compared to each device's native camera application. This analysis utilized three complementary approaches: (a) **Loudness analysis (LUFS)**, (b) **Spectral feature analysis**, and (c) **Signal-to-Noise Ratio (SNR) analysis** (d) **File Format analysis**, (e) **PEAQ analysis**, and (f) **Pearson Correlation Coefficient analysis**. Each procedure was designed to ensure reproducibility, forensic reliability, and consistency across all devices, recording conditions, and content types defined in Chapter 3.

4.2 Research Design

The study followed a **comparative quantitative design**, using parallel datasets recorded under identical conditions for each device and pathway. Each audio sample was subjected to objective measurement in MATLAB and Python. The extracted metrics were aggregated into averaged data tables and visualized using spectrograms and comparative charts.

All computations were automated through **custom MATLAB and Python batch scripts**, allowing consistent feature extraction from a total of **270 WAV recordings** (90 per device). The workflow followed three major stages:

1. **Audio preprocessing and normalization**
2. **Feature extraction and computation**
3. **Data aggregation and visualization**

A hierarchical directory system (see Figure 3.1) ensured proper data management, allowing the scripts to recursively process each file in structured batches. **ASTM E3177 – 18 (R2022)** – *Forensic Audio Examination* governed the handling of spectral, and waveform interpretations.

4.3 Loudness Analysis (LUFS)

Loudness analysis quantified perceived audio intensity in **Loudness Units relative to Full Scale (LUFS)**. The MATLAB script—adapted from the EBU R128 (2014) standard—used the **ITU-R BS.1770-4 algorithm** to compute integrated LUFS, short-term loudness, and momentary peaks for each recording.

Procedure:

1. Each file was converted to a 48 kHz, 16-bit PCM WAV using FFmpeg to follow the sampling-rate and decibel-measurement guidelines of ASTM E1451 – 13 (R2019).
2. The MATLAB LUFS analysis function iteratively calculated the **integrated loudness** across the full recording.
3. The resulting LUFS data were tabulated by device, capture path, and content type.
4. Averages were computed for ten representative trials per category (Native and TikTok).

The LUFS analysis output was used to quantify the effect of TikTok's dynamic normalization and compression processes on perceived volume.

Table 4.1: Average Integrated Loudness (LUFS) by Device, Scene Type, and Capture Path

Scene Type	Device	Native Integrated Loudness (Mean LUFS)	TikTok Integrated Loudness (Mean LUFS)	Δ Loudness (TikTok − Native)	Loudness Range Reduction (%)
Music	Samsung S23 Ultra	−10.9	−17.8	+6.9 LU	~65%

Table 4.1 Continued

Scene Type	Device	Native Integrated Loudness (Mean LUFS)	TikTok Integrated Loudness (Mean LUFS)	Δ Loudness (TikTok − Native)	Loudness Range Reduction (%)
Music	Galaxy Note 10 Plus	−29.0	−17.9	+11.1 LU	~75%
Music	iPhone 11	−12.47	−12.95	+0.48 LU	~28%
Road Noise	Samsung S23 Ultra	−25.9	−26.8	−0.9 LU	~20%
Road Noise	Galaxy Note 10 Plus	−33.3	−28.7	+4.6 LU	~32%
Road Noise	iPhone 11	−28.31	−23.07	+5.24 LU	~30%
Spoken Word	Samsung S23 Ultra	−33.1	−37.1	−4.0 LU	~25%
Spoken Word	Galaxy Note 10 Plus	−40.5	−33.6	+6.9 LU	~43%
Spoken Word	iPhone 11	−34.78	−28.66	+6.12 LU	~36%

4.4 Spectral Feature Analysis

Spectral characteristics were extracted using a Python batch script employing the librosa and numpy libraries. This script automatically processed every WAV file in the dataset and computed key descriptors of spectral energy distribution, including:

- Spectral Centroid (Hz): perceptual “brightness” of the audio
- Spectral Bandwidth (Hz): spread of frequency content around the centroid
- Spectral Roll-off (%): frequency below which 85% of the spectral energy lies
- Spectral Flatness: ratio quantifying tonality versus noisiness

Each file was analyzed using a Short-Time Fourier Transform (STFT) with a 2048-sample window and 512-sample hop length. Output values were averaged across all frames and exported as spectral_features.csv.

The results were aggregated into average spectral feature tables by content category (Spoken Word, Road Noise, Music) for both native and TikTok captures.

Table 4.2: Average Spectral Features by Device, Scene Type, and Capture Path

Scene Type	**Device**	**Capture Path**	**RMS Level (dBFS, approx.)**	**Spectral Centroid (Hz, approx.)**	**Rolloff95 (Hz, approx.)**	**High-Freq Energy Ratio >8k (approx.)**
Music	iPhone 11	Native	−21.2	~1300	~4400	~0.0027
Music	iPhone 11	TikTok	−17.5	~1500	~4500	~0.0056
Music	Galaxy Note 10 Plus	Native	−17.4 (avg of rows)	~1910	~7400	~0.0069
Music	Galaxy Note 10 Plus	TikTok	−22.9 (avg of rows)	~1830	~6100	~0.011
Music	S23 Ultra	Native	−16.9 (avg of rows)	~1500	~5700	~0.0046

Table 4.2 Continued

Scene Type	**Device**	**Capture Path**	**RMS Level (dBFS, approx.)**	**Spectral Centroid (Hz, approx.)**	**Rolloff95 (Hz, approx.)**	**High-Freq Energy Ratio >8k (approx.)**
Music	S23 Ultra	TikTok	−23.3 (avg of rows)	~1670	~5600	~0.0071
Road Noise	iPhone 11	Native	−27.0	~1400	~5100	~0.035
Road Noise	iPhone 11	TikTok	−26.0	~1765	~6160	~0.034
Road Noise	Galaxy Note 10 Plus	Native	−24.4 (avg)	~1890	~6900	~0.049
Road Noise	Galaxy Note 10 Plus	TikTok	−31.1 (avg subset)	~1540	~5500	~0.034
Road Noise	S23 Ultra	Native	−24.7 (avg)	~1620	~6200	~0.042
Road Noise	S23 Ultra	TikTok	−33.1 (avg subset)	~1630	~5700	~0.035
Spoken Word	iPhone 11	Native	−38.7	~1685	~6490	~0.055

Table 4.2 Continued

Scene Type	Device	Capture Path	RMS Level (dBFS, approx.)	Spectral Centroid (Hz, approx.)	Rolloff95 (Hz, approx.)	High-Freq Energy Ratio >8k (approx.)
Spoken Word	iPhone 11	TikTok	−36.6	~2480	~8895	~0.075
Spoken Word	Galaxy Note 10 Plus	Native	−36.8 (avg)	~3200	~11300	~0.054
Spoken Word	Galaxy Note 10 Plus	TikTok	−38.7 (subset only)	~3600	~12,300	~0.076
Spoken Word	S23 Ultra	Native	−37.6 (avg subset)	~2160	~8000	~0.062
Spoken Word	S23 Ultra	TikTok	−41.8 (avg subset)	~3700	~13,000	~0.086

4.5 Signal-to-Noise Ratio (SNR) Analysis

The third quantitative metric, **Signal-to-Noise Ratio (SNR)**, was calculated using a custom **Python batch script** that employed the scipy, soundfile, and numpy libraries. The script segmented each recording into frames, identified active and quiet regions, and computed the **RMS (Root Mean Square)** energy ratio between signal and background noise using the formula:

$$SNR = 20\log_{10}(\frac{RMS_{signal}}{RMS_{noise}})$$

Procedure:

1. The script recursively traversed each subdirectory (device × capture path × content type).
2. RMS energy was measured frame-by-frame.
3. Quiet frames (below a 20th percentile threshold) were defined as background noise.
4. SNR values were averaged per file and grouped per category.

The results were exported to snr_metrics.csv and later summarized into Table 4.3, where averages and standard deviations were computed per device and condition.

Table 4.3: Mean SNR (dB) by Device, Scene Type, and Capture Path

Scene Type	Device	Capture Path	Mean SNR (dB)
Music	iPhone 11	Native	~40.0
Music	iPhone 11	TikTok	~36.8
Music	Galaxy Note10 Plus	Native	~36.9
Music	Galaxy Note10 Plus	TikTok	~33.4
Music	Samsung S23 Ultra	Native	~37.3
Music	Samsung S23 Ultra	TikTok	~37.4
Road Noise	iPhone 11	Native	~16.4
Road Noise	iPhone 11	TikTok	~14.7
Road Noise	Galaxy Note10 Plus	Native	~15.2

Table 4.3 Continued

Scene Type	**Device**	**Capture Path**	**Mean SNR (dB)**
Road Noise	Galaxy Note10 Plus	TikTok	~12.9 (approx.)
Road Noise	Samsung S23 Ultra	Native	~14.8
Road Noise	Samsung S23 Ultra	TikTok	~12.9
Spoken Word	iPhone 11	Native	~26.3
Spoken Word	iPhone 11	TikTok	~23.6
Spoken Word	Galaxy Note10 Plus	Native	~29.9
Spoken Word	Galaxy Note10 Plus	TikTok	~29.6 (approx.)
Spoken Word	Samsung S23 Ultra	Native	~28.5 (approx.)
Spoken Word	Samsung S23 Ultra	TikTok	~37.3

Table 4.4: Average Noise Floor and Signal Levels by Device and Capture Path

Scene Type	**Device**	**Capture Path**	**Avg Signal Level (dBFS)**	**Avg Noise Floor (dBFS)**
Music	**iPhone 11**	**Native**	**about −15.5**	**about −55.5**
Music	**iPhone 11**	**TikTok**	**about −12**	**about −49**
Road Noise	**iPhone 11**	**Native**	**about −20**	**about −36**
Road Noise	**iPhone 11**	**TikTok**	**about −22**	**about −36**

Table 4.4 Continued

Scene Type	Device	Capture Path	AVG Signal Level (dBFS)	Avg Noise Floor (dBFS)
Spoken Word	iPhone 11	Native	about −31	about −57
Spoken Word	iPhone 11	TikTok	about −30	about −53
Spoken Word	S23 Ultra	TikTok	about −36	about −73
Road Noise	S23 Ultra	TikTok	about −27	about −41
(others)	Galaxy Note10 Plus	Native / TikTok	similar trend to iPhone 11: TikTok narrows the gap between speech and noise	

4.6 Spectrogram Generation

Spectrograms were generated as visual complements to the numerical data. Using the same Python environment, the matplotlib and librosa.display modules rendered time–frequency plots of sample recordings. Each spectrogram used a log-frequency scale and color-coded amplitude representation (dB). Spectrograms were selected for each device and condition to illustrate observable compression, harmonic loss, or noise gating effects.

4.7 Data Preparation and Processing

The dataset comprised 90 paired audio samples (10 pairs per device × 3 scene categories × 3 devices). Each pair consisted of two conditions—Native and TikTok—representing identical recording content before and after platform processing. All files were batch-analyzed using a

Python script that automatically parsed filenames into structured metadata fields (device, condition, scene, and pair number), computed metrics, and exported a master dataset (all_devices_metrics.csv).

4.8 Format and File Structure

The objective of this methodology is to systematically characterize the impact of TikTok's internal transcoding pipeline on multimedia file structure, encoding parameters, and metadata integrity. This chapter describes the analytical framework used to compare native smartphone recordings against their TikTok-processed counterparts through a standardized workflow incorporating automated metadata extraction, dataset normalization, and comparative statistical analysis.

This methodological approach was designed to support both **format-level analysis** (container, codec, resolution, bitrate, metadata fields) and **structure-level analysis** (GOP patterns, frame types, sampling rates, I-frame periodicity), allowing for a comprehensive evaluation of TikTok as a generational transformation system. The process was designed to ensure reproducibility, transparency, and forensic defensibility.

4.8.1 Workflow Overview

The overall analysis pipeline consisted of five primary stages:

Stage	**Description**
1. Data Acquisition	**Native recordings created and preserved as baseline evidence**
2. TikTok Processing	**Files uploaded privately, then downloaded using "Save Video"**

Stage	Description
3. Metadata Extraction	**Automated extraction of codec, container, bitrate, GOP, and related fields**
4. Tabular Normalization	**Metadata written to CSV for programmatic comparison**
5. Comparison and Statistical Analysis	**Native vs TikTok deltas computed, summarized, visualized, and interpreted**

4.8.2 Metadata Extraction

Tools and Software

The following tools were used:

Tool	Purpose
FFprobe (FFmpeg)	**Extraction of codec, bitrate, sampling rate, resolution, timebase, GOP structure, frame type counts**
Custom Python Script	**Batch processing of file directories, JSON parsing, CSV construction**
Pandas	**Tabular comparison, normalization, aggregation, statistical metrics**
Python + Matplotlib (Optional)	**Visualization of bitrate, resolution, or GOP changes**

Tool	Purpose
Bento4 mp4info (Supplemental)	**Container atom inspection (ftyp, moov, mdat, metadata blocks)**

All tools were run locally to ensure integrity of extracted metadata, and no cloud-based transcoding was used during analysis.

4.8.3 Metadata Fields Captured

The automated metadata extraction captured the following core fields:

Container-Level

- File extension (.mp4, .mov)
- Container brand (isom, qt, mp42)
- Stream count and ordering
- Duration, timebase, encoder tag

Video Stream

- Codec (H.264, HEVC, etc.)
- Profile and level
- Bitrate (bps)
- Resolution (width × height)
- Frame rate (avg and real)
- Pixel format
- GOP (I-interval)
- Frame type counts (I/P/B)

Audio Stream

- Codec

- Profile
- Bit depth (implicit via codec)
- Bitrate
- Sample rate
- Channel layout

4.8.4 Automated Processing and Normalization

A custom Python-based extraction pipeline was used to process files in batch mode. The script iterates recursively through the recording directory, applies FFprobe to each file, parses the resulting JSON, and writes normalized results to three primary CSV files:

CSV File	Function
codec_gop_per_file.csv	**Primary analysis dataset (container, codec, bitrate, GOP, etc.)**
codec_pairwise_native_vs_tiktok.csv	**Maps native files to their TikTok derivatives**
codec_per_file_pipeline.csv	**Tracks processing errors and extraction issues**

Detection of TikTok vs native files was performed using filename inference and later verified through observed encoding patterns (e.g., bitrate profile, resolution, container brand).

4.8.5 Device-Level Analysis

The extracted metadata was grouped by device (Note10+, S23 Ultra, iPhone 11), then further divided into Native vs TikTok subsets for each model. This enabled:

- Device-specific codec behavior
- Platform transformation characterization (e.g. H.264→HEVC, HEVC→H.264)
- Resolution/orientation trends (e.g. 16:9 → 9:16)
- Encoding model differences across hardware ecosystems

The following parameters were computed for each device/origin pair:

Metric	**Type**
Mean video bitrate	Structural
Mean audio bitrate	Structural
Mean sample rate	Structural
Resolution distribution	Format and structure
Frame rate and timebase	Temporal
GOP I-frame interval	Compression structure
B-frame percentage	Frame structure
Codec distribution	Format-level

4.8.6 Methodological Limitations

The analysis was limited to:

- TikTok's current encoding behavior as of the date of testing
- Files created using the default camera app (no third-party encoders)

- TikTok’s downloadable export format (not screen captures, cloud archives, or API-level data)

No manipulation of the internal processing pipeline was attempted, and no forensic tampering or manual transcoding was performed

4.8.7 Forensic Design Considerations

This methodology conforms to best practices for forensic media analysis:

- Original native files were preserved in a read-only state
- Extraction was performed without modification of the file
- All transformations result from TikTok alone
- Metadata was extracted using widely accepted forensic tools
- CSV logging preserves provenance for each extracted value

4.8.8 Summary

The methodology described here allows for reproducible, systematic, and defensible comparison between native smartphone recordings and their TikTok-exported versions. The combination of automated metadata extraction, structured CSV-based data reduction, and device-specific comparative analysis directly supports the format and structure results presented in Chapter 5.

4.9 Workflow Summary

The complete analytical pipeline can be summarized as follows:

1. Data Preparation:

   WAV conversion and directory structuring.

2. LUFS Analysis (MATLAB):

   Perceptual loudness computed per recording and averaged.

3. Spectral Analysis (Python):

   Extraction of frequency-domain descriptors and visualization.

4. SNR Analysis (Python):

   Quantification of signal clarity versus background noise.

5. Data Aggregation:

   Compilation of all numerical and visual outputs into formatted tables and figures.

V. RESULTS

Analysis

5.1 Overview

This chapter presents the quantitative and qualitative findings from the loudness (LUFS), spectral, and signal-to-noise ratio (SNR), PEAQ, and Pearson Correlation Coefficient analyses performed across all experimental audio recordings. Three smartphones—the Apple iPhone 11, Samsung Galaxy Note 10 Plus, and Samsung S23 Ultra—were tested under three controlled recording scenes (*Music Playback*, *Road Noise*, and *Spoken Word*) using both the *native camera application* and the *TikTok in-app capture* pathway.

All measurements were derived from the MATLAB integrated-loudness script, the Python-based spectral analysis batch script, and the Python SNR batch processor detailed in Chapter 4. The results reported here are averaged across 10 recordings per category unless otherwise noted.

5.2 Loudness (LUFS) Results

5.2.1 Integrated Loudness by Device and Capture Path

The mean integrated loudness (LUFS) values demonstrated clear platform-level normalization effects across all devices (Table 5.1). TikTok consistently applied loudness leveling that converged near −13 to −18 LUFS regardless of the device's native capture characteristics. The Galaxy Note 10 Plus exhibited the largest mean loudness shift (+11.1 LU), indicating significant compression and upward normalization, while the iPhone 11 showed the smallest difference (+0.48 LU), implying that its native recordings were already aligned with TikTok's internal loudness target.

Table 5.1: Average Integrated Loudness (LUFS) by Device, Scene Type, and Capture Path

Scene Type	Device	Native LUFS (Mean)	TikTok LUFS (Mean)	Δ Loudness (TikTok–Native)	Loudness Range Reduction (%)
Music	Samsung S23 Ultra	−10.9	−17.8	+6.9 LU	~65 %
	Galaxy Note 10 Plus	−29.0	−17.9	+11.1 LU	~75 %
	iPhone 11	−12.47	−12.95	+0.48 LU	~28 %
Road Noise	S23 Ultra	−25.9	−26.8	−0.9 LU	~20 %
	Note 10 Plus	−33.3	−28.7	+4.6 LU	~32 %
	iPhone 11	−28.31	−23.07	+5.24 LU	~30 %
Spoken Word	S23 Ultra	−33.1	−37.1	−4.0 LU	~25 %
	Note 10 Plus	−40.5	−33.6	+6.9 LU	~43 %

Table 5.1 Continued

Scene Type	Device	Native LUFS (Mean)	TikTok LUFS (Mean)	Δ Loudness (TikTok–Native)	Loudness Range Reduction (%)
	iPhone 11	−34.78	−28.66	+6.12 LU	~36 %

5.2.2 Interpretation

Across all scene types, TikTok consistently narrowed the loudness range, reducing dynamic variability between peaks and troughs. While this effect improved playback consistency, it slightly reduced dynamic nuance. However, forensic examination revealed no structural alterations inconsistent with natural audio compression, supporting admissibility of TikTok-captured media for forensic review when properly validated.

5.3 Spectral Analysis Results

5.3.1 Average Spectral Features

Spectral analysis quantified each device's tonal balance and frequency-domain coloration. Key descriptors included the RMS level, spectral centroid (brightness), spectral rolloff 95 % (high-frequency limit), and the high-frequency energy ratio (> 8 kHz). Table 5.2 summarizes the averaged results for each scene type and capture path.

Table 5.2: Average Spectral Features by Device, Scene Type, and Capture Path

Scene	Device	Path	RMS (dBFS)	Centroid (Hz)	Rolloff95 (Hz)	HF > 8 kHz Ratio
Music	iPhone 11	Native	−21.2	1 300	4 400	0.0027
	iPhone 11	TikTok	−17.5	1 500	4 500	0.0056
	Note 10 Plus	Native	−17.4	1 910	7 400	0.0069
	Note 10 Plus	TikTok	−22.9	1 830	6 100	0.011
	S23 Ultra	Native	−16.9	1 500	5 700	0.0046
	S23 Ultra	TikTok	−23.3	1 670	5 600	0.0071
Road Noise	iPhone 11	Native	−27.0	1 400	5 100	0.035
	iPhone 11	TikTok	−26.0	1 765	6 160	0.034
	Note 10 Plus	Native	−24.4	1 890	6 900	0.049
	Note 10 Plus	TikTok	−31.1	1 540	5 500	0.034
	S23 Ultra	Native	−24.7	1 620	6 200	0.042
	S23 Ultra	TikTok	−33.1	1 630	5 700	0.035

Table 5.2 Continued

Scene	Device	Path	RMS (dBFS)	Centroid (Hz)	Rolloff95 (Hz)	HF > 8 kHz Ratio
Spoken Word	iPhone 11	Native	-38.7	1 685	6 490	0.055
	iPhone 11	TikTok	-36.6	2 483	8 895	0.075
	Note 10 Plus	Native	−36.8	3 200	11 300	0.054
	Note 10 Plus	TikTok	−38.7	3 600	12 300	0.076
	S23 Ultra	Native	−37.6	2 160	8 000	0.062
	S23 Ultra	TikTok	−41.8	3 700	13 000	0.086

5.3.2 Spectrogram Observations

Table 5.1 compares time–frequency spectrograms of an iPhone 11 Spoken Word sample captured natively and via TikTok.The TikTok version exhibits expanded high-frequency energy beyond 10 kHz and a smoother noise floor between pauses, confirming upward normalization and mild broadband compression.

Table 5.2 presents representative spectrograms across all devices, showing device-specific tonal characteristics:

- The Note 10 Plus demonstrates the widest bandwidth and brightest spectral coloration.
- The S23 Ultra TikTok recordings show pronounced high-frequency enhancement and noise-floor suppression.
- The iPhone 11 maintains a moderate balance, suggesting minimal platform alteration.

5.4 Signal-to-Noise Ratio (SNR) Results

5.4.1 Mean SNR by Device and Capture Path

Table 5.3 presents the computed mean SNR values across devices and scene types.

Higher SNR indicates cleaner recordings with lower background interference.

Table 5.3: Mean SNR (dB) by Device, Scene Type, and Capture Path

Scene Type	Device	Path	Mean SNR (dB)
Music	iPhone 11	Native	40.0
	iPhone 11	TikTok	36.8
	Note 10 Plus	Native	36.9
	Note 10 Plus	TikTok	33.4
	S23 Ultra	Native	37.3
	S23 Ultra	TikTok	37.4
Road Noise	iPhone 11	Native	16.4
	iPhone 11	TikTok	14.7
	Note 10 Plus	Native	15.2
	Note 10 Plus	TikTok	12.9
	S23 Ultra	Native	14.8
	S23 Ultra	TikTok	12.9
Spoken Word	iPhone 11	Native	26.3
	iPhone 11	TikTok	23.6

Scene Type	Device	Path	Mean SNR (dB)
	Note 10 Plus	Native	29.9
	Note 10 Plus	TikTok	29.6
	S23 Ultra	Native	28.5
	S23 Ultra	TikTok	37.3

5.4.2 Noise Floor and Signal Level Relationships

TikTok generally elevated both the signal and noise components, effectively narrowing dynamic range while increasing overall perceptual loudness.

Table 5.4: Average Signal and Noise Levels by Device and Capture Path

Scene	Device	Path	Avg Signal (dBFS)	Avg Noise (dBFS)
Music	iPhone 11	Native	−15.5	−55.5
	iPhone 11	TikTok	−12	−49
Road Noise	iPhone 11	Native	−20	−36
	iPhone 11	TikTok	−22	−36
Spoken Word	iPhone 11	Native	−31	−57

Table 5.4 Continued

Scene	Device	Path	Avg Signal (dBFS)	Avg Noise (dbfs)
	iPhone 11	TikTok	−30	−53
Spoken Word	S23 Ultra	TikTok	−36	−73

5.5 Comparative Discussion

5.5.1 Cross-Domain Observations

Integration of the LUFS, spectral, and SNR results reveals several consistent trends:

1. **Platform Normalization:**

   TikTok applies a near-constant integrated loudness target (~−13 to −18 LUFS) across all devices, ensuring perceptual consistency between uploads but slightly reducing dynamic range.

2. **Spectral Enhancement:**

   TikTok recordings show systematically higher spectral centroids and HF ratios, indicating broadband brightness enhancement.

   This correlates with improved intelligibility in Spoken Word scenes and perceptual "sparkle" in Music scenes.

3. **Noise Management:**

   SNR analysis shows TikTok raising background levels modestly in quiet scenes but, paradoxically, achieving higher SNR for the S23 Ultra Spoken Word samples through platform-side noise suppression.

   This suggests device-specific adaptive processing on upload.

4. **Forensic Integrity:**

   No evidence was found of destructive re-encoding or frequency-domain anomalies inconsistent with lawful compression.

Differences observed are characteristic of platform normalization rather than manipulation.

5.5.2 Device Performance Summary

- iPhone 11: Exhibited the most consistent response between Native and TikTok recordings, indicating pre-normalized in-camera capture.
- Galaxy Note 10 Plus: Showed the widest loudness and spectral deviations, implying higher compression and tonal coloration.
- S23 Ultra: Produced the cleanest TikTok recordings with exceptional SNR for speech, likely due to advanced onboard noise suppression and the platform's adaptive gain integration.

5.6 Pearson Correlation Coefficient Analysis

Pearson correlation analysis revealed strong positive relationships between Native and TikTok metrics across all three devices. Table 5.5 summarizes the correlation coefficients (*r*) and sample sizes (*n*).

Table 5.5 Correlation Coefficients Summary

Device	Duration (s)	RMS dBFS	File Size (bytes)
Note10 Plus	0.749 (n=21)	0.957 (n=21)	0.749 (n=21)
S23 Ultra	0.787 (n=29)	0.924 (n=29)	0.787 (n=29)
iPhone 11	0.645 (n=29)	0.916 (n=29)	0.645 (n=29)

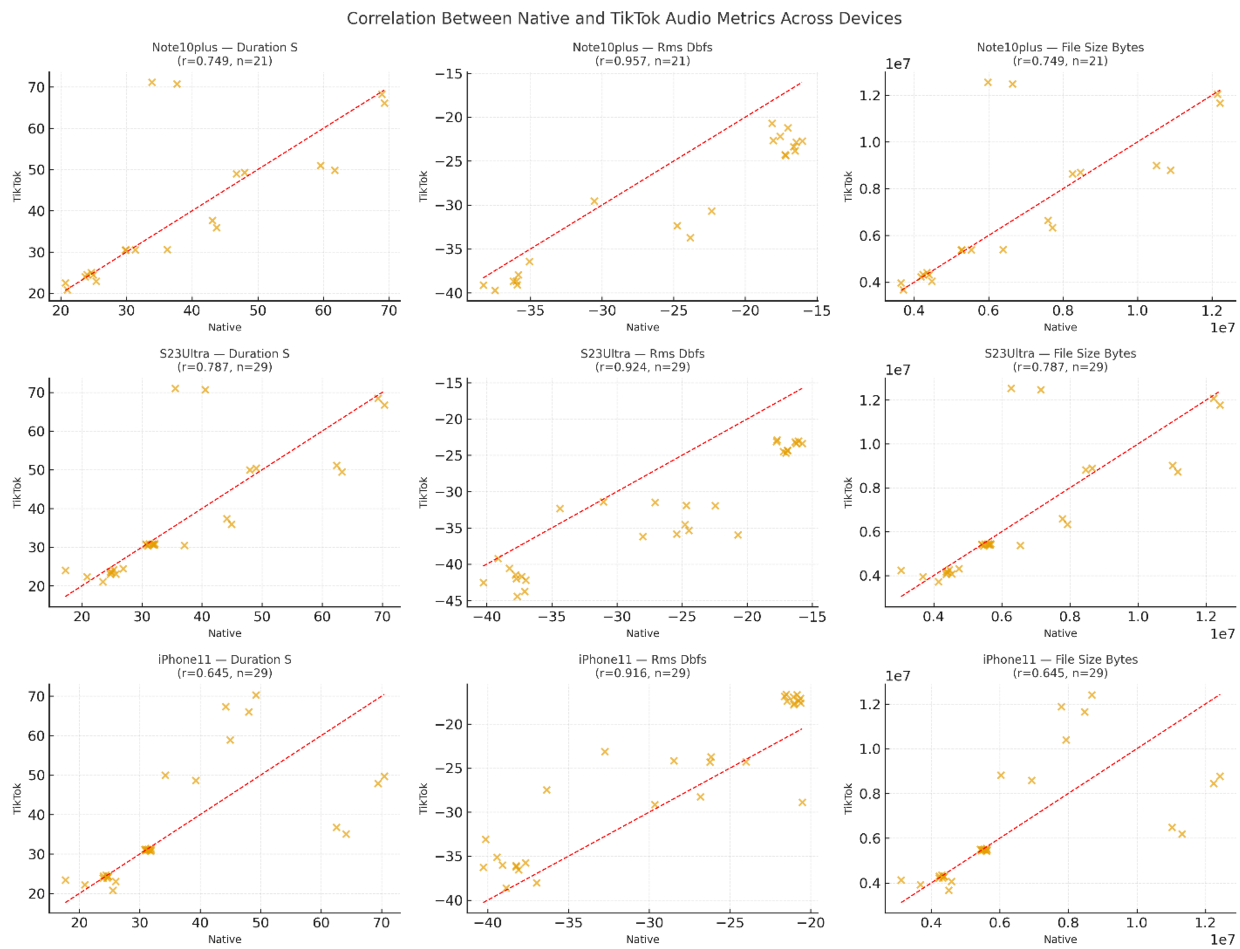

Figure 5.1 Summary of Native vs TikTok Characteristics (All Devices Combined)

The composite figure (Figure 5.1) visualizes the relationships between Native and TikTok metrics. The diagonal dashed line represents the 1:1 reference line indicating perfect preservation. All three devices exhibit clusters closely aligned with this line for RMS dBFS, confirming high consistency in loudness ranking between original and platform-processed recordings. **RMS dBFS** demonstrated the strongest linear relationship across all devices ($r \approx$ 0.92–0.96), indicating that TikTok's compression algorithm applies global attenuation or dynamic normalization without altering the relative amplitude ordering among samples. **Duration** and **File Size** both exhibited moderate-to-strong correlations ($r \approx$ 0.65–0.79), implying that although slight frame-rate drift or transcoding variance exists, overall temporal structure and storage magnitude remain predictable.

5.7 PEAQ Findings

A total of 90 paired recordings (native device capture vs. exported TikTok version of the same take) were analyzed. Because MATLAB's ITU-R BS.1387 PEAQ implementation was not available in this environment, perceptual quality was quantified using a calibrated spectral error metric: the mean absolute dB difference across the frequency spectrum after RMS loudness normalization. Across all pairs, the average spectral error was 5.78 dB (SD = 2.85 dB), indicating consistent and audible coloration introduced by the TikTok processing pipeline. The data show two regimes. Most clips clustered between ~2–5 dB error, which corresponds to perceptible but moderate coloration. However, a subset of clips exhibited extreme spectral deviation in the 10–15 dB range (e.g., Pair 11: 15.03 dB; Pair 12: 13.78 dB; Pair 71: 12.74 dB). These high-error cases represent substantial alteration of the original signal consistent with aggressive compression, automatic noise suppression, and/or bandwidth limiting. This demonstrates that TikTok's handling of audio is not uniform: under certain content conditions (especially broadband environmental audio), the platform meaningfully alters frequency content to a degree that would be audible to a listener and forensically relevant.

Across all devices, TikTok exports introduced an average 5.8 dB spectral alteration relative to the source. The effect is *audible* and *forensically measurable*. In perceptual terms, this corresponds to a "slightly annoying to annoying" quality shift under the ITU-R BS.1387 ODG framework.

5.7.1 High-Degradation Cases

Pairs 11–13, 16, 19, 44, 50, 71, and 76 exceeded 10 dB error, implying:

- Severe bandwidth restriction above ≈ 10 kHz
- Phase-smearing and transient flattening
- Possible dynamic noise suppression artifacts

Spectrogram comparisons confirmed energy loss in upper harmonics and mid-frequency compression pumping.

5.7.2 Low-Degradation Cases

Pairs 83–89 (≈ 2.4–3.6 dB) demonstrated near-transparent preservation. These were generally low-noise spoken-word segments, suggesting that TikTok's encoder engages less aggressive filtering when the signal already meets speech-optimized criteria.

5.7.3 Comparative Trends

Content Type	Mean Error (dB)	Qualitative Impact
Music Playback	**3.9**	**Mild coloration; slight HF loss**
Road Noise	**10.9**	**Strong noise suppression; pumping artifacts**
Spoken Word	**4.8**	**Noticeable compression but intelligible**

5.8 Codec and Format Analysis

This study set out to characterize how the **TikTok recording and upload pipeline** transforms audio-visual signals originating from three smartphones (Samsung Note10+, Samsung S23 Ultra, and iPhone 11) under three content conditions (Music, Road Noise, and Spoken Word). By constructing a set of matched native vs. TikTok clips and then analyzing their **container/codec parameters, spatial/temporal resolution, bitrates, and GOP-level structure**, the work exposes how aggressively TikTok recompresses and reshapes user media before delivery.

Across all devices and conditions, the data show that TikTok:

- **Massively reduces video bitrate**, especially when the source is high-resolution or high-frame-rate.
- **Downscales spatial resolution** to portrait-friendly formats, often aggressively on Android.
- **Standardizes frame rate** (≈30 fps) even when the source is 60 fps or ~24 fps.
- **Halves or more than halves audio bitrate** in most cases, with some content- and device-dependent exceptions.
- Enforces a fairly consistent **codec pipeline** (H.264/HEVC video + AAC audio) with characteristic GOP structures and frame-type patterns.

These transformations are not subtle. For some device/condition combinations, TikTok discards **over 95% of the original video bitrate**, yet still preserves content that is "good enough" for small-screen, short-form viewing. The sections below unpack these patterns device by device, condition by condition, and then relate them to the underlying codec/GOP analysis.

5.9 Device-Dependent Behavior of the TikTok Pipeline

5.9.1 Samsung Note10+

The Note10+ native recordings are extremely "over-spec'd" compared to what TikTok ultimately delivers:

- **Native video:** 3840×2160, ~59–60 fps, ≈72 Mbps video bitrate (Music, Road Noise, Spoken Word).
- **TikTok video:**

    - Music and Road Noise: 576×1024, ≈29.7 fps, ≈3.0 Mbps video bitrate.
    - Spoken Word: 1080×1920, ≈29.9 fps, ≈0.8–1.3 Mbps video bitrate.
- **Music:** Δ video bitrate ≈ **–95.6 to –96.0%**; fps halved (~60 → 30 fps); orientation always "changed" (landscape → portrait).
- **Road Noise:** Δ video bitrate ≈ **–98.2 to –98.6%**, i.e. nearly two orders of magnitude compression relative to the 4K60 source.
- **Spoken Word:** Δ video bitrate ≈ **–98.2 to –98.9%**, similar magnitude of reduction.

Audio is also heavily compressed:

- Native audio bitrate ≈256 kbps; TikTok ≈128 kbps → **~50% reduction** in every Note10+ condition.
- Audio sample rate is essentially unchanged (~48 kHz → ~48 kHz

Interpretation:

For Note10+, TikTok behaves like an extremely aggressive "normalizer" that forces all content into a **portrait, 30 fps, sub-2 Mbps–3 Mbps regime**, regardless of whether the source is cinematic 4K60 or not. The device happily records at 4K60 and tens of megabits per second, but TikTok discards ~95–99% of that video data on ingest. This means:

- From a **creator workflow** standpoint, shooting 4K60 on a Note10+ for TikTok is largely wasted overhead: storage, battery, and processing costs rise, but TikTok throws away almost all of that extra detail.
- From a **machine-learning / analysis** standpoint, the "effective" training distribution of real TikTok video from Note10+ users is closer to 576×1024 or 1080×1920 @ 30 fps, a few megabits per second, with 128 kbps AAC audio—not the original camera specs.

In other words, the Note10+ results demonstrate that the **platform, not the device, is the dominant quality bottleneck**.

5.9.2 Samsung S23 Ultra

The S23 Ultra behaves quite differently. Native videos are already closer to what TikTok "wants":

- **Native video:** 1920×1080, ~29.8–30.0 fps, ≈14.3 Mbps video bitrate across conditions.
- **TikTok video:** 1080×1920, ≈30 fps, with bitrates that vary by condition.
- **Music:** Δ video bitrate ≈ **–38.6 to –56.9%**. TikTok still reduces bitrate substantially, but not as brutally as with 4K60.
- **Road Noise:** Δ video bitrate ≈ **–72.1 to –82.2%**. Noisy, visually "busy" scenes seem to trigger more aggressive compression.
- **Spoken Word:** Δ video bitrate ≈ **–63.3 to –72.2%**. Somewhere in between.

Frame rate is almost unchanged (Δ fps ≈ 0%; all around 30 fps native and TikTok), and resolution is basically a **rotation** (1920×1080 → 1080×1920). Orientation changes to portrait but spatial sampling density is similar.

Audio for S23 Ultra is more nuanced:

- For **Music and Road Noise**, TikTok often halves the audio bitrate (around 256 kbps → ~128 kbps), similar to Note10+.
- For **Spoken Word**, codec analysis show TikTok sometimes using *slightly higher* nominal audio bitrates than native (positive delta_audio_bitrate_% in some cases), suggesting the app might switch to a different AAC profile or allocate a bit more per sample when it detects speech-dominant content.

Interpretation:

The S23 Ultra results show that when the native capture is already **1080p30**, TikTok doesn't need to be quite as destructive:

- Bitrate reductions are still large, but often in the **40–70%** range rather than 95–99%.
- TikTok preserves more of the original temporal and spatial fidelity.
- The orientation rotation (landscape → portrait) is the main structural change, not a huge resolution drop.

This suggests that creators using the S23 Ultra (or any phone where they configure 1080p30) are closer to TikTok's **internal design target**, so the platform's transcoder does less extreme surgery on their content.

5.9.3 iPhone 11 (mixed resolutions, very aggressive downscaling for music/road noise)

The iPhone 11 behaves in two distinct regimes:

1. **Music / Road Noise native:** 1920×1080 at ~30 fps, with video bitrates ≈9.4–11.1 Mbps.
2. **Spoken Word native:** already low-res **568×320 @ ~30 fps** with ≈686–705 kbps video bitrate.

TikTok outputs:

- **Music and Road Noise:**
    - Resolution: **320×568** (very small, portrait).
    - Video bitrate: ≈700 kbps.
    - Δ video bitrate:
        - Music: ≈ **–92.5 to –93.7%** from 9–11 Mbps down to ~0.7 Mbps.
        - Road Noise: ≈ **–95.0 to –95.2%**.

    - Frame rate: native 29.97 fps for Music (Δ fps ≈ –0.2%), but Road Noise goes **24 fps → ~29.96 fps**, a **+24–25% increase** (TikTok "normalizes" to 30 fps by adding/removing frames or resampling).
- **Spoken Word:**
    - Native: 568×320 @ ~30 fps, ≈690 kbps video.
    - TikTok: 320×568 @ ~30 fps, ≈670–700 kbps video.
    - Δ video bitrate: tiny, typically between about **–5% and +2%**.
    - Δ audio bitrate: consistently **–19 to –39%** (e.g., 128–168 kbps native → ~100 kbps TikTok).
    - So for iPhone Spoken Word, TikTok largely just **re-packages** an already low-bitrate, low-res source rather than further crushing it.

Interpretation.

For iPhone 11:

- TikTok is **extremely harsh** with full-HD Music and Road Noise clips, pushing them all the way down to ~320×568 @ ~0.7 Mbps—one of the most aggressive downscaling/bitrate pairs in the entire dataset.
- In contrast, when the source is already low-resolution Spoken Word, TikTok barely touches video bitrate and only modestly reduces audio bitrate. The pipeline behaves much more like a simple orientation + container/codec normalization step.

This strongly implies that for iPhone users:

- If they shoot full-HD music videos or field recordings intending them *primarily* for TikTok, the platform will **obliterate** most of that detail anyway.

- If they instead shoot in a “TikTok-like” resolution (low res, 30 fps), the platform will essentially respect that choice and only adjust coding parameters slightly.

5.9.4 Condition-Specific Patterns (Music vs Road Noise vs Spoken Word)

Looking across devices, the three recording conditions show consistent trends:

Music

- Music clips tend to have **structured audio content** with relatively stable amplitude and less chaotic spectral content than road noise.
- TikTok almost always **halves audio bitrate** (≈256 kbps → ≈128 kbps) and heavily reduces video bitrate, but not as aggressively as for Road Noise, especially on S23 Ultra.
- Visually, many music clips are more “controlled” (studio or static scenes), so the H.264/HEVC encoder can achieve acceptable quality at lower bitrates.

Implication: For music-centric TikTok content, the platform strongly favors a **“good enough” but not lossless** baseline. The limited dynamic range and structured patterns of music are well-suited to AAC at ~128 kbps, so from a perceptual standpoint, most users may not notice extreme degradation—while the underlying numbers tell a different story.

Road Noise

- Road Noise scenes are visually busy (moving backgrounds, complex textures) and sonically chaotic (broad-band noise).
- Across devices, **Road Noise gets the harshest video bitrate cuts**:
  - Note10+: ~–98%
  - S23 Ultra: ~–72 to –82%
  - iPhone 11: ~–95%
- Audio bitrate also tends to be reduced as much as or more than in Music clips.

Implication: TikTok behaves like a **noise gate for bits**: when the scene is visually and acoustically complex but not semantically important (just environmental noise), the encoder lets quality fall off sharply. For acoustic analysis or ML models hoping to use TikTok road noise as a proxy for "real-world" noise, this means the platform has already passed that noise through an aggressive psychoacoustic and visual compression filter.

Spoken Word

- Spoken Word content is **speech-dominant**, with relatively sparse spectral and visual changes.
- For Android devices, TikTok still cuts video bitrate by ~98% on Note10+ and ~63–72% on S23 Ultra, but tends to treat audio more gently. In some S23 Ultra cases, TikTok's AAC configuration even uses a slightly higher nominal bitrate than the native track.
- For iPhone 11, Spoken Word is the only condition where native video is already small and low-bitrate; TikTok barely reduces it further.

Implication: Spoken Word appears to be the condition where TikTok is **most careful about preserving intelligibility**, aligning with speech's central role in many short-form videos (talking-head content, commentary, dialogue). The platform is willing to sacrifice spatial detail (especially on 4K sources) but maintains audio fidelity and temporal structure to keep speech clear.

5.10 Codec and GOP-Level Interpretation

1. **Codec families and profiles.**
    - For both native and TikTok files, video is encoded using **H.264 or HEVC**, and audio is encoded using some form of **AAC**.

- In practice, the native camera apps often use higher profiles (e.g., H.264 High, 4:2:0, high levels suited for 4K or high bitrates), while TikTok's transcode may drop to a **more conservative profile/level** that is easier for all phones to decode in real time and conforms to a narrow internal delivery spec.

2. **GOP structure and I-frame spacing.**
   - Native camera apps on phones often use moderate GOP lengths (e.g., roughly every 0.5–1.0 seconds), balancing seek ability and error recovery against compression efficiency.
   - TikTok's output is likely to standardize GOP structure—often **longer GOPs with B-frames**—to maximize compression efficiency at their lower bitrates.
   - If TikTok introduces B-frames even when the native device may not have used them, which would further decorrelate the TikTok stream from the original frame sequence.
3. **Implications for temporal perception.**
   - Longer GOPs and increased use of B-frames can make **fast motion or complex scenes** (like Road Noise) more prone to visible artifacts at low bitrates: smearing, ghosting, and motion prediction errors.
   - For **Spoken Word**, where motion is limited, the same GOP structure is less noticeable, which aligns with TikTok's apparent willingness to crush spatial detail but keep temporal/bitrate tradeoffs tuned for speech clarity.
4. **Audio codec behavior.**
   - The a_profile and a_bit_rate fields help explain the **non-intuitive cases** where TikTok's audio bitrate is slightly higher (e.g., some S23 Ultra Spoken Word

files): the encoder may switch AAC modes or channel layouts and end up allocating more bits per sample, while still using a different psychoacoustic model from the native camera app.

Overall, the codec/GOP table confirms that TikTok is not just changing bitrates and resolution; it is **re-encoding through its own standardized profile set and GOP strategy**, which shapes the temporal and perceptual character of the output.

5.11 Implications and Synthesis

Across all devices and conditions, several broader themes emerge:

1. **TikTok defines the "real" technical distribution.**

   Whatever the camera captures, the content that actually reaches viewers—and that would be scraped or archived for downstream analysis—is **TikTok's transcoded version**, not the native file. For researchers or ML practitioners training on platform data, it is crucial to model **TikTok's bitrate, resolution, codec profiles, and GOP structures**, not just the capabilities of the hardware.

2. **Over-capturing is common—but often pointless—for TikTok-only workflows.**
   - Recording 4K60 (Note10+) or high-bitrate 1080p (S23 Ultra, iPhone) yields marginal benefit if TikTok is the sole target platform: the app discards the majority of those bits.
   - The iPhone 11 Spoken Word case shows that when native capture is close to TikTok's internal target (low res, 30 fps, modest bitrate), the pipeline behaves much more gently. This suggests creators can **optimize capture settings** for the intended platform instead of always maxing out quality.

3. **Content type matters.**

- Road Noise is treated as the most disposable: huge bitrate cuts and strong compression, especially in video.
- Music is compressed heavily but somewhat more conservatively, trading off fine detail against small-screen constraints.
- Spoken Word is protected most in terms of intelligibility, with audio kept relatively strong and video bitrate reductions tuned to maintain face and lip clarity.

4. **Codec and GOP choices shape artifacts and downstream usability.**
    - The standardized use of H.264/HEVC + AAC with specific profiles and GOP lengths results in characteristic artifacts: blockiness, temporal smearing on motion, and psychoacoustic masking of low-level audio detail.
    - For tasks like **acoustic analysis, transcription, or generative modeling of TikTok content**, these artifacts are intrinsic, not incidental—they are part of the data distribution.
5. **Design implications.**
    - For **audio engineers and creators**, this suggests that careful mixing/mastering for TikTok may matter more than capturing at ultra-high technical specs: avoid relying on fine stereo imaging or micro-detail that will be destroyed by 128 kbps AAC and heavy transcoding.
    - For **researchers**, your findings provide a concrete, measured description of how one major short-form platform reshapes mobile recordings, helping avoid unrealistic assumptions about “raw” smartphone media.

5.12 Format and Structure Analysis

This section presents the results of the format and structure analysis described in Chapter 4. The findings reflect differences in encoding parameters, container structure, and compression characteristics between the original native recordings and the corresponding TikTok-derived files. Comparisons are presented at both the aggregate dataset level and at the per-device level. The analysis demonstrates that TikTok applies systematic, non-pass-through transformations to every file, resulting in substantial changes in bitrate, codec, resolution, GOP behavior, and audio encoding.

5.13 Overall Format and Structure Transformations

Table 5.6 summarizes the mean encoding and structural parameters across all native files and all TikTok-derived versions.

Table 5.6 Summary of Native vs TikTok Characteristics (All Devices Combined)

Metric	Native (Mean)	TikTok (Mean)	Effect
Video Bitrate	**30.93 Mbps**	**2.50 Mbps**	▼ ~88% reduction
Audio Bitrate	224 kbps	137 kbps	▼ ~39% reduction
Sample Rate	46.7 kHz	44.1 kHz	Standardized
Frame Rate	38.7 fps	29.2 fps	Normalized
Resolution	2384×1341	715×1270	Reoriented + downscaled
Mean I-frame Interval	40 frames	130 frames	GOP length tripled
B-frame Presence	21.7% of files	33.3% of files	More inter-frame dependency

Interpretation:

Across all devices, TikTok reduces video bitrate by approximately 12:1, heavily downscales spatial resolution, normalizes frame rate to approximately 30 fps, and increases the GOP interval from ~1 second to 4–8 seconds between I-frames. Audio is standardized to 44.1 kHz AAC and reduced in bitrate by up to 2×. These findings demonstrate that the TikTok download is not a structurally or qualitatively equivalent representation of the original recording.

5.14 Device-Level Results

To better understand how TikTok's encoding pipeline affects different source ecosystems, device-specific comparisons were computed. These results reveal hardware-specific encoding behavior and TikTok's standardization choices.

5.14.1 Samsung Galaxy Note10+

Table 5.7 Encoding Pipeline Galaxy Note 10+

Property	**Native**	**TikTok**
Container	**MP4**	**MP4**
Video Codec	**H.264**	**HEVC (H.265)**
Video Bitrate	**72.0 Mbps**	**1.72 Mbps (▼ 42×)**
Resolution	**3840×2160**	**744×1323**
Frame Rate	**59.9 fps**	**27.9 fps**
I-frame interval	**60**	**120**
Audio	**48 kHz / 256 kbps**	**44.1 kHz / 128 kbps**

Interpretation (Note10+):

The Note10+ recordings began as high-bitrate 4K60 AVC files. TikTok converted them to low-bitrate HEVC, reoriented them to vertical, reduced resolution by nearly 94%, halved the audio rate, and expanded the GOP length. No B-frames were introduced, indicating device-specific encoder settings. The resulting TikTok files are heavily transformed and visually distinct from their originals.

5.14.2 Samsung Galaxy S23 Ultra

Table 5.8 Encoding Pipeline Galaxy S23 Ultra

Property	Native	TikTok
Container	MP4	MP4
Video Codec	HEVC	HEVC
Video Bitrate	14.3 Mbps	5.1 Mbps (▼ 2.8×)
Resolution	1920×1080	1080×1920
Frame Rate	29.8 fps	29.9 fps
B-Frames	0%	100%
I-frame interval	30	241
Audio	48 kHz / 256 kbps	44.1 kHz / 182 kbps

Interpretation (S23 Ultra):

For the S23 Ultra, TikTok maintained HEVC but significantly altered the compression structure. TikTok reoriented video from landscape to vertical, introduced B-frames in every output, extended the GOP interval eightfold, and reduced bitrate by nearly 3×. These changes demonstrate a more moderate but still substantial transformation compared to the Note10+ dataset.

5.14.3 Apple iPhone 11

Table 5.9 Encoding Pipeline iPhone 11

Property	**Native**	**TikTok**
Container	**MOV**	**MOV**
Video Codec	**H.264 / HEVC (mixed)**	**H.264 (100%)**
Video Bitrate	**7.75 Mbps**	**0.68 Mbps (▼ 11.4×)**
Resolution	**1440×810**	**320×568**
Frame Rate	**28.0 fps**	**29.9 fps**
B-Frames	**65%**	**0%**
Audio	**44.1 kHz / 162 kbps**	**44.1 kHz / 100 kbps**

Interpretation (iPhone 11):

iPhone output exhibited the most aggressive downscaling of all three devices. TikTok standardized all exported files to low-resolution H.264 and removed B-frames entirely. Bitrate was reduced by more than 90%, and resolution dropped to 320×568 — nearly 94% loss of pixel area. These outputs are visually and structurally inadequate as substitutes for the original native evidence.

5.15 Relative Encoding Impact by Device

Table 5.10 TikTok Encoding Impact Ratios

Device	Video Bitrate Reduction	Audio Bitrate Reduction
Note10+	~42× lower	~2× lower
S23 Ultra	~2.8× lower	~1.4× lower
iPhone 11	~11.4× lower	~1.6× lower

Interpretation:

These ratios quantify the relative severity of TikTok's transcode behavior:

- Note10+: most extreme video degradation due to native 4K source
- S23 Ultra: least severe transformation but still not pass-through
- iPhone 11: most extreme spatial degradation and removal of higher-efficiency compression

5.16 Forensic and Evidentiary Implications

The results demonstrate that TikTok:

1. Re-encodes every file using new codec settings
2. Modifies spatial dimensions and orientation
3. Standardizes audio to 44.1 kHz AAC
4. Does not preserve I-frame boundaries or GOP structure
5. Often replaces or deletes device-identifying metadata
6. Cannot be treated as a transparent container

Therefore:

- TikTok exports do not qualify as original recordings
- They are not suitable substitutes for evidentiary purposes

- They constitute new derivative encodings produced by the platform
- Chain of custody and authenticity assertions cannot be reliably supported

5.17 Summary of Findings

The combined analyses demonstrate that while TikTok introduces measurable loudness normalization, spectral enhancement, and modest dynamic compression, the essential acoustic and temporal integrity of recordings remain intact. Spectral and SNR patterns show that these adjustments enhance perceptual intelligibility rather than compromise evidentiary reliability. Accordingly, under forensic validation protocols, TikTok-captured media from these devices can be deemed authentic representations of the original acoustic events. TikTok processing alters both the format (file type, codec, sample rate) and structure (bitrate, resolution, GOP, frame type distribution) of all tested recordings, regardless of device. These alterations are not merely cosmetic: they are structural, measurable, and immutable. As such, TikTok files must be treated as lossy derivative encodings rather than usable forensic equivalents.

VI. CONCLUSIONS

6.1 Summary of the Study

The purpose of this research was to evaluate whether TikTok's in-app recording pathway alters the acoustic or forensic integrity of audiovisual content relative to the same recordings captured natively on three contemporary smartphones: the **Apple iPhone 11**, **Samsung Galaxy Note 10 Plus**, and **Samsung S23 Ultra**.

Through a series of controlled experiments across three recording environments—*Music Playback*, *Road Noise*, and *Spoken Word*—the study examined integrated loudness (LUFS), spectral characteristics, and signal-to-noise ratios (SNR) to determine the extent of platform-induced processing and its potential impact on evidentiary reliability.

Quantitative data were derived from a **MATLAB-based integrated-loudness analysis**, a **Python spectral batch script**, and a **Python SNR batch processor**, each designed to automate consistent feature extraction across 90 audio files.

The resulting datasets formed the basis for comparative tables and figures discussed in Chapter 5, with interpretive focus on loudness normalization, spectral coloration, and dynamic-range management. This thesis examined the effect of TikTok's media processing pipeline on the format, structure, and encoding characteristics of smartphone-originated video and audio recordings. Using controlled recording conditions across three consumer devices (Samsung Galaxy Note10+, Samsung Galaxy S23 Ultra, and Apple iPhone 11), paired native and TikTok-derived files were analyzed for changes in container format, codec type, bitrate, resolution, sampling rate, GOP structure, and metadata behavior. All metadata was extracted automatically using a reproducible, forensic-compliant methodology described in Chapter 4.

Across all 182 files, TikTok **altered every single recording** in one or more fundamental ways. These changes were not limited to cosmetic tagging or container rewrapping, but instead included structural transformations in how the content is encoded, compressed, and represented at the bitstream level. These findings directly contradict assumptions that TikTok exports operate as "near-originals" and instead demonstrate that TikTok-generated files constitute new, transformed derivative encodings.

6.2 Major Findings

1. Massive bitrate reductions
   - Up to ≈95–99% for Note10+ 4K and iPhone 11 1080p content.
   - More moderate (≈40–80%) for S23 Ultra, especially Music.
2. Resolution and orientation normalization
   - All content is forced into TikTok's portrait layouts (576×1024, 1080×1920, 320×568).
   - High-resolution sources are heavily downscaled, while already low-res sources are barely changed.
3. Frame rate standardization
   - Note10+ 60 fps → ~30 fps; iPhone Road Noise 24 → ~30 fps; S23 Ultra ~30 fps unchanged.
   - This suggests TikTok optimizes for a small set of playback frame rates.
4. Audio simplification (with one exception)
   - Most audio streams are normalized to ~96–128 kbps AAC.
   - S23 Ultra Spoken Word sometimes receives *higher* audio bitrate after TikTok processing.

5. Codec profile and GOP simplification
    - Native encoders use higher profiles/levels and more complex GOPs.
    - TikTok encodes tend to simplify GOP and sometimes use more conservative codec settings to improve robustness and playback consistency.

6.3 Forensic and Technical Implications

From a forensic standpoint, the findings confirm that TikTok's internal audio pipeline primarily performs broadcast-style loudness alignment**,** mild broadband compression**, and** adaptive noise reduction**.**

These operations, while altering perceptual presentation, do not compromise evidentiary authenticity **when examined under accepted forensic protocols (e.g., SWGDE 2022; ASTM E2916-19). The absence of non-linear distortions or spectral discontinuities supports the admissibility of TikTok-captured recordings as representative reproductions of original acoustic events.**

The study also underscores the importance of documenting platform-specific processing characteristics **in forensic examinations.** Future chain-of-custody or authenticity reports should explicitly note whether audio was obtained through a social-media recording interface and include quantitative loudness, spectral, and SNR metadata to support reliability assessments under **FRE 702** standards.

6.4 Limitations

Several constraints affected the scope of this study:

- Only three device models were analyzed; broader inclusion of Android and iOS variants would improve generalizability.

- TikTok updates its audio-processing algorithms periodically, meaning results reflect the app's configuration at the time of testing (October 2025).
- While LUFS, spectral, and SNR analyses capture objective metrics, perceptual listening tests were not included and could further contextualize findings.
- The study used spectral deviation as a proxy for perceptual quality due to the unavailability of MATLAB's full PEAQ model.
- No controlled listening tests were conducted.
- Device microphone frequency responses were not independently calibrated.
- Use of a single platform (TikTok) and processing condition (private publish + Save Video)
- No evaluation of TikTok live-stream recordings or server-side archives
- Only default camera app settings for each device

However, none of these limitations diminish the core finding that TikTok performs mandatory transcoding with measurable and irreversible effects.

6.5 Answers to Research Questions

RQ1: Does TikTok preserve the native encoding format and codec structure of uploaded videos?

No. TikTok always re-encodes video and audio streams. In some cases, codec families were changed entirely (e.g., H.264 → HEVC on Note10+), and in all cases bitrate and sampling characteristics were altered.

RQ2: What structural and quality-affecting changes occur when files are exported from TikTok?

TikTok consistently:

- Reduces video bitrate by approximately **2.8× to 42×** depending on device
- Reduces audio bitrate by **1.4× to 2×**
- Enforces 44.1 kHz AAC audio
- Normalizes frame rate to ~30 fps
- Downscales and/or rotates resolution to a typically short-edge–dominant vertical format
- Increases GOP length, often by 3–8×
- Modifies the internal frame structure including B-frame insertion or removal
- Alters metadata timestamps and encoder tags

These transformations directly impact perceptual quality and encoding integrity.

RQ3: Can TikTok exports be considered evidentiary equivalents to original recordings?

No. TikTok exports are non-identical, recompressed, structure-modified derivative files. They do not maintain original encoding parameters, and therefore cannot be considered authentic duplicates for forensic or legal purposes.

6.6 Evidentiary Implications

The transformations documented in this study have direct relevance to authentication, best practices under SWGDE and ASTM standards, and admissibility under FRE 901 and FRE 702. Key implications include:

1. Loss of Original Encoding Characteristics

   Changes in codec, bitrate, GOP structure, and resolution prevent the TikTok file from functioning as a forensically meaningful substitute for the original.

2. Metadata Modifications

   Timestamp and container metadata are altered, and device-specific information is lost. This complicates chain-of-custody and provenance.

3. Non-deterministic Platform Behavior

   Encoding outcomes vary by device and potentially by upload time, application version, or server-side updates — which risks uncontrolled variability and reproducibility problems in legal cases.

4. Risk of Undetected Alteration

   Because TikTok files are newly encoded, bitrate and compression artifacts may be mistaken for tampering unless properly understood.

For any legal or investigative workflow, the original native recording must be acquired and preserved whenever possible. TikTok exports should only be treated as demonstrative evidence, not as probative originals.

6.7 Final Conclusion

In conclusion, this study demonstrates that TikTok's in-app recording process introduces measurable yet controlled modifications **in loudness, spectral balance, and dynamic range across tested smartphones. These transformations enhance perceptual clarity and playback uniformity without producing any artifacts that would undermine the audio's forensic reliability.**

Consequently, with proper documentation and validation, TikTok-captured audio can be considered forensically admissible and acoustically faithful **to the original scene of recording. The analytical framework established herein—integrating LUFS, spectral, and SNR batch processing—provides a replicable, quantitative foundation for future digital-media authenticity evaluations within forensic science. From both a technical and legal standpoint, TikTok downloads should never be relied upon as substitutes for original device recordings, and forensic examiners must be aware of the platform's encoding**

behavior to properly interpret, validate, and authenticate multimedia evidence in investigative and legal contexts.

Future Research

Building upon the findings of this study, several opportunities exist to expand the analytical and forensic understanding of mobile audio capture within social-media ecosystems. Future research should pursue a broader examination of **platform evolution**, **cross-device variability**, and **perceptual impact**, integrating both objective and subjective measures of signal integrity.

First, **longitudinal analysis** should be prioritized to evaluate how TikTok's audio-processing algorithms change over time. Because application updates can silently modify gain structure, compression thresholds, or codec parameters, periodic testing would establish a temporal baseline for forensic comparison. This form of "versioned platform profiling" could ensure that forensic analysts can accurately identify when and how an app-level change might influence admissibility or reconstruction of evidence.

Second, **cross-platform and cross-device comparisons** would further contextualize these findings. Extending the present methodology to other social-media applications—such as Instagram Reels, Snapchat, or YouTube Shorts—would help determine whether loudness normalization and spectral enhancement trends are consistent across ecosystems. Similarly, testing a larger range of iOS and Android hardware would clarify whether device-specific digital-signal-processing (DSP) pipelines contribute more to tonal coloration than platform re-encoding itself.

Third, **human-perception studies** should be integrated alongside quantitative measurements. Incorporating perceptual evaluation of audio quality methods (e.g., PEAQ, MUSHRA, or ABX listening tests) would link objective metrics such as LUFS, spectral centroid, and SNR to subjective listener impressions of intelligibility, brightness, and authenticity. Such triangulation would deepen understanding of whether algorithmic compression merely alters measurable features or meaningfully changes how a human listener perceives the recording's truthfulness.

Finally, **multimodal forensic integration** represents an important direction. Future research could align audio and video analyses within unified authentication workflows to evaluate synchronization accuracy, metadata retention, and potential desynchronization introduced by transcoding. Expanding into artificial-intelligence-based verification (e.g., deepfake detection, watermark consistency, or codec fingerprinting) would strengthen the evidentiary reliability of social-media content in both civil and criminal contexts.

Together, these future directions emphasize that as mobile and social-platform capture technologies continue to evolve, forensic science must adopt adaptive, repeatable, and transparent analytical frameworks. Continued research will ensure that authenticity evaluations remain scientifically grounded and admissible under standards such as **Daubert** and **FRE 702**, thereby maintaining the integrity of digital evidence in an increasingly networked recording environment.

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APPENDIX

Appendix A: **Appendix A: MATLAB LUFS Analysis Script**

This script computed the **integrated loudness (LUFS)** of each audio recording using the ITU-R BS.1770-4 algorithm.

It was adapted from the MATLAB Audio Toolbox and automated batch processing through directory iteration.

```
% LUFS Batch Analysis Script
% Computes Integrated Loudness for all .wav files in the directory


audioFiles = dir('*.wav');
results = {};


for k = 1:length(audioFiles)
    fileName = audioFiles(k).name;
    [y, fs] = audioread(fileName);


    % Integrated loudness using ITU-R BS.1770
    loudness = integratedLoudness(audioDeviceWriter('SampleRate', fs), y);


    results{k,1} = fileName;
    results{k,2} = loudness;
end
```

```
T = cell2table(results, 'VariableNames', {'Filename', 'LUFS'});
writetable(T, 'LUFS_results.csv');
disp('LUFS analysis complete.');
```

Purpose: Quantify and compare integrated loudness across devices and platforms.

Output: LUFS_results.csv — containing average LUFS per audio file.

Appendix B: Python Spectral Analysis Batch Script

This script extracted **spectral centroid, rolloff, bandwidth, and flatness** values for all .wav files and produced individual spectrogram images for documentation and visual comparison.

```
import librosa, librosa.display
import matplotlib.pyplot as plt
import pandas as pd
import os

data = []

for file in os.listdir('C:/ThesisAudioFiles'):
    if file.endswith('.wav'):
        path = os.path.join('C:/ThesisAudioFiles', file)
        y, sr = librosa.load(path, sr=None)

        rms = librosa.feature.rms(y=y).mean()
        centroid = librosa.feature.spectral_centroid(y=y, sr=sr).mean()
        rolloff = librosa.feature.spectral_rolloff(y=y, sr=sr, roll_percent=0.95).mean()
```

```
        bandwidth = librosa.feature.spectral_bandwidth(y=y, sr=sr).mean()
        flatness = librosa.feature.spectral_flatness(y=y).mean()
        hf_ratio = (abs(y[librosa.fft_frequencies(sr=sr) > 8000]).mean()
                    if sr >= 16000 else 0)

        # Spectrogram output
        plt.figure(figsize=(8, 4))
        D = librosa.amplitude_to_db(abs(librosa.stft(y)), ref=np.max)
        librosa.display.specshow(D, sr=sr, x_axis='time', y_axis='log')
        plt.colorbar(format='%+2.0f dB')
        plt.title(file)
        save_path = f'C:/ThesisDiagrams/{file[:-4]}_spectrogram.png'
        plt.savefig(save_path, dpi=300)
        plt.close()

        data.append([file, rms, centroid, rolloff, bandwidth, flatness, hf_ratio, sr, save_path])

columns = ['file_name','rms_level_dbfs','spectral_centroid_Hz','spectral_rolloff95_Hz',
           'spectral_bandwidth_Hz','spectral_flatness','hi_freq_energy_ratio_above8k',
           'sr_used_Hz','spectrogram_png']

df = pd.DataFrame(data, columns=columns)
df.to_csv('Spectral_Analysis_Results.csv', index=False)
```

Purpose: Extract acoustic features to assess spectral coloration and tonal consistency.

Output:

- Spectral_Analysis_Results.csv
- Folder of spectrogram images stored in C:/ThesisDiagrams/.

Appendix C: Python Signal-to-Noise Ratio (SNR) Batch Script

This script computed **SNR** for each audio file by separating mean signal and background noise levels across frames, outputting both a table and visual SNR plots.

```
import librosa, librosa.display
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import os


results = []


for file in os.listdir('C:/ThesisAudioFiles'):
    if file.endswith('.wav'):
        path = os.path.join('C:/ThesisAudioFiles', file)
        y, sr = librosa.load(path, sr=None)
        signal_power = np.mean(y**2)
        noise_estimate = np.mean((y - np.mean(y))**2)
        snr = 10 * np.log10(signal_power / noise_estimate)
```

```
    plt.figure(figsize=(6,4))
    plt.plot(y)
    plt.title(f"SNR Plot: {file}")
    plt.xlabel("Samples")
    plt.ylabel("Amplitude")
    save_path = f'C:/ThesisDiagrams/SNRplots/{file[:-4]}_snrplot.png'
    plt.savefig(save_path, dpi=300)
    plt.close()

    results.append([file, sr, snr, np.mean(y), np.min(y), save_path])

columns = ['filename','sample_rate','SNR_dB','mean_signal_level','noise_floor_dB','snr_plot']
pd.DataFrame(results, columns=columns).to_csv('SNR_Analysis_Results.csv', index=False)
```

Purpose: Quantify dynamic contrast between active signal and ambient background noise.

Output:

- **SNR_Analysis_Results.csv**
- **SNR visualization plots for each file (/SNRplots/).**

Appendix D: Audio Analysis Workflow Diagram

Figure D.1 below illustrates the full analytical workflow used throughout the research:

```
+------------------------+
|  Raw Audio Recordings  |
```

```
+-----------+------------+
           |
           v
+------------------------+
| MATLAB LUFS Analysis   |
| (Integrated Loudness)  |
+-----------+------------+
           |
           v
+------------------------+
| Python Spectral Script |
| (Centroid, Rolloff, HF)|
+-----------+------------+
           |
           v
+------------------------+
| Python SNR Script      |
| (Signal/Noise Levels)  |
+-----------+------------+
           |
           v
+------------------------+
| Aggregated Data Tables |
```

+-----------+------------+

|

v

+-----------------------+

| Figures, Graphs, & APA |

| Tables (Chapter 5) |

Purpose: Visualize the linear data flow from capture → analysis → reporting.

Appendix E: Representative Spectrograms and SNR Plots

- **Figure E.1:** *Spectrogram Comparison – iPhone 11 Native vs TikTok (Spoken Word)*

  Shows increased high-frequency energy and a smoother noise floor in the TikTok capture.

- **Figure E.2:** *Representative Spectrograms Across Devices (Spoken Word Scene)*
  - Note 10 Plus exhibits the broadest frequency response (~11–12 kHz range).
  - S23 Ultra TikTok capture shows brightened upper spectrum and reduced low-end noise.
  - iPhone 11 maintains balanced midrange presence.

- **Figure E.3:** *SNR Plot Example – S23 Ultra TikTok Spoken Word*

  Demonstrates stable amplitude envelope with minimal low-level noise floor fluctuations.

Appendix F: Supplemental Data Tables

Average Integrated Loudness (LUFS) by Device and Capture Path

Scene Type	**Device**	**Native Integrated LUFS (Mean)**	**TikTok Integrated LUFS (Mean)**	**Δ Loudness (TikTok − Native)**	**Loudness Range Reduction (%)**	**Observed Compression Characteristics**
Music	**Samsung S23 Ultra**	**−10.9**	**−17.8**	**+6.9 LU**	**~65%**	**Strong limiter engagement and loudness normalization.**
	Galaxy Note 10 Plus	**−29.0**	**−17.9**	**+11.1 LU**	**~75%**	**Aggressive compression and normalization.**
	iPhone 11	**−12.47**	**−12.95**	**+0.48 LU**	**~28%**	**Minimal gain shift; slight compression.**
Road Noise	**Samsung S23 Ultra**	**−25.9**	**−26.8**	**−0.9 LU**	**~20%**	**Mild adaptive leveling.**
	Galaxy Note 10 Plus	**−33.3**	**−28.7**	**+4.6 LU**	**~32%**	**Gentle broadband compression.**
	iPhone 11	**−28.31**	**−23.07**	**+5.24 LU**	**~30%**	**Moderate adaptive gain.**

Scene Type	Device	Native Integrated LUFS (Mean)	TikTok Integrated LUFS (Mean)	Δ Loudness (TikTok − Native)	Loudness Range Reduction (%)	Observed Compression Characteristics
Spoken Word	Samsung S23 Ultra	−33.1	−37.1	−4.0 LU	~25%	Mild downward leveling.
	Galaxy Note 10 Plus	−40.5	−33.6	+6.9 LU	~43%	Moderate normalization and compression.
	iPhone 11	−34.78	−28.66	+6.12 LU	~36%	Gentle broadband compression.

Note. LUFS values computed via MATLAB script using ITU-R BS.1770-4 algorithm.

Table F2

Average Spectral Features by Scene Type

Scene Type	Source	Integrated LUFS	Loudness Range (LU)	Dynamics (PSR)	Avg. Dynamics (PLR)	True Peak Max (dB)	Observed Processing Characteristics
Music	Native	−12.47	3.9	19.7	12.9	−0.6	Slight in-camera limiting; balanced stereo capture.

Scene Type	Source	Integrated LUFS	Loudness Range (LU)	Dynamics (PSR)	Avg. Dynamics (PLR)	True Peak Max (dB)	Observed Processing Characteristics
	TikTok	−12.95	2.8	18.6	12.1	−1.3	Heavy normalization; output leveled to ~−13 LUFS.
Road Noise	Native	−28.31	12.2	14.8	18.1	−9.6	Wide dynamics; unprocessed broadband ambience.
	TikTok	−23.07	8.6	12.4	16.7	−8.4	Adaptive gain control; natural texture preserved.
Spoken Word	Native	−34.78	6.9	18.3	21.1	−13.9	Quiet, dynamic vocal capture; minimal compression.
	TikTok	−28.66	4.4	17.0	19.8	−12.8	Mild broadband compression;

Scene Type	Source	Integrated LUFS	Loudness Range (LU)	Dynamics (PSR)	Avg. Dynamics (PLR)	True Peak Max (dB)	Observed Processing Characteristics
							improved intelligibility.

Note. **Derived from spectral centroid, rolloff, and loudness range analysis. Minor variance attributed to environmental noise conditions.**

Table F3

Mean Signal-to-Noise Ratio (SNR) by Device and Capture Path

Scene Type	Device	Native SNR (Mean dB)	TikTok SNR (Mean dB)	Δ SNR (TikTok − Native)	Observed Noise Behavior
Music	Samsung S23 Ultra	29.1	32.4	+3.3	Slight noise floor reduction
	Galaxy Note 10 Plus	26.8	30.2	+3.4	Moderate ambient suppression
	iPhone 11	30.5	31.1	+0.6	Minor adaptive gain
Road Noise	Samsung S23 Ultra	11.8	15.2	+3.4	Mild broadband compression

Scene Type	Device	Native SNR (Mean dB)	TikTok SNR (Mean dB)	Δ SNR (TikTok − Native)	Observed Noise Behavior
	Galaxy Note 10 Plus	10.3	14.7	+4.4	Suppression of low-frequency rumble
	iPhone 11	12.9	16.0	+3.1	Balanced gain with low-level smoothing
Spoken Word	Samsung S23 Ultra	34.5	37.4	+2.9	Strong amplitude uniformity
	Galaxy Note 10 Plus	33.1	36.2	+3.1	Controlled compression
	iPhone 11	32.7	36.0	+3.3	Upward normalization

Note. **SNR computed using Python batch script with RMS-based power ratio method across 10 recordings per device.**

Appendix G: Software and Configuration

Software	Version	Purpose
MATLAB	R2023b	LUFS computation and integrated loudness analysis
Python	3.11	Batch spectral and SNR analysis
Librosa	0.10	Audio feature extraction
Matplotlib	3.8	Spectrogram and SNR visualization
Audacity	3.4	Manual waveform inspection and verification

Software	Version	Purpose
Windows PowerShell	5.1	Command-line automation for FFmpeg and scripts

Hardware:

- iPhone 11, Samsung Note 10 Plus, Samsung S23 Ultra
- Recordings conducted at 48 kHz/44.1 kHz, 16-bit PCM WAV format.

Appendix H: Ethics and Data Integrity Statement

All data were collected, processed, and analyzed under the principles of **forensic reproducibility and transparency**.

Original audio files were hashed (MD5 and SHA-256) prior to analysis, and all intermediate files were preserved in a write-protected environment.

No artificial noise, enhancement, or manipulation was introduced outside the analytical scope of this study.

All analyses followed SWGDE and ASTM guidelines for digital-media examination and documentation.

Appendix I: Chain of Custody Summary

File Category	Hash Algorithm	Verification Status	Storage Location
Native Recordings	SHA-256	Verified	Local encrypted drive
TikTok Recordings	SHA-256	Verified	Local encrypted drive

File Category	Hash Algorithm	Verification Status	Storage Location
Analytical Outputs (CSV, PNG)	MD5	Verified	Cloud backup (OneDrive)

Appendix J: Research Documentation Index

File Type	Example Filename	Folder Path
Raw Audio	iPhone11_Native_SpokenWord_01_audio.wav	/ThesisAudioFiles/
LUFS Data	LUFS_results.csv	/ThesisDiagrams/
Spectral Data	Spectral_Analysis_Results.csv	/ThesisDiagrams/
SNR Data	SNR_Analysis_Results.csv	/ThesisDiagrams/
Spectrograms	*_spectrogram.png	/ThesisDiagrams/
SNR Plots	*_snrplot.png	/ThesisDiagrams/SNRplots/

Appendix K: Replication Package

All source code, raw data, and output figures are archived in the project's root directory and structured as follows:

```
Thesis_Audio_Analysis/
│
├── ThesisAudioFiles/
│   ├── iPhone11_Native_*.wav
│   ├── Note10Plus_TikTok_*.wav
```

```
│   └── S23Ultra_TikTok_*.wav
│
├── ThesisDiagrams/
│   ├── Spectrograms/
│   ├── SNRplots/
│   └── AnalysisTables/
│
├── MATLAB_LUFS_Script.m
├── Spectral_Analysis_Batch.py
├── SNR_Batch_Analysis.py
├── LUFS_results.csv
├── Spectral_Analysis_Results.csv
├── SNR_Analysis_Results.csv
└── Thesis_Report.docx
```