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**From Virality to Visibility: A Multilevel Modeling of Short-Form Video Platform Influence
on Streaming Chart Dynamics Using Acoustic Feature Data**

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Introduction

From vinyl records to viral TikTok hits, the music industry has undergone a profound evolution in distribution and consumption. In the mid-20th century, music reach was largely constrained by physical media like vinyl, with success being measured in vinyl sales (Malhotra, 2024). The transition to compact discs (CDs) in the 1990s not only enhanced audio quality and portability while maintaining a consumer model based on the ownership and collection of physical media, but it also served as a catalyst for the digital disruption of the music industry (Daniel, 2019). The late 1990s and early 2000s marked a pivotal shift in music distribution with the widespread adoption of the MP3 format and the emergence of peer-to-peer file sharing networks, which disrupted traditional industry structures by enabling direct and decentralized access to digital music (Feyre, 2020). This transformation was a key step in the democratization of music consumption, which built the foundation for later advancements while simultaneously challenging established revenue models and copyright enforcement mechanisms (Feyre, 2020). A pivotal moment came in 2001 when Apple launched the iTunes Store, the first legal digital marketplace for purchasing and downloading music, which revolutionized how music was distributed and consumed (Guo, 2023). This shift from physical ownership to digital access fundamentally changed listener behavior, freeing music from the constraints of shelves and geographical availability. It is important to distinguish between digitization (converting analog media to digital formats) and digitalization (the broader socio-technical restructuring of the music industry around digital platforms). The latter facilitated the emergence of platform based distribution models, which have fundamentally transformed traditional industry power dynamics (Brusila, 2022). By the 2010s, subscription-based streaming services became the dominant mode of music consumption, offering vast catalogs on demand and monetizing access rather than ownership.

Today music distribution is predominantly controlled by streaming services such as Spotify, Apple Music, and YouTube Music (Duarte, 2025), which have not only redefined music consumption patterns but also transformed monetization strategies and industry revenue models. Globally, streaming has grown to account for the majority of recorded music revenue. For example, in the United States, streaming contributed over 83% of total music industry revenue by 2021 (Richter, 2021). This streaming takeover has generated new revenue models centered on subscriptions and advertising, while dramatically reducing sales of physical media and digital downloads. However, with this dominance has come an important shift in control. Whereas in the physical era, listeners curated their own libraries by selecting which records or CDs to purchase, modern audiences rely heavily on algorithmic recommendations and curated playlists pushed by the platforms. Streaming services are operating as multi-sided platforms that mediate interactions between listeners, artists, and advertisers, often prioritizing their own strategic interests in determining which content receives visibility (Nieborg & Poell, 2018). This centralized control has positioned platform algorithms as the primary gatekeepers of music culture, shaping audience exposure and influencing which songs achieve widespread reach. Scholars have noted that these algorithms operate as opaque “black boxes,” making their decision criteria invisible and largely beyond external audit or accountability (Gryz, 2021; Nieborg & Poell, 2018). The result is a power imbalance wherein artists and users have limited influence over content distribution compared to the platform itself (Colbjørnsen, 2020). Given this lack of transparency in how music is recommended or surfaced, it becomes critical to systematically study the factors that drive a song’s success in the streaming era.

Parallel to the streaming revolution, the 2020s have witnessed the meteoric rise of short-form content platforms like TikTok, Instagram Reels, and YouTube Shorts (Rajendran, 2024). These platforms specialize in user-generated videos that typically range in length between 6 seconds to a few minutes (Wu, 2021). TikTok, in particular, has rapidly ascended as a dominant platform in this domain, accumulating a global user base approaching two billion by the mid-2020s (Singh, 2025), supported significantly by its advanced and influential content recommendation algorithm. TikTok's "For You Page" algorithm suggests content based on individualized interest as well as trending hashtags and sounds rather than solely on who one follows when compared to traditional social media platforms (Klug et al., 2021), enabling content (and the music within it) to go viral rapidly across the user base (Coulter, 2022). The platform's unique algorithmic design promotes a wide diversity of content (Klug et al., 2021) and can propel obscure songs or old back catalog tracks to sudden popularity if they become part of a trend (Matos, 2024). For example, Fleetwood Mac's 1977 song "Dreams" re-entered global charts in 2020 after a TikTok video featuring the song went viral (Riemer, n.d.). In essence, these short-content platforms have become a new discovery layer in the music industry, where viral user engagement can dictate what a broad audience wants to listen to on streaming services afterward.

Another critical dimension in understanding modern music success is the research area of Hit Song Science (HSS). HSS refers to the use of data analytics and machine learning to predict a song's likelihood of commercial success based on its attributes (Seufitelli, 2023). Researchers in HSS analyze audio features such as melody, harmony, rhythm, tempo, energy, and lyrics, as well as contextual or extrinsic factors, to identify patterns that distinguish hit songs from non-hits. With the advent of streaming platforms and open data access, HSS research has accelerated, leveraging large datasets of songs and their audio features (Seufitelli, 2023). Notably, audience co-creation of hits through platforms like TikTok represents an extrinsic factor largely outside the scope of traditional HSS. This raises the intriguing possibility that integrating HSS with an understanding of social media virality could improve the ability to explain and predict which viral moments translate into lasting success.

To date, academic literature has begun to document the impact of TikTok virality on streaming performance (e.g. Ta et al., n.d.; Winkler et al., 2024), but to the best of the author's knowledge no published research has yet applied a Hit Song Science framework to examine the moderating role of song features in this relationship. In other words, existing studies might explain how a viral TikTok dance increases Spotify streams for the featured song, but they don't yet explore whether the musical characteristics of that song (e.g., its danceability or energy level) make the streaming boost more or less pronounced. This represents a critical oversight given that not every song that goes viral on TikTok has the same trajectory afterward. Some become one-hit wonders tied to a trend, while others convert that momentum into enduring popularity. By leveraging Hit Song Science (HSS) as a moderating lens, this study investigates whether intrinsic song features influence the degree and longevity of success that TikTok virality translates onto Spotify.

Investigating the spillover effect from TikTok to Spotify with HSS moderation has practical and theoretical significance. For music marketing and artist promotion strategies, a deeper understanding of this dynamic can guide how resources should be allocated. If certain song attributes enhance the conversion of TikTok virality into streams, record labels and independent artists could focus on producing or highlighting those elements in their marketing strategies. It could also inform campaign timing, by understanding whether a viral moment needs to be

quickly followed by playlist placements or other support to sustain interest. For artists, especially emerging ones, insights from this research can guide how they engage with short-form content platforms. From a digital music analytics perspective, this research contributes to an emerging cross-platform view of music consumption. As data science increasingly drives decision-making in the music industry, an integrated model that includes both social media metrics and song audio features can improve forecasting of a track's success. This study bridges two traditionally separate domains, namely social media marketing effects involving an ecosystem of platforms, and music content analysis, thereby enriching the literature on media synergy and cultural diffusion in the platform era. By addressing the identified research gap, the study will offer novel insights into how viral social media phenomena intersect with the intrinsic appeal of music, ultimately helping to explain what makes a song break out in today's algorithm-driven music landscape.

In light of the above, this paper seeks to quantify the spillover effect between TikTok virality and Spotify streaming performance and to determine how Hit Song Science metrics moderate this relationship. The central research question can be formulated as: *How does viral success on short-form content platforms lead to sustained growth in streaming performance, and how do a song's acoustic features influence this effect?*

By exploring this research question, this paper fills a notable gap in the literature and provides evidence based conclusions relevant to stakeholders across the music industry and academia.

Literature Review

The Rise of Streaming Services

Platformization & Access Models

Before reviewing the literature, it is essential to define a platform. Poell et al. (2022, p. 1987) define a platform as “data infrastructure that facilitate, aggregate, monetize, and govern interactions between end-users and content and service providers.” This definition highlights that platforms actively shape market dynamics, determine content visibility through algorithms, and influence which cultural products, including music, gain traction. Digital platforms are reshaping cultural production through platformization (Helmond, 2015). In the music industry, platforms now drive production, distribution, and consumption by using algorithms to boost artist visibility and success (Ta et al, n.d.). This shift has redefined power dynamics and spurred new economic models based on metrics like streams and user engagement. Terje Colbjørnsen (2020) further discusses how streaming services, unlike traditional media, standardize and control the interface between music and listeners, often prioritizing scale and efficiency over niche or locally curated experiences. Specifically, Colbjørnsen mentioned how streaming power “is exercised through relationships of access, control, and exposure” (Colbjørnsen, 2020). As a result, there is concern that streaming could lead to a homogenization of popular music or reinforce the dominance of already successful artists, since the algorithms often reward songs that are already getting traction. The platformization of the music industry has not only reshaped how music is distributed and consumed but has also redefined global competition, lowering barriers to entry for artists worldwide (Hampton-sosa, 2019). Unlike traditional music distribution channels that relied on record labels and gatekeepers to curate and approve releases, music streaming

platforms such as Spotify and Apple Music operate on an open access model, allowing virtually anyone with a laptop to upload a song and make it instantly available to a global audience (Hampton-sosa, 2019). This "publish-then-filter" approach contrasts with the "filter-then-publish" strategy of legacy music distribution, where record labels determined what music reached the public (Poell et al., 2022). Illustrating the scale of this transformation, Universal Music Group's CEO stated in 2022 that over 100,000 tracks were being uploaded to streaming platforms every day (Stassen, 2022). This highlights the vast volume of music now competing for visibility in an increasingly crowded marketplace.

The emergence of subscription streaming platforms in the late 2000s and early 2010s (pioneered by platforms like Spotify, which launched in 2008) fundamentally shifted music consumption from an ownership model to an access model (Hjelmbrekke, 2019). This shift dramatically lowered barriers to music discovery, since listeners can sample millions of songs effortlessly. This also contributed to what some describe as the "attention economy" in music, where the competition is for listener attention rather than one-time sales (Léveillé Gauvin, 2018). The impact on industry economics has been profound, since after a period of decline in the 2000s due to piracy and collapsing CD sales global music revenues have rebounded strongly on the back of streaming (Conte, 2023). According to the International Federation of the Phonographic Industry (IFPI), global recorded music revenue grew for the seventh consecutive year in 2021, with streaming being the primary driver (IFPI, 2022). In the US market, streaming's share of revenue grew from near zero in 2005 to about 83% of total recorded music revenue by 2021, as noted earlier (Richter, 2021).

Algorithmic curation, playlists, and consumption patterns

A distinguishing feature of streaming platforms is their heavy reliance on algorithms and curated playlists to personalize the user experience (Werner, 2020). Unlike the radio era, where DJs or program directors selected a relatively small set of hits for broadcast, streaming platforms individualize recommendations at scale using big data and machine learning. Spotify leverages a sophisticated mix of algorithmically generated and curated playlists to enhance music discovery, significantly influencing listener engagement and track popularity (Werner, 2020). Playlists such as Spotify's "Discover Weekly" and "Release Radar" are generated for each user by these algorithms (Kloboves, 2021), offering a tailored selection of music that often surfaces relatively unknown songs that the user might like. In parallel, Spotify's editorial team creates influential curated playlists (e.g., "Today's Top Hits," "RapCaviar," "Hot Country") (Sharma, 2024), which have millions of followers and can dramatically boost a featured song's streams. According to Aguiar and Waldfogel (2018), being featured on Spotify's "Today's Top Hits," for instance, can result in millions of additional streams, underlining the powerful gatekeeping role Spotify's algorithms and curators play in shaping listener exposure to new music. These algorithmic and editorial interventions mean that what users hear on streaming platforms is far from neutral or purely user-driven, but it is filtered through layers of data driven curation (Werner, 2020). As a consequence, success on streaming is tightly intertwined with visibility on the platform.

Empirical research on streaming user behavior reveals interesting patterns shaped by algorithmic consumption. While algorithms used by streaming services can broaden listener exposure beyond their typical preferences, Schedl et al. (2018) highlight the inherent bias toward popularity, noting that when recommender systems face several similarly suitable song choices, they often

default to ranking songs based on their existing popularity, potentially reinforcing established hits rather than promoting diverse or less-known content. In this environment, achieving a viral moment or landing in a high-traffic recommendation position within the algorithm is critical.

Streaming services have not only changed how consumers listen to music but also who or what decides what they listen to (Ta et al, n.d.). The combination of algorithmic gatekeeping and the sheer scale of content means that success in the streaming era is deeply intertwined with platform dynamics. Understanding these dynamics is a prerequisite for investigating how an external shock, such as a viral trend on TikTok, might translate into changes in streaming performance. This interplay sets the stage for the cross-platform spillover effects discussed in the next section.

Short-Form Content Platforms and Music Virality

The TikTok revolution in music discovery

TikTok, launched internationally in 2017 by ByteDance after merging with Musical.ly, has rapidly become a key platform for music discovery (Su, 2024). Its rise is driven by technological advancements, a shift toward fast-paced, video-based content, and the influence of both mainstream and creator-driven digital culture. The short-video format, popularized in the U.S. by Vine in 2012, was further propelled by Chinese platforms that initially targeted domestic audiences before expanding globally (Su, 2024). By 2020, Western social media had adopted strategies pioneered by these Chinese apps, underscoring their global impact on digital consumption trends (Su, 2024). TikTok now has 1.12 billion monthly active users (Backlinko, 2025). TikTok exemplifies how an entertainment-focused, algorithm-driven platform can convert limited attention spans into extended usage. Unlike traditional social networks centered on personal connections, TikTok operates as a "content graph" where discovery relies on algorithmic amplification rather than subscriptions (Jain, 2022). Its For You Page (FYP) functions as a hyper-personalized auto-discovery engine, prioritizing content that rapidly attracts strong viewer interaction (Kates, 2025). Studies show that the recommendation algorithm learns user preferences within minutes, selecting about 95% of videos based on past behavior to maximize watch time (Jain, 2022). Any engaging video can swiftly reach millions, a process often described as "explosive" compared to the slower, friend-centric feeds of traditional platforms (Meller, 2024).

Unlike networks centered on following friends or celebrities, TikTok's design can propel content from ordinary users to viral fame through engagement-based algorithms. When a video features a particular song the platform enables viewers to explore other videos using that song or integrate it into their own content (Radovanović, 2022). This network effect for music exponentially increases a song's exposure as trending tracks are further amplified in a self-reinforcing loop. TikTok functions as a modern analog to radio with decentralized content creation and near-instantaneous global feedback. Industry analyses note TikTok's significant role in launching new artists; in 2021, seven of the top ten rising artists were TikTok-driven (Chartmetric, 2021). Moreover, a study commissioned by TikTok found that 67% of its users are more likely to seek out songs on streaming platforms after encountering them on the app, and the "Music Impact Report" (2022) indicates that viral TikTok songs often see significant boosts in streams and downloads (Luminate, 2022). Nowadays, TikTok even offers in app integration that allows users

to directly add official songs that they find on the app to their personal Apple Music or Spotify library (TikTok, 2025).

Quantifying the spillover effect

A recent cluster of studies exploits Universal Music Group's (UMG) temporary removal of its catalog from TikTok as a quasi-natural experiment to measure spillover effects. Magie et al. (2024) analyzed this February–May 2024 licensing dispute using a difference-in-differences design with songs from other labels as controls (Magie et al., 2024). They found that, on average, removing UMG songs from TikTok did not significantly change overall streaming demand for those songs on platforms like Spotify and YouTube. However, there were notable heterogeneous effects: UMG tracks that had previously been popular on TikTok saw a 2–3% increase in streaming when removed from TikTok, indicating a substitution effect where TikTok had been cannibalizing a small portion of streams. This substitution boost mainly applied to well known songs from famous artists. In contrast, UMG songs that were not on TikTok prior to the dispute experienced a 1–3% decline in streams after removal, a complementary effect suggesting those lesser-known tracks lost a valuable discovery channel (Magie et al., 2024). TikTok's promotional role appeared especially important for emerging or niche songs, which saw streaming demand fall without TikTok exposure.

Winkler et al. (2024) report very similar findings from the same shock: using UMG's TikTok exit and a difference-in-difference comparison, they also observe an average +2–3% increase in Spotify streams for removed songs, alongside significant heterogeneity (Winkler et al., 2024). In their data (covering ~50% of the U.S. and 94% of the German streaming markets), older songs and those with little alternate promotion actually lost streaming momentum when pulled off TikTok, which serves as evidence that TikTok helps users discover catalog content they weren't actively searching for. Newer hit songs, by contrast, showed modest gains in streams once TikTok access was cut off, consistent with a minor cannibalization effect.

Bairathi et al. (2024) provide a complementary analysis focusing on short-run effects and the role of discovery mechanisms. They document a significant immediate drop in Spotify streams for UMG artists right after the early-2024 TikTok removal. The authors attribute this drop to reduced discovery: they show that user searches for songs on Shazam (a song-identification app often used when people hear music they want to identify) fell for UMG tracks post-removal. In other words, TikTok was driving listeners to seek out those songs (e.g. by hearing a snippet on TikTok and then using Shazam or Spotify), and this pipeline was disrupted. The decline in discovery was most pronounced for newly released songs and those heavily used in TikTok videos, indicating TikTok's importance in surfacing fresh music to audiences. This study underlines TikTok's role as a promotional platform: when that channel was shut off, consumption on other services briefly suffered, especially for music that relied on TikTok for initial exposure. The contrasting findings of Bairathi et al.'s study as well as industry reports outlined earlier when compared to Winkler et al. and Magie et al.'s studies highlight the need for further research.

To gain a clearer understanding of this interaction effect, the following hypothesis is proposed:

H1: TikTok chart performance can significantly boost future Spotify chart performance.

While a positive relationship between TikTok virality and Spotify success may appear intuitive, particularly in light of numerous previously mentioned industry reports and marketing case studies linking viral TikTok moments to chart surges, the academic landscape remains more nuanced. Prior evidence cited from United Music Charts (UMC), for instance, indicated instances where TikTok popularity failed to correspond with Spotify success. This apparent inconsistency makes H1 particularly compelling to test: if the majority of anecdotal and commercial observations point toward virality translating into streaming gains, yet empirical studies offer more ambiguous results, then a formal hypothesis test grounded in longitudinal data and rigorous modeling becomes essential for resolving this tension. Thus, while a positive directional expectation is warranted based on industry consensus, validating or falsifying this claim with robust data remains a central objective of the present study.

Beyond these one-time removal experiments, other researchers have examined organic TikTok virality and its cross-platform ripple effects. Matos et al. (2024) focus on older songs that found new popularity via TikTok. The research tracked songs released before TikTok's 2016 launch which later trended on the app, using data from TokBoard (which measures TikTok song usage popularity) and Google Trends as a proxy for overall interest. Their analysis shows that TikTok virality often precedes a surge in broader online search interest for a song, suggesting a causal influence of TikTok on renewed popularity. In fact, using Granger causality tests, the authors found that TikTok trend metrics could predict upticks in Google search activity for many songs, indicating TikTok was driving people to seek out those songs outside the app. They also fitted viral spread patterns to a Bass diffusion model (Matos et al., 2024). In other words, a song going viral on TikTok follows a rapid rise in the song's search and streaming trajectory. This provides initial evidence that TikTok can resurrect older catalog songs and push them into mainstream consciousness, a phenomenon increasingly noted anecdotally (e.g. the resurgence of Fleetwood Mac's 1977 song "Dreams" via a TikTok trend). Matos et al.'s findings, while preliminary, confirm that TikTok has become a new vehicle for music discovery. By providing a platform for user-generated clips set to legacy tracks, it can generate fresh waves of interest that spill over into increased searches and presumably streaming for those songs.

Furthermore, an interesting cross-platform perspective comes from Ta et al. (2024), who compared hit songs on TikTok versus Spotify over two years. Rather than looking at spillovers in one direction, they examined which platform leads in breaking hits. Their data reveal that the types of songs that go viral on TikTok differ in genre and features from those that succeed on Spotify, reflecting each platform's distinct audience and algorithmic biases. Moreover, they found evidence that, for many songs, Spotify popularity actually preceded TikTok virality. In such cases, a song might first become a hit on streaming and only afterward trend on TikTok, contrary to the popular narrative of TikTok creating hits from scratch. This finding underscores that spillover can be bidirectional. TikTok can make a song blow up, but a song that's already a hit can gain a second life or added visibility on TikTok.

Overall, these additional studies reinforce that TikTok and streaming platforms have a complex, intertwined relationship that can be complicated to quantify. Viral TikTok exposure often does translate into measurable upticks in streaming or search demand, especially for back-catalog songs or new artists, but it is not a guaranteed path to long-term success.

Comparative Analysis of Methodologies, Findings, and the Research Gap

Methodological Approaches and Inconclusive Evidence

To summarise, the current literature on TikTok's spillover effects on streaming performance employs both quasi-experimental and observational methods. On one side, studies such as Magie et al., Winkler et al., and Bairathi et al. use quasi-experimental designs, leveraging catalog removal events to compare treated songs with unaffected controls. This design enhances causal inference by isolating changes in streaming behavior due to altered TikTok exposure. In contrast, other studies (e.g., Matos et al.) use time-series correlations and Granger causality. These observational approaches capture temporal lead-lag patterns that hint at TikTok's influence but are less definitive on causation because of potential confounding factors. Despite methodological differences, all studies agree on the existence of TikTok's spillover effects, yet they report contradictory findings regarding the direction and size of these impacts. Some research points to a complementary role, where TikTok exposure boosts streaming, while other studies suggest a substitution effect, with heavy TikTok use potentially cannibalizing streaming demand. Furthermore, the influence appears to vary depending on external factors such as previous popularity, song lifecycle, or music genre.

Underexplored Internal Determinants of Success

Prior investigations have focused on these external factors to explain the variations in spillover effects. While such factors undoubtedly shape audience behavior, there is a logical rationale for also considering internal characteristics. Intrinsic features have the potential to influence a song's receptivity in a music platform, independently of various external characteristics and contexts. This proposed shift in focus is grounded in the idea that not every song trending on TikTok is equally primed for sustained streaming success. Instead, some songs might be inherently structured to capitalize on the initial burst of attention, while others may be less so. In this context, incorporating a framework that explores such intrinsic characteristics offers a complementary angle to understanding spillover effects in the music industry. By focusing on these intrinsic musical features, researchers can better discern whether the internal make-up of a song contributes to, or detracts from, the benefits brought by TikTok virality.

Hit Song Science (HSS) as a Predictor of Music Success

Origins of HSS

Hit Song Science (HSS) is a field of study at the intersection of music analytics and predictive modeling, concerned with identifying the traits that make songs successful. Specifically, it constitutes a specialized task within the field of Music Information Retrieval (MIR), a broader domain of research focused on the systematic extraction and analysis of information from musical data (Pachet, 2011). The term gained popularity in the early 2000s with the advent of companies like Polyphonic HMI, which claimed to use algorithms to predict hits from audio features (Seufitelli et al., 2023). While the commercial hype was initially met with skepticism (Pachet & Roy, 2008), it spurred academic interest in systematically analyzing hits. At its core, HSS attempts to quantify the intrinsic qualities of music's audio that correlate with popularity. A literature review done by Seufitelli et al. (2023) categorizes HSS prediction based on intrinsic

and extrinsic features. Under intrinsic features they include audio features such as acoustic features, song metadata, and lyrics-based features. On the other hand, extrinsic features include artist-based features, album-based features, cultural features, rank-based features, social media features, and temporal information (Seufitelli et al., 2023).

Key findings from HSS research

Over the past two decades, numerous studies have been done in this field. The comprehensive survey by Seufetelli et al. (2023) reviewed over 100 papers in this domain and provides a useful summary of trends. Early studies often used relatively small datasets (e.g., a few hundred songs that charted vs. not charted) and basic machine learning classifiers. For example, Dhanaraj and Logan (2005) conducted an analysis of hit song prediction by extracting key audio features that characterize a song's primary sound components. Specifically, they utilized Mel-frequency Cepstrum Coefficients (MFCCs) to capture timbral properties, emphasizing the role of these features in distinguishing hit songs from non-hits.

Building on these audio-based approaches, Singhi and Brown (2014) explored hit song prediction using lyrical features alone, analyzing rhyme density, syllable patterns, and linguistic complexity as key indicators of a song's commercial success. Their findings suggested that textual elements, independent of musical composition, could provide predictive value in forecasting chart performance. Expanding on this, Singhi and Brown (2015) combined lyrical analysis with acoustic features, incorporating danceability, loudness, energy, tempo, and timbral variations, demonstrating that integrating both text and audio attributes enhances the accuracy of hit song prediction models. They find that lyric based features outperform acoustic based features in discerning hits. Among the audio features analyzed, loudness emerged as the sole statistically significant predictor of hit status, with higher loudness levels correlating with an increased likelihood of a song underperforming (Singhi & Brown, 2015).

Applying Singhi and Brown's findings to the context of platform spillover effects, the following hypothesis is derived:

H2: TikTok chart performance boosts Spotify chart performance less for louder songs.

Building on the work of Singhi and Brown (2014, 2015), who found that loudness was the only significant acoustic predictor of a song's chart performance, negatively associated with hit status, this hypothesis extends their insight into the cross-platform domain. If louder songs are systematically less successful in traditional streaming contexts, possibly due to listener fatigue, it is plausible that these tracks may also translate less effectively from TikTok virality into Spotify success. Given that TikTok videos often rely on emotionally resonant or contextually adaptive audio clips, intensely loud songs might offer limited flexibility for user-generated content.

When Spotify opened its API, providing easily accessible acoustic feature data, and The Echo Nest (an earlier music intelligence platform) was integrated into Spotify, researchers gained access to large-scale data (Seufetelli et al., 2023). Some musical features exhibit varying effects on success across different genres, highlighting the complexity of hit song prediction. However, studies have identified certain audio features as strong predictors of song success. Ni et al. (2011) study temp, time signature, song duration, and loudness by looking at UK chart data over a period of 50 years. They deploy a shifting perceptron model, demonstrating that hit prediction

significantly outperforms random guessing. They challenge earlier skepticism, particularly that of Pachet & Roy (2008), by showing that statistical patterns in musical features can predict chart success with notable accuracy. Important findings include that listeners in the current era prefer faster songs, longer songs, as well that higher loudness is an important hit deciding factor (Ni et al., 2011). This contradicts findings from Singhi and Brown, further underlining the complicated nature of such analyses.

Applying these findings to the platform spillover context, the following hypotheses are proposed:

H3: TikTok chart performance boosts Spotify chart performance more for songs with higher tempo.

Ni et al. (2011) found that modern listeners tend to prefer faster songs, with tempo emerging as one of the most important predictors of chart success in their 50-year UK dataset. In the context of TikTok, where high-energy segments and rhythmic hooks are often repurposed as dance or meme material, a faster tempo may increase a track's suitability for viral content creation. If higher-tempo songs more effectively capture attention and prompt user interaction on TikTok, this may, in turn, enhance their ability to convert virality into Spotify chart momentum. Thus, the moderating effect of tempo is hypothesized: while TikTok virality generally boosts Spotify performance, this effect is likely amplified for faster-paced tracks that align more naturally with the kinetic, short-form nature of TikTok videos.

H4: TikTok chart performance boosts Spotify chart performance more for songs with higher duration.

Ni et al. (2011) also identify longer song durations as a positive predictor of chart success, possibly reflecting broader musical structure, lyrical development, or increased streaming potential. In the context of TikTok-to-Spotify spillover, duration may interact with platform norms in complex ways. While TikTok thrives on brevity, it often extracts iconic moments from longer tracks, meaning longer songs may offer more “clippable” segments that can serve different TikTok trends or moods. This versatility could enhance a song’s chances of translating short-form attention into sustained full-length streaming. Therefore, it is proposed that longer songs receive a stronger boost from TikTok virality than shorter ones, suggesting a moderating effect where track length amplifies the effectiveness of TikTok exposure on Spotify success.

Similarly, Herremans et al. (2014) explore hit song prediction within the dance music genre, analyzing over 21,000 charting dance tracks from Billboard’s Dance Club Songs and the UK Dance Chart. Using features extracted from The Echo Nest API, they examined tempo, loudness, timbre, beat variation, and danceability, identifying tempo and timbre as key predictors of success. Applying machine learning models, they found that logistic regression outperformed other models (e.g., decision trees, SVM), achieving an AUC of 0.81 in distinguishing top 10 hits from lower-charting songs. Their study also revealed evolutionary trends in dance music, noting a rise in loudness and tempo but a decline in danceability over time.

Once again applying the context of platform spillover, the following hypothesis is therefore proposed:

H5: TikTok chart performance boosts Spotify chart performance more for songs with lower danceability.

Herremans et al. (2014) identify tempo and timbre as primary drivers of dance track success but note a counterintuitive decline in danceability among hit songs over time. This suggests that while traditionally "danceable" songs were central to club success, mainstream chart performance has increasingly favored tracks with more varied rhythmic structures or emotional expression, potentially aligning better with listening rather than dancing contexts. When this trend is situated within the platform spillover framework, an interesting hypothesis emerges: TikTok virality, often driven by short, choreographed dance clips, might not translate as effectively to Spotify success for highly danceable songs. While these tracks might dominate on TikTok due to their suitability for trend-driven movements, they may offer less long-term replay value or streaming depth on Spotify. Conversely, songs with lower danceability might perform better on Spotify if they appeal more to passive listening or emotional resonance. Therefore, danceability may moderate the cross-platform effect, reducing the strength of TikTok-driven boosts for tracks that are overly dance-oriented, leading to the hypothesis that TikTok virality is more effective for less danceable songs.

While such a hypothesis actually contradicts general consensus behind TikTok virality outlined in earlier sections, such as dance challenges, this further highlights the need to apply such frameworks to the unique setting of platform spillovers. Since there is no research yet on the effect of such acoustic features on the inter-platform dynamics, this paper's hypotheses assume that the same relationships outlined in the HSS literature will hold for cross platform effects.

Askin and Mauskapf (2017) examine the relationship between musical features and chart success, analyzing 27,000 Billboard Hot 100 songs from 1958 to 2016 using computational tools. The study introduces the concept of optimal differentiation, arguing that songs balancing familiarity and novelty tend to perform best. While conventional wisdom suggests that successful songs closely follow past hits, the findings show that songs that are too typical or too different struggle on the charts. Instead, hit songs exhibit a moderate level of differentiation from their peers. Using data extracted from The Echo Nest API, the study quantifies sonic features such as tempo, mode, valence, danceability, and energy. Their analysis finds that songs with lower acousticness tend to perform well, while extreme energy levels correlate negatively with chart success.

The final two hypotheses are therefore proposed:

H6: TikTok chart performance boosts Spotify chart performance more for songs with lower acousticness.

While acoustic songs might thrive within TikTok's visually intimate and short-form environment, it is unclear whether that appeal translates into sustained audio-only streaming engagement. Drawing on Askin and Mauskapf (2017), who show that lower acousticness predicts greater success on traditional charts, this study explores whether this relationship also moderates the spillover effect from TikTok to Spotify. Their theory of "optimal differentiation" suggests that

successful tracks balance novelty and familiarity, qualities that may be disrupted by overly acoustic arrangements that stand too far from mainstream production norms. In the context of TikTok virality, highly acoustic songs may attract attention due to their novelty or emotional rawness, but may lack the sonic polish required for high performance on streaming platforms like Spotify. Therefore, it is hypothesized that TikTok-driven gains in Spotify success will be stronger for tracks with lower acousticness.

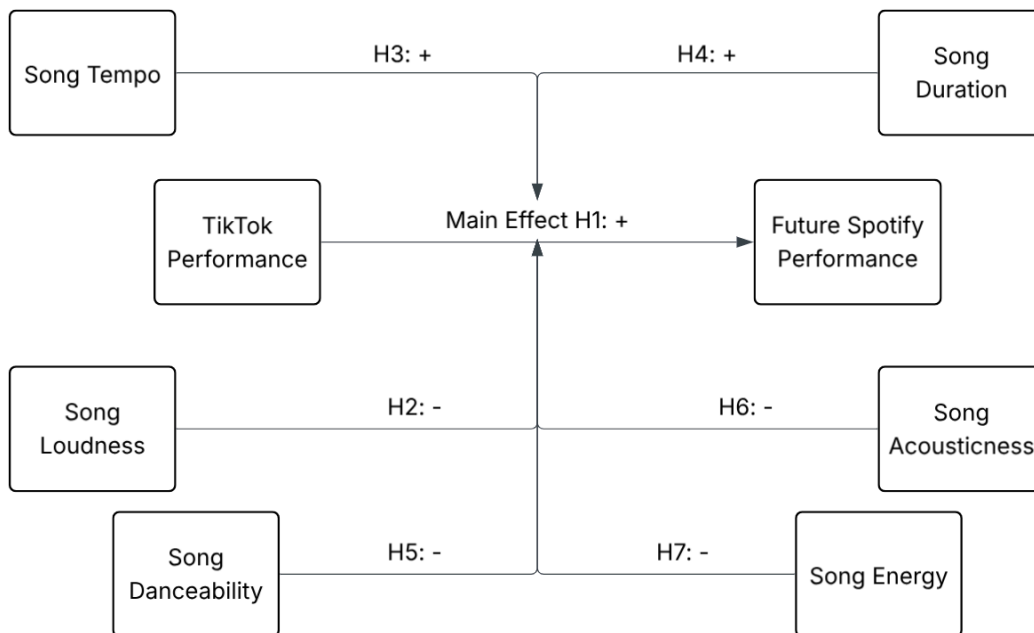
H7: TikTok chart performance boosts Spotify chart performance less for songs with very high energy levels.

Building on Askin and Muaskapf's (2017) study, it is plausible that songs with very high energy may perform well on TikTok, where short bursts of intensity often dominate, but may be less effective in converting that virality into sustained engagement on Spotify. The streaming environment favors full-track listening and replayability, which may be compromised by overly aggressive or fatiguing sonic profiles. Therefore, the following hypothesis is proposed:

Conceptual Framework

Based on the 7 hypotheses outlined above, the following multidirectional conceptual framework is proposed.

Figure 1: Conceptual Framework



Furthermore, below a summary table can be found that restates the research question and hypotheses that the methodology will aim to answer.

Table 1

Summary of Research Question and Hypotheses

Research Question	How does viral success on short-form content platforms lead to sustained growth in streaming performance , and how do a song's acoustic features influence this effect?
H1:	TikTok chart performance can significantly boost future Spotify chart performance.
H2:	TikTok chart performance boosts Spotify chart performance less for louder songs.
H3:	TikTok chart performance boosts Spotify chart performance more for songs with higher tempo.
H4:	TikTok chart performance boosts Spotify chart performance more for songs with higher duration.
H5:	TikTok chart performance boosts Spotify chart performance more for songs with lower danceability.
H6:	TikTok chart performance boosts Spotify chart performance more for songs with lower acousticness.
H7:	TikTok chart performance boosts Spotify chart performance less for songs with very high energy levels.

Methodology

Data Collection

The dataset used for this analysis has been collected from Chartmetric for two major streaming platforms, TikTok and Spotify.

The TikTok dataset spans from the 18th of april, 2021 until the 23rd of march, 2025 . The TikTok charts are dated on the Sunday of each week, representing the song performance throughout said week. The TikTok dataset on a weekly basis includes the top 200 performing songs, featuring key variables such as Rank, Change, Track, Charted Song ID, Artists, Internal Link, External Link, Release Date, All Time Rank, Video Count, All-time video count, Peak Position, Peak Date, Weeks on Chart, 7-day Velocity, and ISRC.

On the other hand, the Spotify dataset spans from the 15th of april, 2021 until the 27th of march, 2025. The Spotify charts are dated on the Thursday of each week, representing the song performance from Friday 12:00 AM - Thursday 11:59 PM UTC (Spotify, 2025). The Spotify dataset on a weekly basis includes the top 50 performing songs, featuring key variables such as Rank, Change, Track, Internal Link, External Link, Artists, Album, Label, Track Genre, Release Date, Peak Position, Peak Date, 7-day velocity, Weeks on Chart, and ISRC.

There were 3 inconsistencies in the dates of the TikTok files downloaded from Chartmetric. First, there was a week for 06-08-2023, for 08-08-2023, and for 13-08-2023. 08-08-2023 was a Tuesday, so this outlier is removed. Second, 12-08-2024 was a Monday, but there is a dataset file with this date. To address this, the dataset's date is adjusted to 11-08-2024. Finally, the same issue is apparent with one week's dataset being labeled 04-11-2024, which was again a Monday. The file is renamed to 03-11-2024. Thereafter, all the individual TikTok charts are merged in R Studio, resulting in a total of 40,208 observations. Notably, there is also an inconsistency in the number of expected observations since there are 206 files with 200 expected songs each, which in turn should be 41,200 observations. Upon investigation, many of the files contain only 197 or 198 songs, which explains the discrepancy. To ensure consistency with the spotify chart data, any observations past rank 50 are removed from the dataset, resulting in 10,300 observations ($206 * 10,300$).

The Spotify charts are also merged in R Studio. The merged Spotify charts had 19800 observations. Again, there is an inconsistency in the number of expected observations since there are 216 files, with 50 expected songs each which in turn should be 10800 observations. Upon closer investigation, the first 60 weeks of the dataset include data in the top 200 songs and not just the top 50. After double checking this seems to be a mistake on the chartmetric site. The observations past rank 50 are deleted to ensure consistency.

Using Track and Artists as unique identifiers, 2,897 unique songs are observed on spotify, and 1,523 are observed on tiktok. In total, 4,157 unique songs are observed throughout the ~4 year period of the downloaded charts across both platforms. Using this list of unique songs with both Track and Artists variables, the spotify track ID is accessed using Python and a spotify web API developer account. Due to limitations associated with a basic Spotify Web API account, specifically, restricted access to acoustic features at scale, an alternative solution was implemented using Pipedream, a cloud-based automation and integration platform. A custom workflow was built in Pipedream that connected to a Google Sheets document containing all Spotify track IDs. The workflow used a Node.js (v20) script to authenticate with the Spotify Web API through a registered Spotify app and systematically request the full set of acoustic features. These features included Danceability, Energy, Key, Loudness, Mode, Speechiness, Acousticness, Instrumentalness, Liveness, Valence, Tempo, and Duration (in milliseconds). The results were compiled and exported as a CSV file, enabling the acoustic feature dataset to be completed despite the restrictions of the default Spotify API access.

Table 2

Description of song characteristic variables

Variable	Description	Range
Danceability	Danceability refers to how appropriate a song is for dancing, based on features like tempo, rhythmic consistency, strength of the beat, and the overall pattern of the music. Scores range from 0.0 (not danceable) to 1.0 (highly danceable).	0.0 to 1.9
Energy	Energy is a perceptual metric ranging from 0.0 to 1.0 that captures the intensity and activity level of a track. Songs with high energy often sound fast, loud, and aggressive, such as heavy metal, whereas more subdued pieces, like a classical piano	0.0 to 1.0

prelude, tend to score lower. This measure is influenced by factors like dynamic range, loudness, timbre, the rate of note onsets, and overall sound complexity.

Key	The key of a track is represented as an integer corresponding to musical pitches based on standard Pitch Class notation, for example, 0 = C, 1 = C \sharp /D \flat , 2 = D, etc. If the key cannot be determined, it is assigned a value of -1.	-1 to 11
Loudness	Loudness refers to the average volume level of a track, measured in decibels (dB), and typically falls between -60 and 0 dB. It represents the perceived intensity of the sound and is calculated across the full duration of the track. This measure helps compare how loud one track is relative to another and reflects the psychological perception of a sound's physical amplitude.	-60.0 to 0.0
Mode	Mode refers to the type of musical scale that a track is based on, indicating whether it follows a major or minor key. In this system, a value of 1 denotes a major mode, while 0 represents a minor mode.	0 or 1
Speechiness	Speechiness measures how much spoken word content is present in a track. Tracks that consist almost entirely of speech, such as podcasts or spoken-word performances, receive values near 1.0. Scores above 0.66 typically indicate primarily spoken content, while values between 0.33 and 0.66 suggest a mix of speech and music, like many rap tracks. Values below 0.33 generally correspond to tracks that are mostly musical, with little to no speech-like elements.	
Acousticness	This feature reflects the model's confidence that a track is acoustic, expressed on a scale from 0.0 to 1.0. A value closer to 1.0 indicates a high likelihood that the track consists primarily of acoustic sounds rather than electronic or synthesized elements.	0.0 to 1.0
Instrumentalness	This feature estimates the likelihood that a track is entirely instrumental, meaning it contains no vocal content. Non-lyrical sounds like "ooh" and "aah" are considered instrumental, while speech or rap counts as vocal. The score ranges from 0.0 to 1.0, with higher values indicating stronger confidence that the track lacks vocals. Scores above 0.5 suggest a song is likely instrumental, with certainty increasing as the value nears 1.0.	0.0 to 1.0
Valence	Valence is a metric ranging from 0.0 to 1.0 that captures the emotional tone or positivity of a track. Higher values indicate a more upbeat, cheerful, or euphoric feel, while lower values suggest a mood that is more somber, melancholic, or tense.	0.0 to 1.0
Tempo	Tempo refers to the estimated speed of a track, measured in beats per minute (BPM). It reflects the average rate at which beats occur, indicating how fast or slow a piece of music feels overall.	> 0.0
Duration_ms	The total length of the track, measured in milliseconds, representing the full playback time from start to finish.	> 0.0

Note: Paraphrased Official Definitions from Developers Spotify (n.d.).

Data Cleaning

The merged dataset contained weekly Top 50 chart entries from TikTok and Spotify across a four-year period. Given the longitudinal structure and heterogeneous nature of the sources, rigorous data cleaning procedures were essential to ensure consistency, reduce noise, and enable valid statistical modeling. All cleaning steps were implemented in R Studio.

Handling Inconsistent Chart Formats

First, an inconsistency was identified in the Spotify charts: for the first 60 weeks, the files contained Top 200 rankings rather than the intended Top 50. After verifying that this discrepancy stemmed from Chartmetric's chart format rather than download errors, these surplus observations were removed by filtering each week's dataset to retain only the top 50 songs. This procedure was similarly applied to the TikTok dataset, which also occasionally exceeded 50 entries per week.

Track and Artist Standardization

Due to the possibility of duplicate song names across different artists, Track and Artist names were treated jointly as the unique identifier when merging across datasets. This decision ensured more accurate matching during subsequent steps like Spotify ID retrieval and feature merging.

Spotify ID and Acoustic Feature Retrieval

Following the creation of a unified list of unique track-artist pairs, Python scripts interfacing with the Spotify Web API were used to retrieve Spotify track IDs. However, due to limitations associated with a basic developer account, including rate limiting and endpoint access restrictions, these scripts occasionally failed to return acoustic features, especially for songs with missing artist data or ambiguous naming. To resolve this, a Node.js (v20) script was deployed via a custom-built Pipedream workflow. This script accessed Google Sheets populated with Spotify IDs and authenticated with a registered Spotify Web API app to fetch acoustic features in bulk. The result was a complete CSV export of key acoustic features including Danceability, Energy, Key, Loudness, Mode, Speechiness, Acousticness, Instrumentalness, Valence, Tempo, and Duration (ms).

ID Matching

Both TikTok and Spotify datasets were enriched with the retrieved Spotify track IDs, and then joined with the acoustic feature dataset using a left join on track ID. Duplicate track IDs in the original data, resulting from minor inconsistencies in API responses, were resolved by retaining the first occurrence per unique ID. A similar de-duplication was applied to the acoustic feature set.

Further missing values in Spotify acoustic features were addressed by extracting track IDs from embedded Spotify hyperlinks (`external_link` fields) using regular expressions. These extracted IDs were again queried through the Spotify API and appended back into the dataset.

Some Spotify track IDs remained unretrievable ($n = 1,448$) due to a lack of artist data, which made accurate identification unfeasible.

Duplicate Weeks

Song appearances on TikTok and Spotify charts were originally reported with different weekday anchors (Sunday vs. Thursday). To standardize this temporal alignment, all dates were converted to the Monday of their respective weeks using `floor_date()` with `week_start = 1`. While this means that events from both platforms are initially aligned to the same week, causal assumptions are handled later through explicit lag structures in the analysis. This approach supports consistent week-on-week comparisons while allowing for meaningful temporal modeling of causal relationships.

Within-week duplicates were identified, particularly due to overlapping chart windows within a week. These were addressed by retaining only the first chart occurrence per song-artist-week triple, preferring entries with higher Spotify ranks (or TikTok ranks where applicable). It is also important to note, that the TikTok charts do not have an entry for the week of the 25th of November, 2024, due to an inconsistency in the available chart data, as well as the week of the 24th of March of 2025 (Spotify chart ranged 1 more week). In total, for the Spotify chart there are 207 unique weeks, while for TikTok charts there are 205 unique weeks.

Chart Merging

After applying consistent filtering across all weeks, the Spotify dataset contains 10,350 observations, while the TikTok dataset contains 9,616 observations. Thereafter, these datasets are not stacked but instead merged with a left join based on a unique combination of track, artists, and week_start. This ensures that each row represents a unique track-week pairing across both platforms. The final merged dataset comprises 19,005 rows, accounting for both overlapping and platform-unique chart entries. In total, 961 rows of a unique song & week combination have charted on both the Spotify and TikTok charts.

Outlier Detection and Imputation

All acoustic features were subjected to boxplot-based outlier analysis using IQR fences. Where outliers were clearly misclassified by Spotify's algorithm (e.g., reggaeton songs with anomalously low danceability), manual inspection of the artist discography and qualitative listening led to targeted median imputation. Notably:

For three Bad Bunny reggaeton songs, danceability and energy were replaced by the artist-genre median due to Spotify misclassification of complex rhythmic changes. For speechiness, Spotify occasionally classified music as spoken-word or rap inappropriately. Selected misclassifications (e.g., "Drive You (Jersey Club)" and "Aloha") were replaced by genre-appropriate medians (hip-hop or overall median). Loudness values above 0 decibels, which violate Spotify's own stated range, were capped at 0 to align with audio standards.

Where acoustic outliers were found to be musically plausible (e.g., long instrumental ambient tracks or songs with extreme tempos), values were retained. The goal was to balance statistical robustness with musical validity.

Variable Cleaning and Standardization

To facilitate comparability in regression models, all continuous acoustic features were standardized via z-scoring (mean = 0, SD = 1). Categorical variables for key and mode were converted into factor variables, with mode explicitly labeled as "Major" or "Minor."

Finally, to measure time-lagged spillover effects, lag variables were created for both TikTok and Spotify ranks (one-week lag per song). Lagged NA values were imputed with a placeholder rank of 1000 for robustness in certain models, while separate models were also built excluding these imputations to test for sensitivity.

The cleaned dataset (merged_chart.csv) has 19,005 observations with acoustic features, chart positions, time-lagged variables, and forms the empirical basis for all subsequent model estimations.

Summary Statistics

Table 3

Summary Statistics of cleaned base dataset variables

Variable	Mean	SD	Min	25%	Median	75%	Max	NA Count
spotify_rank	25.5	14.432	1	13	25	38	50	8655
tik_tok_rank	25.16	14.478	1	13	25	38	50	9389
danceability	0.665	0.156	0.000	0.559	0.678	0.784	0.984	2,466
energy	0.604	0.180	0.000	0.500	0.619	0.734	0.966	2,466
key	5.175	3.635	0	1	5	8	11	2,466
loudness	-7.370	3.654	-60.000	-8.529	-6.647	-5.176	0.000	2,466
mode	0.646	0.478	0	0	1	1	1	2,466
speechiness	0.120	0.119	0.000	0.039	0.062	0.157	0.946	2,466
acousticness	0.258	0.266	0.000	0.038	0.152	0.413	0.996	2,466
instrumentalness	0.045	0.171	0.000	0.000	0.000	0.000	0.995	2,466
valence	0.489	0.242	0.000	0.290	0.488	0.685	0.987	2,466
tempo	124.5	29.559	0.0	101.0	124.1	144.0	228.1	2,466
duration_ms	195,058	80,198.12	22,047	157,877	189,545	227,239	2,760,520	2,466

Note: Values are rounded to the third decimal when appropriate

Modeling

To investigate the relationship between TikTok chart performance and subsequent Spotify popularity, a multi-model strategy was employed. This sequential modeling approach was guided by both theoretical considerations and empirical performance, enabling a robust exploration of different types of relationships (binary, ordinal, and continuous) in the data. Each model captures a distinct dimension of streaming success: the first assesses the likelihood of any chart appearance, the second models relative chart tier (rank buckets) as an ordinal outcome, and the third predicts exact chart position as a continuous measure. Together, these models provide a layered understanding of how TikTok virality influences Spotify outcomes, allowing the research

question, and its associated hypotheses, to be addressed at multiple levels of granularity, depending on how "success" is defined.

Before modeling, continuous acoustic features were standardized (z-scored) to facilitate interpretability and comparability across predictors. Categorical variables such as musical key (key) and mode (mode) were encoded as factor variables to reflect their non-ordinal nature, with mode being labeled “Minor” (0) and “Major” (1). Lagged rank variables for TikTok were computed to reflect the temporal delay between a track’s appearance on TikTok and subsequent Spotify performance. The primary independent variable of interest, lagged TikTok rank, was first inverted by subtracting it from 51 (so that higher values align with better ranks), and then mean centered. Similarly, an inverted and mean centered version of Spotify rank was also created.

Across all three statistical models, namely binary, ordinal, and continuous, the overarching goal is to assess whether and how TikTok virality and acoustic features predict different levels of Spotify chart success. Each model evaluates the same set of hypotheses (found in Table 1), adapted to the structure of the outcome variable. That is, while Model 1 tests predictors of entry into the Spotify Top 50, Model 2 examines progression to higher tiers of success, and Model 3 captures fine-grained differences among charting tracks. Hypotheses are formally tested by examining statistical significance of model coefficients, using two-sided tests with a conventional alpha threshold of 0.05. Accordingly, each result either rejects or fails to reject the relevant null hypothesis based on this standard.

Model 1: Spotify Chart Rank as a binary variable

To assess whether TikTok virality, in combination with a song's acoustic characteristics, predicts the binary outcome of Spotify chart presence, a multistage logistic regression framework was constructed. This approach addresses the foundational research question: does prior popularity on short-form video platforms translate into formal streaming visibility, and if so, which musical traits moderate that relationship? The logistic model was selected due to its suitability for binary classification and its interpretability in terms of odds. Moreover, this modeling framework allows retention of all observations for which the outcome variable (Spotify chart presence) is defined, regardless of missing values in Spotify chart rank, maximizing the effective sample size and generalizability.

Data Preparation

Prior to model estimation, multiple preprocessing steps were applied to satisfy assumptions of logistic regression and to ensure conceptual alignment of the predictors. The outcome variable, `on_spotify`, was defined as a binary indicator of whether a song appeared on the Spotify chart in a given week.

Initial model development used 80/20 stratified splitting to partition the dataset into training and testing subsets, preserving class balance across splits. Because the outcome is imbalanced and the positive class (Spotify presence) is of primary interest, final classification thresholds were tuned based on maximizing the F1 score for each model. This ensured an optimal balance between precision and recall.

Model Building Strategy

Model 1A began with a base specification including TikTok virality and all standardized acoustic features along with categorical key and mode factors. Model 1B extended this specification by introducing interaction terms between TikTok rank and each acoustic variable and mode factor, excluding key initially due to its high cardinality. Model 1C included full interaction terms, now incorporating key_factor to examine conditional effects across all musical key levels.

Linearity and Multicollinearity Assumptions

To validate model assumptions, particularly the linearity of the logit, a Box-Tidwell approach was employed by constructing interaction terms between continuous predictors and their log-transformed counterparts. Significant non-linearities were identified, prompting the use of restricted cubic spline transformations for several predictors. Natural splines ($df = 2$) were applied to variables such as loudness, tempo, duration, acousticness, and instrumentality to flexibly model these non-linear relationships without violating model assumptions.

Following spline transformation, multicollinearity diagnostics were conducted using variance inflation factors (VIF). These revealed that the interaction term between TikTok rank and the first spline component of loudness exhibited problematic multicollinearity. As a result, this interaction was excluded from the final model to ensure stable coefficient estimation. Additionally, the second spline term for duration was removed based on both VIF results and non-significance in preliminary models, helping to streamline the final specification.

This enhanced specification formed the basis for Model 1D. Linearity checks confirmed that spline-transformed variables adequately addressed violations of the logit linearity assumption. Performance metrics including AUC, F1 score, log loss, and classification accuracy were recalculated using the updated spline-enhanced model on the holdout dataset.

Temporal Correlation

To account for potential within-track correlation and unobserved heterogeneity, Model 1E was estimated as a mixed-effects logistic regression with a random intercept for track. Additionally, residual diagnostics (e.g., ACF plots (Appendix Figure 1) indicated the presence of temporal autocorrelation in model residuals. To correct for this, Model 1F incorporated an AR(1) structure nested within track, allowing the model to capture dependencies across weekly time intervals.

Residual simulation diagnostics (DHARMA) confirmed appropriate specification with no evidence of residual bias or unmodeled structure, or influential outliers (Appendix, Figure 3). Model performance was evaluated using ROC curves, AUC, F1 score, precision, recall, and information criteria (AIC). This progression from basic logistic regression to spline-augmented and mixed-effect models with autoregressive structures reflects a principled, diagnostics-informed modeling strategy that aligns with best practices for predictive inference and causal interpretation in logistic models.

The full version of model 1 (Model 1F) is specified as follows:

$$\text{logit}(\Pr(\text{on}_{\text{spotify}} = 1)) = \beta_0 + \beta_1 \text{TikTokRank}_{i(t-1)} + \sum_{k=1}^K \beta_{2k} X_{ik} + \sum_{k=1}^K \beta_{3k} (X_{ik} \cdot \text{TikTokRank}_{i(t-1)}) + u_i + \rho \epsilon_{i(t-1)} + \epsilon_{it}$$

Where:

$\text{logit}(\Pr(\text{on}_{\text{spotify}} = 1))_{i(t)}$ represents the log odds of track i appearing in the top 50 charts on Spotify at week t .

β_0 is the fixed intercept

$\text{TikTokRank}_{i(t-1)}$ is the mean-centered and inverted TikTok rank for track i at week $t-1$, where lower rank values indicate higher virality

X_{ik} denotes the set of acoustic and musical features for track i , including spline-transformed predictors (e.g., loudness_ns1, loudness_ns2., tempo_ns1...) and categorical variables (e.g., mode, key).

β_1 captures the main effect of lagged TikTok rank

β_{2k} represent interaction effects between TikTok rank and each feature k

β_{3k} captures the individual interaction effect between InvertedTikTokRank $i(t-1)$ and each intrinsic song characteristic k

$u_i \sim N(0, \sigma_{\text{track}}^2)$ is the random intercept for track i , accounting for unobserved heterogeneity

$\rho \epsilon_{i(t-1)}$ captures the AR(1) autocorrelation structure over weekly time intervals

ϵ_{it} is the residual error term, assumed independent and identically distributed after accounting for temporal correlation

Model 2: Spotify Chart Ranking as an ordinal variable

To model not just whether a song appears on the Spotify chart but how well it performs relative to others, Model 2 employed an ordinal logistic regression framework. This approach addresses a central dimension of the research question, chart performance intensity, by treating Spotify chart ranks as ordered categories. The outcome variable, rank_bucket, was constructed by partitioning Spotify chart ranks into five ordinal levels: Top10, Top20, Top30, Top40, and Top50. This transformation allows for the retention of rank order information while mitigating noise from small fluctuations in absolute ranks.

Data Preparation

The dataset was filtered to include only records where a track appeared on the Spotify chart and had non-missing TikTok rank and acoustic feature values. TikTok ranks were inverted and mean-centered to reflect increasing virality, while acoustic predictors were standardized to z-scores. The ordinal outcome was encoded as an ordered factor with higher levels indicating higher popularity.

The dataset was split into training and test subsets using stratified sampling (80/20 split) to preserve the distribution of the ordinal outcome. Class imbalance was addressed via inverse-frequency weighting, scaled to maintain interpretability. Ten-fold cross-validation was applied on the training data for performance tuning, and all models were evaluated using a comprehensive set of ordinal-specific metrics, including Accuracy, MAE, Quadratic Weighted Kappa, C-index, Brier Score, and AIC.

Model Building Strategy

Model development proceeded in a stepwise manner. Model 2A included only main effects for TikTok lag rank and acoustic features. Model 2B introduced interaction terms between TikTok lag and all continuous predictors, excluding `key_factor` due to high cardinality. Model 2C incorporated full interactions, including both key and mode factors.

To test the linearity assumption of the logit, interaction terms between each continuous predictor and its log-transformed variant were included in a diagnostic model. Several predictors (e.g., danceability, energy, loudness, tempo, duration, and valence) showed evidence of non-linearity. In response, Model 2D employed restricted cubic spline transformations with 2 degrees of freedom for these variables. To reduce multicollinearity introduced by spline-based interactions, only one spline basis per predictor was retained in interaction terms, selected based on contribution to model fit and VIF diagnostics. The final spline-enhanced model included the second basis function for danceability, energy, loudness, duration, and valence, and the first basis for tempo.

Extension to Hierarchical and Bayesian Modeling

Given the presence of repeated measures for songs across time, Model 2E explored a mixed-effects ordinal logistic regression function with a random intercept for track. However, convergence issues arose due to the sparse structure of the data, most songs appeared in only one week. To address this, a Bayesian hierarchical cumulative logit model was estimated using the `brms` package in R, which applies partial pooling to handle sparse random effects more robustly. Model evaluation included posterior predictive checks and residual autocorrelation assessment (via ACF plots). Influential observations were identified using Pareto-smoothed importance sampling (PSIS-LOO), with ~6% exceeding the diagnostic threshold, though retained based on substantive grounds (Appendix Table).

Finally, residual autocorrelation was formally assessed using an autocorrelation function (ACF) plot of prediction errors, revealing no significant temporal structure. This result (Appendix, Figure 2) supports the assumption of independence over time and confirms that autocorrelated error terms were not a concern in the ordinal modeling framework.

This progression from simple to spline-transformed and Bayesian mixed-effects ordinal models offers increasing granularity and robustness. It enables the evaluation of not only whether but also how strongly TikTok virality translates into Spotify chart success, accounting for non-linearities, class imbalance, and hierarchical data structure.

The full version of model 2 is specified as follows:

$$\text{logit} \left(\Pr(\text{rank_bucket}_{i(t)} \leq j) \right) = \theta_j - \left[\beta_0 + \beta_1 \cdot \text{TikTokRank}_{i(t-1)} + \sum_{k=1}^K \beta_{2k} X_{ik} + \sum_{k=1}^K \beta_{3k} (X_{ik} \cdot \text{TikTokRank}_{i(t-1)}) + u_i \right]$$

Where:

θ_j represents the threshold for the j -th category of the ordinal response (e.g., Top50, Top40, ... Top10).

β_0 is the fixed intercept.

$\text{TikTokRank}_{i(t-1)}$ is the mean-centered and inverted TikTok rank of song i at time $t-1$, where higher values denote higher virality.

X_{ik} denotes the spline-transformed or standardized value of acoustic or categorical feature k for song i .

β_1 captures the main effect of prior TikTok virality.

β_{2k} are the fixed effects of each acoustic or categorical feature.

β_{3k} capture interaction effects between TikTok virality and individual features, reflecting moderation.

$u_i \sim \mathcal{N}(0, \sigma^2)$ is the song-level random intercept accounting for repeated observations of the same track.

The logit link function maps the cumulative probability of each ordinal category to the latent scale.

Model 3: Spotify Chart Ranking as a continuous variable

Model 3 expands upon the binary and ordinal frameworks used in previous models by predicting continuous chart success among already-charting songs. The goal of this model is to understand the degree of chart performance (i.e., relative rank within Spotify's Top 50) as a function of

TikTok virality and song-level acoustic features. Only observations where the track appeared on the Spotify chart were retained ($n = 1,061$), ensuring that the analysis remains focused on differentiating among charting songs. The response variable, Spotify chart rank, was inverted and mean-centered to ensure higher values represent better ranks and to facilitate interpretability.

Data Processing and Initial Model Specification

As in prior models, the dataset was randomly split into an 80/20 train-test split using stratified sampling. TikTok rank (lagged by one week) was mean-centered and inverted to reflect increasing popularity, and all acoustic features were standardized. The baseline model (Model 3A) was an Ordinary Least Squares (OLS) regression including only main effects for TikTok rank and acoustic features. Performance was assessed via MAE, RMSE, , and AIC.

Expanding Model Complexity: Interactions, nonlinearities, and orthogonalization

Model 3B introduced interaction terms between TikTok virality and each acoustic predictor (excluding `key_factor`), while Model 3C extended this to include full interaction terms for `key_factor` and `mode_factor`. To assess the linearity assumption, diagnostic terms of the form were included, revealing nonlinearity in several variables: danceability, energy, loudness, and tempo.

Model 3D incorporated restricted cubic splines with 2 degrees of freedom for these predictors. To reduce multicollinearity, only one spline basis was retained per variable based on VIF diagnostics. However, even after reducing the number of spline terms, multicollinearity persisted, particularly for TikTok rank interactions.

Model 3E introduced orthogonalized spline interaction terms. Each interaction was regressed onto its constituent marginals and replaced with the residuals, ensuring orthogonality. The resulting model resolved multicollinearity, and diagnostic tests showed satisfactory performance across all OLS assumptions except for temporal autocorrelation, which can be seen in Appendix Figure 4.

Modeling Autocorrelation and Hierarchical Structure

To address residual autocorrelation, Model 3F employed a Linear Mixed Effects (LME) model with an AR(1) autocorrelation structure and random intercepts by track. This model significantly improved diagnostics, with less evidence of remaining autocorrelation or residual non-normality (Appendix Figure 5). However, heteroskedasticity was still detected via Breusch–Pagan testing ($p = 0.01425$).

Final Specification: Bayesian Censored and Beta Mixed Models

Given the structural constraints of Spotify rank data (bounded between 1 and 50), Model 3G introduced a Bayesian Beta regression model using a transformed version of the rank outcome. This approach ensured predictions remained in the valid transformed 0–1 range, accounting for boundedness, non-normality, and heteroskedasticity. Assumption diagnostics confirmed linearity (via conditional effects plots), minimal residual autocorrelation (via ACF plots), and tolerable levels of heteroskedasticity. Importantly, the model avoided out-of-bound predictions and handled hierarchical and temporal dependencies efficiently.

The final version of Model 3 (3G) is specified as follows:

$$\text{logit}(\mu_{it}) = \beta_0 + \beta_1 \cdot \text{InvertedTikTokRank}_{i(t-1)} + \sum_k \beta_{2k} X_{ik} + \sum_k \beta_{3k} (X_{ik} \cdot \text{InvertedTikTokRank}_{i(t-1)}) + u_i + \phi \cdot \text{AR1}_{it} + \varepsilon_{it}$$

Where:

μ_{it} is the expected value of the rescaled Spotify rank $y_{\text{beta}} \in (0, 1)$ for song i at week t .

$\text{logit}(\mu_{it})$ denotes the log-odds transformation used in the Beta regression framework.

β_0 is the global intercept.

$\text{InvertedTikTokRank}_{i(t-1)}$ is the centered and inverted TikTok rank of song i at week $t-1$, where higher values indicate better TikTok performance.

X_{ik} represents individual acoustic features and categorical variables (e.g., danceability, energy, loudness, tempo, valence, duration, acousticness, instrumentalness, speechiness, key_factor, and mode_factor).

β_{2k} are the fixed effects for each song feature.

β_{3k} are the interaction effects between TikTok rank and each song feature.

$u_i \sim \mathcal{N}(0, \sigma_{\text{track}}^2)$ is a track-specific random intercept.

$\phi \cdot \text{AR1}_{it}$ represents an autoregressive term of order 1 for repeated observations of the same track across time.

ε_{it} is the residual error modeled through the Beta distribution.

Hypothesis Testing

Across all three models, formal hypothesis testing is carried out by evaluating the significance and directionality of predictors relative to the stated hypotheses. Model 1 tests predictors of initial Spotify

chart entry (binary outcome), Model 2 examines progression across ordered chart categories (ordinal outcome), and Model 3 provides a fine-grained analysis of chart position as a continuous outcome (bounded 0–1). Each model, therefore, addresses the full set of hypotheses with increasing specificity regarding the degree of chart success. Null hypotheses are rejected where statistically significant evidence is found in the expected direction; otherwise, the null is retained. Interpretation of interaction effects considers both coefficient significance and marginal effects where applicable.

Results

Overview and Model Performance

This section examines the relationship between viral success on short-form content platforms and sustained growth in streaming performance, with particular attention to the moderating role of a song's acoustic features. To capture this complexity, a multi-model strategy is employed, examining Spotify chart performance at three levels of granularity. The first model, a logistic regression, estimates the likelihood that a song enters the Spotify charts at all, capturing the threshold of initial streaming success. The second model, an ordinal logistic regression, assesses chart performance in terms of broad rank categories or "rank buckets," offering a view of relative success levels (e.g., top 10, top 50, lower tiers). The third model predicts precise daily chart positions, enabling a fine-grained analysis of fluctuations in a song's popularity over time. This tiered approach allows for a comprehensive understanding of how short-form virality and acoustic features interact to shape different dimensions of streaming success.

Model 1: Spotify Chart Ranking as a binary variable

Model performance was evaluated using a held-out test dataset and eight key performance metrics throughout the incremental model building process of Model 1 using: AIC, Accuracy, Area Under the Curve (AUC), LogLoss, Mean Squared Error (MSE), F1 Score, Precision, and Recall. Table 3 presents a summary of these results for all six model stages of model 1.

Table 4

Performance Metrics for Model 1: Baseline model (A), Partial Interaction Model (B), Full Interaction Model (C), Full Model transformed for linearity and multicollinearity (D), and Full Mixed Effect Model (E).

Model	AIC	Accuracy	AUC	LogLoss	MSE	F1 Score	Precision	Recall
Model 1A	3,832	0.589	0.700	0.450	0.145	0.438	0.825	.0298
Model 1B	3,826	0.615	0.699	0.454	0.146	0.447	0.802	0.310
Model 1C	3.824	0.620	0.705	0.452	0.145	0.435	0.755	0.306
Model 1D	3,740	0.6780	0.724	0.450	0.142	0.447	0.679	0.335
Model 1E	1,441	0.958	0.963	0.246	0.037	0.888	0.858	0.919
Model 1F	1,189	0.961	0.983	0.213	0.037	0.908	0.949	0.870

Note: Values are rounded to the third decimal when appropriate

While the differences in classification performance between models 1A-1C are modest, the full interaction model (Model 1C) demonstrated the lowest AIC (3,824), indicating superior fit relative to model complexity, even though key dummy variables added 11 levels to the model. It also achieved the lowest mean squared error ($MSE = 0.145$) and highest recall (0.306), suggesting improved sensitivity in identifying true positives. Upon addressing issues of linearity and multicollinearity through spline transformations (Model 1D), the model showed further improvements across most metrics, including accuracy (0.678) and AUC (0.724), alongside a reduction in AIC to 3740, signaling better overall model fit.

A substantial performance leap was observed with the introduction of random effects in Model 1E. By implementing a mixed-effects logistic regression that accounts for grouping by track, classification accuracy rose dramatically to 95.8%, and the model's AUC surged to 0.963. Correspondingly, LogLoss and MSE dropped sharply (0.246 and 0.037, respectively), and the F1 score climbed to 0.888, suggesting a highly discriminative model with excellent balance between precision and recall. Finally, Model 1F extended this by incorporating an AR(1) structure to account for temporal autocorrelation. This resulted in modest but meaningful gains in key metrics: AUC increased to 0.983, LogLoss decreased further to 0.213, and the F1 score reached 0.908. Although accuracy only slightly improved to 96.1%, the precision rose to 0.949, demonstrating the model's strong ability to correctly identify positive cases while maintaining stability over time. Overall, Models 1E and 1F highlight the considerable advantages of mixed-effects modeling in classification performance, especially when temporal dynamics and hierarchical structure are present in the data.

Finally, the mixed-effects logistic regression model is checked for influential outliers (Appendix, Figure 3). The DHARMA package was used, which simulates scaled residuals via a parametric bootstrap procedure. This approach allows for a standardized evaluation of model residuals that is robust to the structure of generalized linear mixed models. The test was insignificant ($p = 0.148$), indicating that no residuals stood out as statistically extreme. The diagnostic plots further supported this interpretation: residuals appeared approximately uniformly distributed, and the quantile quantile (QQ) plot showed no substantial deviation from the expected uniform distribution, indicating well-behaved residuals overall.

Thereafter, all the assumptions required for logistic regressions are validated and the results of the model can be interpreted. The mixed-effects model incorporated random intercepts for 1,206 unique songs in the training dataset, capturing variation in baseline likelihoods of Spotify chart appearance across tracks. Notably, several predictors that were statistically significant in Model 1A-D lost their significance in the mixed-effects specification (Model 1E & 1F). These included variables such as `danceability_z`, `energy_z`, multiple `key_factor` levels, and several spline-transformed acoustic features. Additionally, three interaction terms that were previously (model 1D) significant no longer reached significance. This is a critical finding, as it indicates that earlier models, those that did not account for random effects associated with individual tracks, likely attributed track-specific variation to fixed predictors in the dataset. By not modeling this within-song dependency, these models may have overstated the influence of certain variables that were actually capturing differences between songs. Interestingly, the

interaction between `tiktok_rank_lag1_centered` and `key_factor11`, which was not significant in Model 1D, became marginally significant in the mixed model.

A full output summary of model 1F can be found in Appendix Table 9. The significant parameters are found below:

Table 5

Significant Outputs Model 1F

Predictor	Estimate	Std. Error	z value	P value	Odds Ratio
(Intercept)	-23.1474751	11.97706	-1.932651	0.053.	9.27e-11
tiktok_rank_lag1_centered:key_factor11	-0.4739781	0.25632	-1.849188	0.064.	0.6225

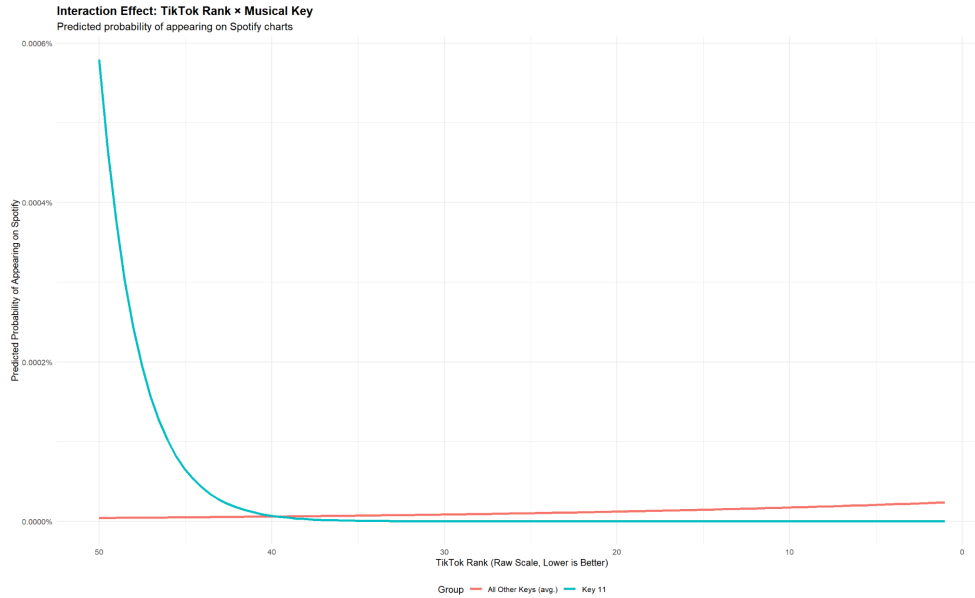
*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

In models 1A-D, several main effects and interaction effects were significant. However, after accounting for random effects and an AR1 correlation structure, these terms soak up a lot of the predictive structure through these latent components. The fixed effects only explain what remains after accounting for subject-level and temporal structure. The only marginally (at the 10% level) significant variable is the interaction between `tiktok_rank_lag1_centered` and `key_factor11`.

From the output of Model 1F it can be said that for songs in key 11, a 1-unit increase in TikTok virality (relative to the mean) is associated with a 38% decrease in the odds of charting on Spotify, compared to songs in the baseline key category (key 0).

Overall, model 1 does not show support for any of the outlined hypotheses.

Figure 2: Interaction effect between TikTok rank lag and Musical Key 11



The plot displays the predicted probability that a song appears on the Spotify charts, depending on its TikTok virality and whether it is in key 11 or another musical key, holding all other predictors constant. On the x-axis, TikTok rank is shown in raw scale, where lower ranks (closer to 1) indicate higher virality, these appear on the right side of the plot. On the y-axis, the predicted probability of charting is shown, which is low overall but varies meaningfully by TikTok rank and musical key.

The red line represents the average predicted probabilities for songs in all musical keys except key 11, showing a modest upward trend: higher TikTok virality (rightward on the axis) increases the likelihood of Spotify charting. The blue line, representing songs in key 11, remains flat and notably lower across most of the TikTok rank range. Even at the highest levels of virality, songs in key 11 remain substantially less likely to chart than songs in other keys, consistent with the negative interaction effect found in the model.

However, at the left end of the plot, corresponding to lower virality or worse TikTok ranks, the predicted probability for songs in key 11 rises exponentially, diverging from the trend of the other group. This nonlinear increase suggests that for less viral songs, being in key 11 may slightly improve charting odds, suggesting the interaction effect between TikTok virality and acoustic features like musical key may vary more across the virality spectrum than the model currently reflects.

The confusion matrix (Table 5) for Model 1F, which incorporates both mixed effects and an AR(1) structure to account for temporal autocorrelation, revealed exceptional predictive performance. The model achieved an overall accuracy of 96.1%, further improving upon the already strong performance of Model 1E. Sensitivity (true positive rate) remained high at 87.0%, while specificity (true negative rate) increased to 98.1%, indicating a notable gain in the model's

ability to correctly identify songs that do not appear on the Spotify chart. Precision (positive predictive value) rose to 94.9%, reflecting a high level of confidence in positive classifications.

Table 6

Confusion Matrix Model E

		Reference	
		no	yes
Prediction	no	747	10
	yes	28	187

These improvements suggest that the inclusion of track-level random effects as well as accounting for time based residual correlation helps the model not only generalize better, but also resolve the challenge of class imbalance more effectively, achieving high performance on both minority and majority classes. This level of discriminative power highlights Model 1E as the most reliable version for predicting cross-platform success from TikTok to Spotify.

Model 2: Spotify Chart Ranking as an ordinal variable

Model performance was evaluated using a held-out test dataset and 7 key performance metrics: AIC, R squared (Pseudo R2 for ordinal rank models, Bayesian R2 for bayesian ordinal rank model), Accuracy, MAE, QuadraticKappa, C-Index, and Brier Score. Table 3 presents a summary of these results for all 5 model stages of model 2.

Table 7

Performance Metrics for Model 2: Baseline model (A), partial interaction model (B), full interaction model (C), full interaction model transformed for linearity and multicollinearity using splines (D), and bayesian ordinal rank model (E).

Model	AIC	Pseudo R2	Accuracy	MAE	Quadratic Kappa	C-Index	Brie Score
Model 2A	2701.393	0.034	0.325	1.426	.222	0.601	0.767
Model 2B	2690.202	0.045	0.306	1.469	0.177	0.580	0.773
Model 2C	2696.334	0.051	0.297	1.434	0.206	0.591	0.778
Model 2D	2711.566	0.043	0.292	1.507	0.199	0.598	0.780
Model 2E	WAIC: 2511.976	Bayesian R2: 0.729	0.545	0.694	0.345	0.781	0.550

Note: Values are rounded to the third decimal when appropriate; For Model 2E, value in column 2 is WAIC, since Bayesian models don't allow for AIC calculations, and R2 is a Bayesian R2.

Model 2's performance metrics are summarized in Table 3, which contrasts five increasingly complex specifications. Among the fixed-effect models, the partial interaction specification (2B) yielded the lowest AIC (2690.20) but suffered from modest predictive accuracy (30.6 %) and a relatively high mean absolute error (MAE = 1.47), indicating limited discrimination of rank buckets. Additionally, Model 2C achieved the highest pseudo R2, but unlike the process in Model 1, adding 11 key factor levels increased the AIC, implying worse model fit relative to complexity. Introducing spline-based corrections in Model 2D offered negligible gains, with accuracy and MAE actually getting slightly worse. In stark contrast, the Bayesian ordinal model (2E) achieved the highest accuracy (54.5 %), the lowest MAE (0.69), and superior concordance metrics (Quadratic Kappa = 0.345; C-Index = 0.781), despite a moderate Brie Score (0.550). However, the information criterion to evaluate model fit is not directly comparable, since WAIC and AIC are calculated in different ways. The same goes for Pseudo R2 and Bayesian R2. These results demonstrate that incorporating song-level random intercepts via a Bayesian framework materially enhances the model's ability to rank songs into Top 10–Top 50 buckets, reflecting the importance of accounting for unobserved heterogeneity, due to temporal and hierarchical structures, in chart data.

A full output summary of model 2E can be found in Appendix Table 10. The significant parameters are found below:

Table 8

Significant Outputs Model 2E

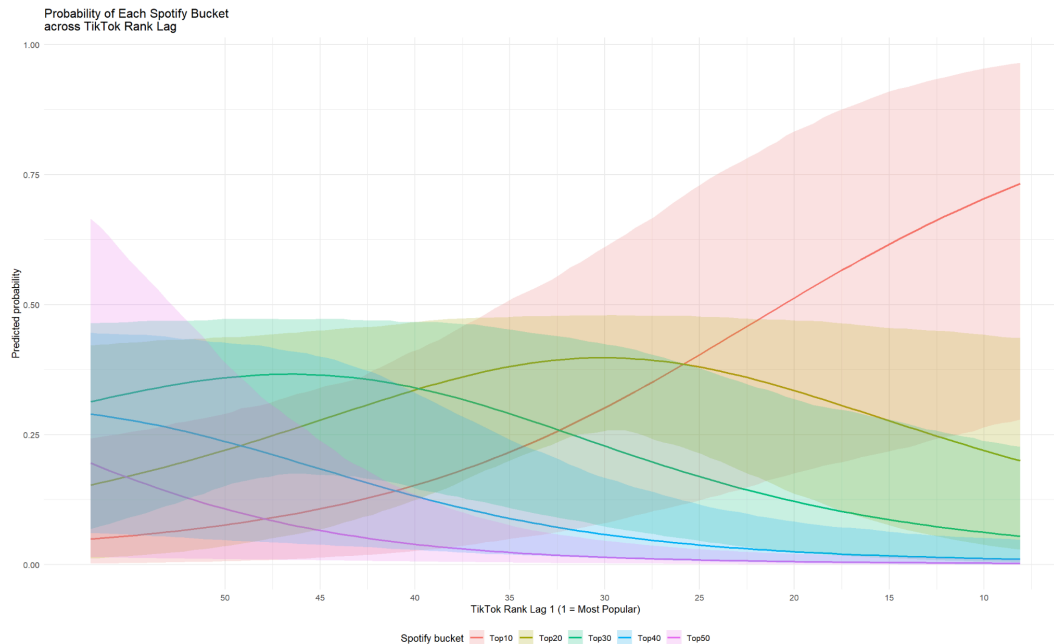
Predictor	Estimate	Std. Error	z value	P value (approx)	Odds Ratio
tiktok_rank_lag1_centered	0.0989	0.0410	2.41	0.0158	1.104
tiktok_rank_lag1_centered:key_factor9	-0.0944	0.0388	-2.43	0.0150	0.91

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

From the output of Model 2E, it can be said that a 1-unit increase (better rank) in the previous week's TikTok charts increases the odds that a song is in a higher spotify chart success category in the current week, e.g., moving from "Top 50" to "Top 40," or from "Top 20" to "Top 10", versus staying in the same or a lower category, by about 10.4%.

Model 2 shows support for hypothesis 1, and therefore rejects the null hypothesis of H1.

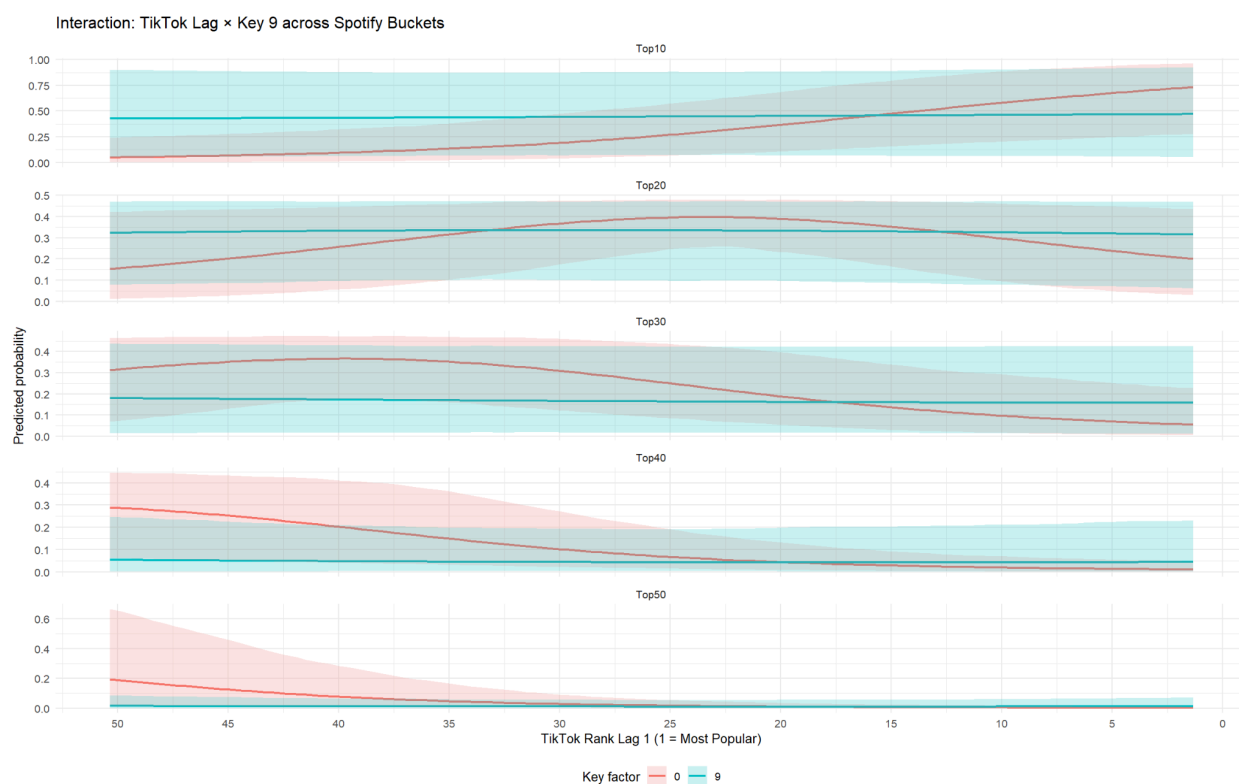
Additionally, the interaction between TikTok virality and key 9 reveals that, for songs in key 9, each one-unit increase in TikTok chart position (better rank) is associated with approximately a 9% decrease in the odds of moving into a higher chart success category, compared to songs in the reference key category (0).

Figure 3: Effect of TikTok Lag Rank on Spotify Rank Buckets

The plot visualizes how a song's TikTok rank at a prior time point (lag 1) relates to its probability of appearing in different Spotify chart buckets, from Top 10 to Top 50. Importantly, the x-axis uses the original TikTok rank scale, where lower values indicate higher virality, meaning songs become more popular on TikTok as you move rightward. As TikTok performance in the previous week increases (toward lower ranks), the probability of being in higher Spotify chart buckets, especially Top 10, increases sharply. This supports the positive relationship between TikTok popularity and streaming success, as seen in Model 2E.

When comparing the trajectories of the Spotify rank buckets in terms of probability across TikTok lag, the visual hints are more precise mechanisms. Around TikTok lag rank ~40 the predicted probability of a song landing in the Top 20 of Spotify begins to exceed that of the Top 30, indicating a threshold-like dynamic: once a song achieves a certain level of TikTok virality, it enters a steeper probability curve for higher-tier Spotify success. The same happens around TikTok lag rank ~25, where the predicted probability of a song landing in the Top 10 of Spotify exceeds the predicted probability of landing in the top 20.

Figure 4: Interaction effect of TikTok Rank Lag and Key 9 on Spotify Chart Buckets



The plot illustrates how the relationship between prior TikTok virality (lag 1) and Spotify chart success is moderated by a song's musical key, specifically, comparing songs in key 9 (blue) to those in the baseline key 0 (red). As in the previous visualization, the x-axis retains the original TikTok rank scale, where lower ranks (right side) reflect greater performance. It can be seen that

the probabilities for the top 10 bucket are higher for songs not in key 9 for more popular tiktok (top 15) songs in the previous week. However, the effect is opposite for the top 20 and 30 rank buckets. Furthermore, in the lower rank buckets of spotify charts (top 40 & 50), it can be seen that the probability is higher for lower tiktok ranks in keys not in key 9.

Table 9

Confusion Matrix Model 2E

Prediction	Reference: Top 50	Top 40	Top 30	Top 20	Top 10
Top 50	10	7	0	1	3
Top 40	2	6	8	1	0
Top 30	5	6	10	10	2
Top 20	2	3	7	7	9
Top 10	6	1	7	16	81

Table 4 presents the confusion matrix for Model 2E, illustrating how accurately the ordinal model predicted each rank tier of the Spotify Top 50. The majority of predictions aligned well with the true labels, particularly for songs in the Top 10, where 81 of 111 were correctly classified, demonstrating strong sensitivity for identifying top-performing tracks. However, some systematic misclassifications occurred in adjacent tiers, which is expected in ordinal classification tasks where boundaries are gradual. For example, several Top 20 and Top 30 songs were predicted one tier higher or lower, indicating reasonable model uncertainty around rank cutoffs. Misclassifications spanning multiple tiers (e.g., Top 50 predicted as Top 10) were rare. Overall, the model showed good ordinal alignment, especially in distinguishing elite chart positions from lower ones, suggesting the model captures meaningful structure in cross-platform chart dynamics.

Model 3: Spotify Chart Ranking as a continuous variable

Model performance was evaluated using a held-out test dataset and four key performance metrics: MAE, RMSE, R-squared, and an information criterion (AIC for regular OLS models, LOOIC for Bayesian models). Table 3 presents a summary of these results for all four model stages of model 1.

Table 10

Performance Metrics for Model 3: Baseline model (A), partial interaction model (B), full interaction model (C), full model transformed for linearity and multicollinearity using splines (D), full model with orthogonalised variables to account for heterogeneity (E), bayesian model to account for autocorrelated residuals (F), and final bayesian beta regression model (to censor y-value) (G)

Model	MAE	RMSE	R-squared	IC
Model 3A	12.7	15.1	0.0529	6,913 (AIC)
Model 3B	12.5	14.9	0.0692	6,910 (AIC)
Model 3C	12.3	14.7	0.0796	6,293 (AIC)
Model 3D	12.2	14.7	0.0816	6,293 (AIC)
Model 3E	13.8	17.3	0.00823	6,893 (AIC)
Model 3F	14.6	16.6	0.105 (Bayesian R ²)	6,183 (LOOIC)
Model 3G	13.0	15.1	0.918 (Bayesian R ²)	-1,726 (LOOIC)

Note: Bayesian Model R² and Information Criterion should not be compared to Models A-E.

Progressive refinements improved model performance through stages A to D, with small but consistent reductions in error and increases in R-squared. Model 3C and 3D performed similarly, though 3D incorporated spline transformations to better handle nonlinearity and multicollinearity. Notably, Model 3E, which introduced orthogonalised predictors to account for heterogeneity, showed a decrease in predictive performance (higher MAE/RMSE, lower R-squared). Models 3F and 3G, both Bayesian, are evaluated with Bayesian R² and LOOIC, which are not directly comparable to frequentist R² or AIC. However, within the Bayesian context, Model 3G substantially outperformed 3F, achieving a much higher Bayesian R² (0.918) and significantly lower LOOIC (−1,726) as well as MAE and RMSE, suggesting strong predictive accuracy and model fit when accounting for both residual autocorrelation and bounded outcome values using beta regression.

A full output summary of model 3G can be found in Appendix Table 11. The significant parameters are found below:

Table 11

Significant Outputs Model 3G

Predictor	Estimate	Std. Error	z value	Approx P value
tiktok_rank_lag1_centered	0.0361	0.1493	-2.36	0.0182
speechiness_z	-0.353	0.0064	5.65	< 0.00001
tiktok_rank_lag1_centered:intercept_energy_ns1_resid	-0.0057	0.0028	-2.03	0.0428
duration_ms_z:tiktok_rank_lag1_centered	0.0146	0.0056	2.62	0.0088
valence_z:tiktok_rank_lag1_centered	0.0080	0.0033	2.41	0.0158
instrumentalness_z:tiktok_rank_lag1_centered	0.0192	0.0083	2.33	0.0198

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

A significant positive effect was found for lagged TikTok rank, with an estimated coefficient of 0.0361 ($p = 0.0182$). Since the model is a Beta regression with a logit link, coefficients reflect changes in the log-odds of the mean predicted value on a 0–1 scale, not raw Spotify rank. To aid interpretation, marginal predictions were computed simulating a 2-unit increase in centered TikTok rank (equivalent to a shift from 1 SD below to 1 SD above the mean), representing a realistic gain in virality. This shift resulted in a 0.11-position improvement on the 1–50 Spotify chart. In practical terms, songs gaining momentum on TikTok tend to see modest upward movement on Spotify in the following week, holding other factors constant.

Like model 2, model 3 therefore supports H1, also rejecting the null hypothesis of H1.

Using the same interpretive logic, a significant negative effect was found for speechiness, with an estimated coefficient of -0.353 ($p < 0.00001$). Using marginal effects, a one-standard-deviation increase in standardized speechiness (from 0 to +1) led to a decline of 4.31 chart positions. This suggests that more speech-like or talk-driven vocal styles are associated with lower Spotify chart performance, even when TikTok popularity and other audio features are held constant.

A significant interaction was also found between TikTok virality and energy (spline-transformed), with a coefficient of -0.0057 ($p = 0.0428$). Although energy was modeled using restricted cubic splines and orthogonalized interactions, making direct interpretation

complex, marginal predictions show that a 2-unit increase in TikTok rank, when energy is high, corresponds to a 0.11-position improvement on the Spotify chart. This suggests that energetic tracks may benefit slightly less from TikTok gains than expected.

Therefore, Model 3 rejects Hypothesis 7, which hypothesized that higher energy songs actually benefit less from the cross platform spillover effect.

For song duration, a significant interaction with TikTok rank was observed (coefficient = 0.0146, $p = 0.0088$). Holding duration at +1 SD above the mean, the same 2-unit TikTok rank increase led to a 0.44-position improvement. This implies that longer songs may be better positioned to capitalize on social media attention in driving Spotify chart gains.

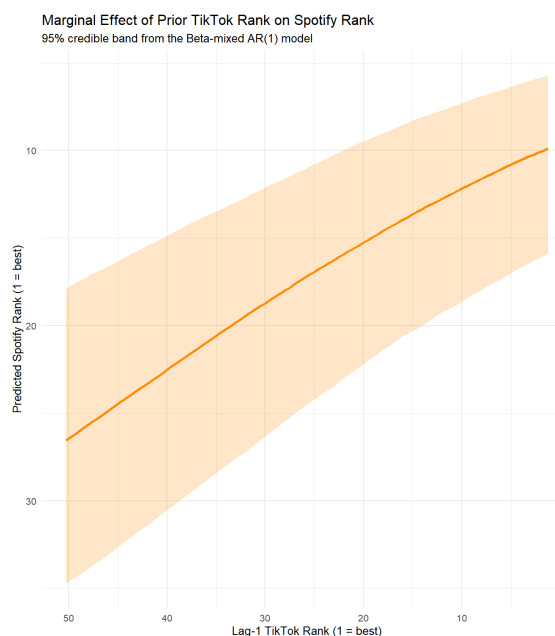
This finding supports H4, and therefore Model 3 rejects the null hypothesis of H4.

Valence also moderated the effect of TikTok virality, with a significant interaction coefficient of 0.0080 ($p = 0.0158$). When valence was set to +1 SD (i.e., more positive emotional tone), a 2-unit increase in TikTok rank yielded a 0.4-position chart improvement. This suggests emotionally uplifting tracks may more effectively convert viral exposure into streaming performance.

Finally, the interaction between TikTok rank and instrumentality was significant, with a coefficient of 0.0192 ($p = 0.0198$). At +1 SD instrumentality, the 2-unit TikTok increase corresponded to a 0.6-position improvement on the Spotify chart. This finding indicates that more instrumental tracks, despite lacking vocal content, may benefit slightly more from TikTok-driven visibility than expected, hinting at unique cross-platform dynamics for these song types.

Figure 5: Marginal Effect of TikTok Lag Rank on Spotify Rank

The plot illustrates the marginal effect of lagged TikTok rank on Spotify chart performance, based on the full Beta-mixed model with AR(1) autocorrelation and random track intercepts. As TikTok rank improves (moving from left to right), the predicted Spotify rank also improves (lower numbers), with a clear upward trend in the chart, visually reinforcing the positive influence of prior TikTok virality on subsequent Spotify success. This pattern aligns with the effect reported earlier, where a 2-unit increase in centered TikTok rank was associated with a 0.11-position improvement on the Spotify Top 50. However, it's important to note that the numerical estimate comes from a



fixed-effects-only version of the model without the AR(1) structure, which excludes temporal autocorrelation and random effects to simplify interpretation. This explains the slight difference in magnitude: the AR(1) model in the plot captures within-track, time-dependent dynamics more fully, producing a steeper overall effect. Both results point in the same direction and tell a consistent story, better TikTok performance is linked to better Spotify chart outcomes, but they reflect different modeling layers: the plot shows overall fitted predictions, while the paragraph quantifies a marginal fixed-effect contrast.

Figure 6: Marginal Effect of Speechiness

The plot displays the marginal effect of standardized speechiness on predicted Spotify chart rank, using the full Beta-mixed AR(1) model. As speechiness increases (moving rightward on the x-axis), the predicted Spotify rank worsens (higher rank values on the y-axis), indicating a clear negative association between speech-like vocal content and chart success. This aligns closely with our earlier estimate, where a 1-standard-deviation increase in speechiness was associated with a decline of 4.31 chart positions on average. It is important to note that the estimate in the paragraph came from a simplified fixed-effects version of the model (without the AR(1) autocorrelation term), whereas the visualized trend here includes the full hierarchical structure and time-dependency. As with TikTok rank, both versions of the model lead to the same substantive conclusion: more spoken-word or rap-like vocal delivery appears

to systematically reduce a track's likelihood of achieving a higher Spotify chart position, all else being equal. The visualization further confirms that this effect is relatively linear across the central range of speechiness values, with some uncertainty at more extreme levels.

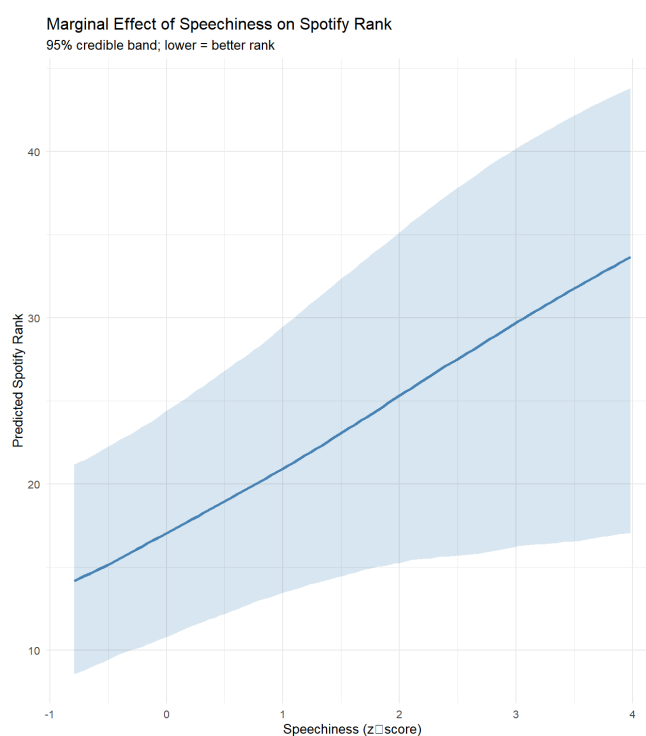


Figure 7: Effect of interaction between TikTok Lag Rank and Song Duration on Spotify Rank

The plot illustrates how the impact of prior-week TikTok rank on Spotify chart performance varies depending on a song's duration. The three curves represent predicted Spotify ranks at the 10th (134 seconds), 50th (192 seconds), and 90th (261 seconds) percentiles of the duration distribution, with lower values on the y-axis indicating better chart positions. Across all durations, improved TikTok rank (closer to 1) predicts higher Spotify success. However, the strength of this relationship increases with song length: the slope is steepest for the longest tracks, suggesting they benefit more from TikTok virality. This is consistent with earlier marginal effect results, specifically, that a 2-unit improvement in TikTok rank at +1 standard deviation of duration (near the 90th percentile) leads to an average Spotify chart improvement of 0.44 positions. By contrast, shorter songs (e.g., 10th percentile) show a more modest response to the same TikTok gain. These results suggest that longer songs may be better positioned to capitalize on TikTok traction. .

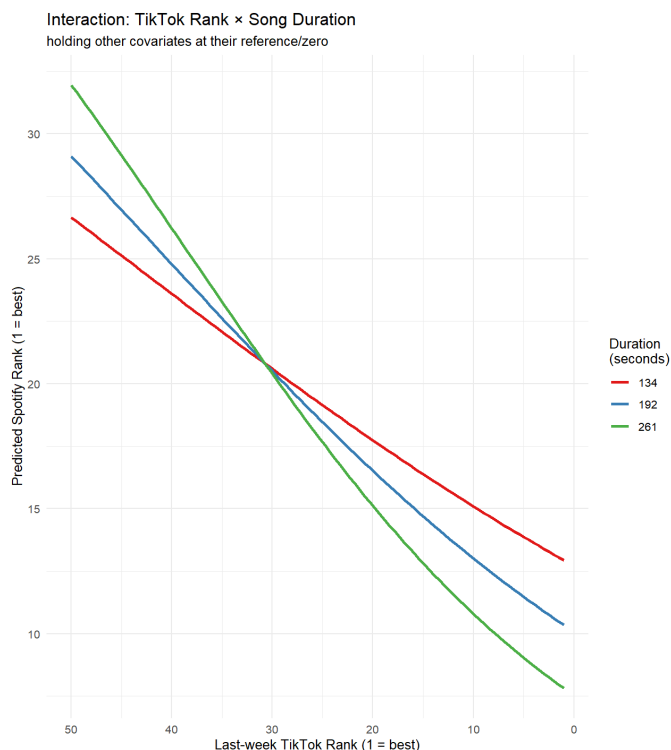
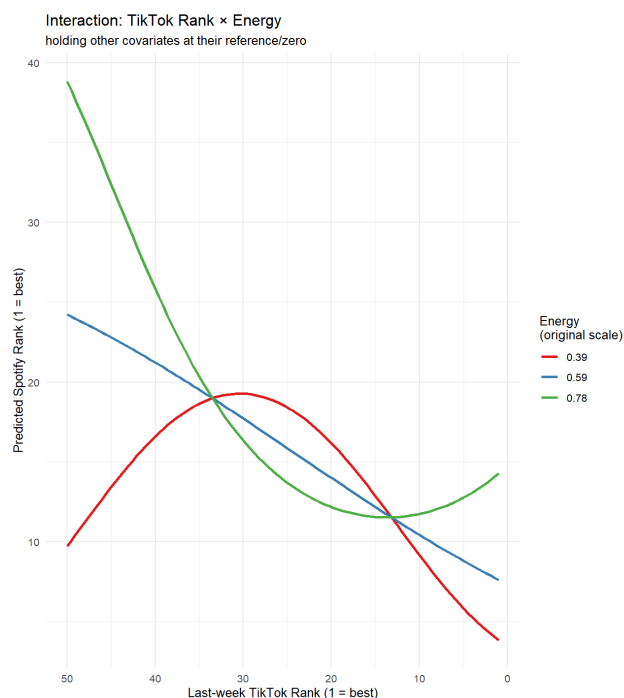


Figure 8: Interaction of TikTok Rank and Energy on Spotify Chart Success

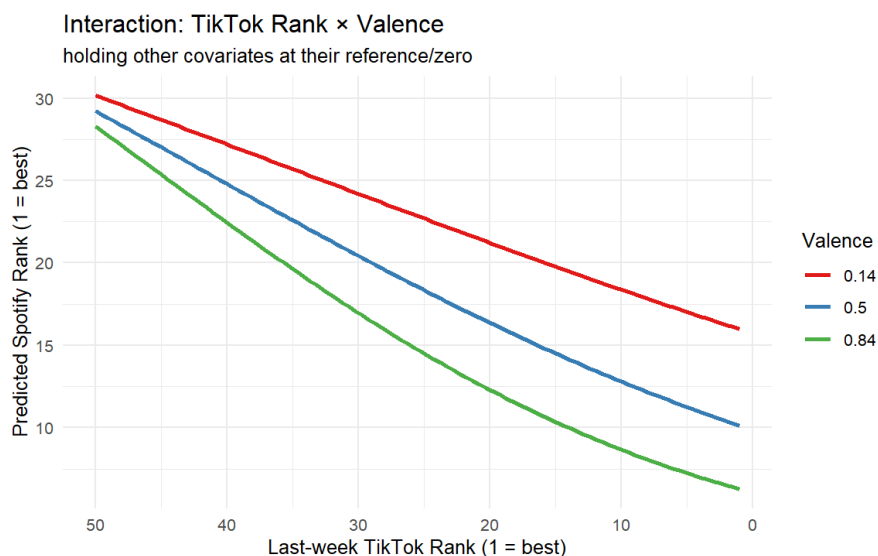
This plot displays how the predictive relationship between TikTok virality and Spotify chart performance is moderated by a song's energy level. The three curves represent songs at the 10th (0.39), 50th (0.59), and 90th (0.78) percentiles of the energy distribution, using the original (non-z-scored) scale. Interestingly, the effect of TikTok rank varies non linearly across energy levels. For low-energy tracks (red line), the benefit of TikTok virality is minimal and may even reverse at weaker chart positions. Mid-energy tracks (blue) show a steady linear improvement with better TikTok ranks. High-energy tracks (green), however, show the strongest gains in Spotify performance as



TikTok rank improves, particularly at the top of the TikTok chart. This is consistent with the marginal effect estimate indicating that a 2-unit improvement in TikTok rank at high energy leads to a 0.11 position gain on the Spotify chart. The nonlinearity captured by the spline transformation likely reflects how energy interacts with virality in complex ways.

Figure 9: Interaction of TikTok Rank and Valence on Spotify Chart Success

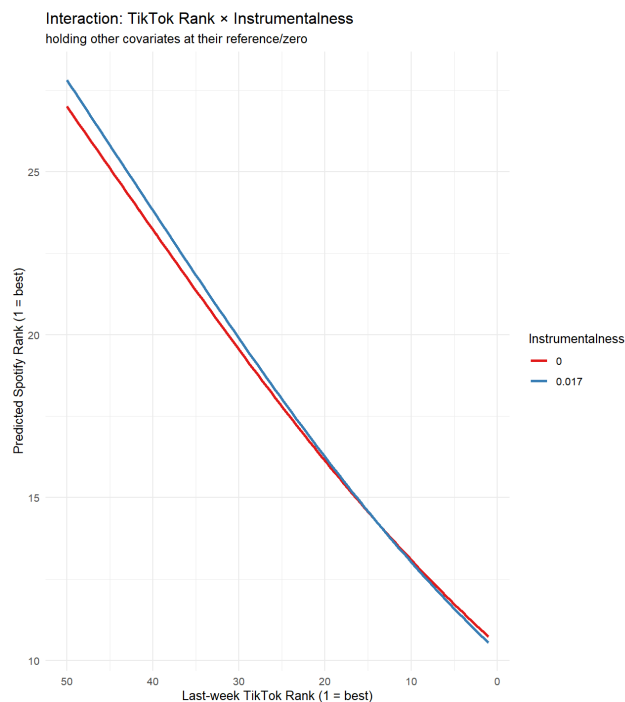
This visualization illustrates how the effect of TikTok virality on Spotify performance varies across different levels of musical valence, a measure of a track's emotional positivity. The lines represent predicted Spotify ranks for songs at the 10th (0.14), 50th (0.5), and 90th (0.84) percentiles of valence on the original scale. As TikTok rank improves (moving left to right), all



songs tend to perform better on Spotify. However, the steepness of the slope increases with valence: high-valence tracks (green) benefit more from improved TikTok positioning than lower-valence tracks (red). This is in line with the model, which as previously mentioned estimates that at +1 SD valence, a 2-unit improvement in TikTok rank leads to a 0.4-position boost on the Spotify chart (not accounting for AR1). This suggests that emotionally upbeat or positive songs may be more effective at converting TikTok exposure into streaming gains possibly due to their mood-enhancing or shareable qualities.

Figure 10: Interaction of TikTok Rank and Instrumentalness on Spotify Chart Success

This plot illustrates the interaction between TikTok virality and instrumentalness in predicting Spotify chart outcomes. Due to the highly skewed distribution of instrumentalness in the dataset, where the median, mean, and 75th percentile are all zero, only two representative levels are shown: 0 (completely vocal, which represents the vast majority of tracks) and 0.017. The model reveals a subtle divergence between these two groups: while songs with better TikTok performance consistently improve in Spotify rank (moving right to left), this benefit is slightly more pronounced for tracks with higher instrumentalness. As mentioned previously, at +1 SD instrumentalness, a 2-unit improvement in TikTok rank yields an estimated 0.6-position improvement on the Spotify chart, compared to a slightly smaller gain for fully vocal tracks. Although the effect is modest, it suggests that more instrumental songs may derive a small but meaningful advantage from TikTok momentum in driving Spotify chart success.



Summary of Hypotheses per Model

Table 12

Overview of supported & rejected hypotheses

Hypothesis	Model 1	Model 2	Model 3
H1:	Failed to reject	Supported	Supported
H2:	Failed to reject	Failed to reject	Failed to reject
H3:	Failed to reject	Failed to reject	Failed to reject
H4:	Failed to reject	Failed to reject	Supported
H5:	Failed to reject	Failed to reject	Failed to reject
H6:	Failed to reject	Failed to reject	Failed to reject
H7:	Failed to reject	Failed to reject	Rejected

Discussion

Findings

This study set out to investigate how TikTok virality and song-level audio features jointly shape a track's success on Spotify, using a three-model Bayesian analytical framework. Each model captured a different facet of “success”: (1) whether a song charts at all (binary), (2) the ordinal position of relative chart success (ranked categories), and (3) the relative positioning within the Top 50 (continuous Beta-distributed rank). The results provide converging, though not always consistent, evidence for the role of TikTok momentum and musical features in driving cross-platform streaming performance. Below, each model's findings are discussed in detail, organized by hypotheses where appropriate, and concluded with an integrative summary.

In line with the theoretical framework, Hypothesis 1 (H1), that TikTok virality positively predicts Spotify chart performance, was robustly supported across two out of three models. In contrast, Hypotheses H2 through H7, which concerned interaction effects between TikTok virality and specific musical features, received minimal support. They were unsupported in Model 1, and Model 2, while Model 3 supported H4 but also rejected H7.

The first model tested whether TikTok rank in the previous week predicted whether a song would appear on the Spotify Top 50 the following week. H1 (TikTok virality positively predicts Spotify success) was supported: the lagged TikTok rank had a significant positive effect, suggesting that higher virality on TikTok meaningfully increases the probability of Spotify chart entry. However, the other hypotheses H2-H7 received little to no support in this model. No significant interaction terms between TikTok rank and musical features emerged. This may reflect the relatively high noise and low variance in the binary outcome merely charting or not. However, the model achieved exceptionally high predictive performance metrics, which further indicates that TikTok rank alone is a highly reliable predictor of whether a track will break into the Spotify Top 50, even without accounting for specific musical features. This finding has important implications: in the earliest phase of Spotify chart success, crossing the threshold into visibility, momentum and exposure on TikTok appear to outweigh traditional acoustic characteristics such as danceability, valence, or loudness. This suggests a "gatekeeping" role for virality: TikTok may serve as a binary filter, where only tracks that achieve sufficient social traction gain Spotify visibility, regardless of their sonic content. Musical traits may still matter, but only once a track is already on the chart. In other words, TikTok virality may determine if a song gets noticed, while its musical properties shape how far it climbs. An additional point of interest is that the lack of interaction effects in this model could reflect a form of nonlinearity or ceiling effects. Once a song reaches high virality, musical features may matter less for whether it charts (a binary threshold), but may matter more for chart position or longevity, which warrants further exploration.

The ordinal model provided a more fine-grained look at a song's success by segmenting the chart into rank-based tiers (e.g., Top 50, Top 40, Top 30, Top 20, Top 10). H1 was again supported, with a significant positive effect for lagged TikTok rank. A 1-unit improvement in TikTok rank increased the odds of moving into a better Spotify tier by roughly 10.4%, reinforcing the notion that TikTok virality is not only a gateway to chart entry (as shown in Model 1), but also continues to play a measurable role in how far a song ascends within the Spotify charts. However, consistent with Model 1, there was again limited support for H2 through H7: only one interaction effect between TikTok virality and musical attributes reached significance. This may initially appear surprising, especially given the richer ordinal outcome variable, which offers greater variance than a binary success/failure definition. Yet, several methodological and theoretical considerations may help explain this pattern. One likely factor is the inclusion of track-level random intercepts, which absorb a large portion of the between-song variance. This makes intuitive sense: many musical traits do not vary over time for a given track. By accounting for persistent track-specific effects, the model isolates only the unique track dynamics over time. While this is statistically rigorous, it also reduces the power to detect main effects of musical features. Interestingly, however, a significant interaction emerged between TikTok rank and Key 9. Specifically, higher TikTok virality was associated with a lower probability of success for tracks in this key relative to the reference key. While this effect must be interpreted cautiously, it raises intriguing possibilities. One possibility is that the tonal profile of this key may interact poorly with the kind of moments that tend to "go viral" on TikTok (e.g., fast, quirky segments or beat drops), reducing cross-platform conversion efficiency. Another possibility is that this key-related moderation effect reflects genre clustering within the key, meaning that certain styles (e.g., commercial EDM or pop-rap hybrids) that are common in key 9 perform differently in the streaming ecosystem than on TikTok, which often favors novelty, nostalgia, or rawness over polish. This supports the broader idea that the mechanisms of virality and streaming success are not always aligned, and certain sonic or stylistic features may help on one platform but hinder on the other.

The third model offered the most granular perspective on Spotify success, modeling chart position as a continuous variable using a Beta regression framework. This allowed for fine-scale estimation of how TikTok virality and musical features interact to shape exact placement on the Spotify Top 50, rather than just whether a song charts or which rank tier it enters. As in the previous models, H1 was strongly supported: lagged TikTok rank exerted a significant positive effect on Spotify chart position, even after accounting for numerous acoustic predictors and track-level random effects. Notably, the model predicted that a two-unit improvement in TikTok rank, equivalent to a realistic move from one standard deviation below to one above the mean, was associated with a 0.11-position improvement on the Spotify chart. While modest in size, this effect is statistically robust and practically meaningful given the competitiveness of the chart's upper echelons. Unlike the first two models, Model 3 revealed multiple significant interaction effects between TikTok virality and musical features, providing stronger evidence for musical

features playing a moderating role in the cross platform spillover effect. These included interactions with energy, duration, valence, instrumentalness, and speechiness. The significance of these interactions suggests that the influence of TikTok virality on Spotify chart performance is not uniform across all tracks, but instead depends on specific musical properties. For instance, tracks with higher energy or longer durations benefited more from TikTok virality, while tracks with higher speechiness were penalized, perhaps due to the lower replay value or narrower appeal of spoken-word segments on audio-first platforms like Spotify. These findings could potentially indicate that once a song breaks into the chart, musical traits begin to matter more, shaping the extent to which TikTok momentum can translate into streaming success. Interestingly, these nuanced effects only emerged in the continuous Beta model, likely due to the greater sensitivity of the model to subtle shifts in rank position.

Model 3 also reinforces the idea that musical features do not drive chart entry in isolation, but rather shape how far a track can climb once it has been introduced into the streaming ecosystem through viral exposure. For instance, instrumental tracks, which might be overlooked in earlier models, showed stronger gains from TikTok virality in this model, suggesting an underexplored synergy between TikTok's visual format and instrumental audio content that supports certain types of content. Meanwhile, emotional valence appeared to moderate the effectiveness of TikTok virality, with more positive-sounding tracks converting viral attention into higher ranks more efficiently. These insights not only support the core hypotheses but also expand them: the interaction between music and virality is highly conditional, and musical structure plays an enabling or constraining role in determining how much virality can convert into durable streaming momentum.

Taken together, Model 3 delivers the clearest picture of cross-platform success dynamics. It validates the predictive power of TikTok rank, affirms that musical features shape the magnitude of this effect, and highlights how modeling decisions, such as the choice of outcome variable, can profoundly affect which patterns emerge. This comprehensive framework suggests that while virality remains a key driver of success, it is musical distinctiveness and structure that ultimately determine the staying power and peak performance of a track once it has entered the public ear.

Implications

The findings of this thesis carry several important implications for academics, industry professionals, and digital music marketers. From an academic standpoint, the methodology presented here sets a robust foundation in studying cross platform effects in the lens of HSS. The multilevel modeling approach adopted here demonstrates that viral exposure and acoustic characteristics are not uniformly predictive across stages of streaming success. This suggests the need for future research to model platform success as a dynamic, multistage process rather than a static outcome. Additionally, the study confirms that interaction effects, particularly those between TikTok virality and musical attributes like energy, speechiness, instrumentalness, and duration, are crucial to understanding how content flows across platforms. This calls for more work on moderation and nonlinear effects in digital media diffusion models.

From a managerial and label strategy perspective, the results suggest that not all songs benefit equally from TikTok momentum. While most acoustic features do not significantly increase the likelihood of initial Spotify chart entry (Model 1), the extent of upward movement within the charts (Models 2 and 3) is moderated by specific musical attributes. For instance, songs with longer duration, lower speechiness, or more instrumental content appear to better capitalize on viral exposure. This suggests that music marketers and A&R professionals should not only aim for TikTok traction but also evaluate whether a track's acoustic profile supports cross-platform conversion. Labels might consider investing more heavily in promotional efforts for viral tracks that also score favorably on features shown to enhance Spotify translation, or tailor TikTok campaign strategies to emphasize acoustic moments most likely to resonate on streaming platforms.

Finally, at an industry level, the findings highlight a potential tension between what works on TikTok and what sustains success on Spotify. For example, tracks with high speech content or shorter formats may go viral but underperform on streaming platforms, reflecting differing platform norms (e.g., visual novelty vs. audio replay value). This platform mismatch could influence how artists and producers design and release tracks, potentially leading to a new genre of hybrid songs optimized for both attention and retention. As short-form platforms continue to shape music discovery, these dynamics warrant closer attention from both streaming services and content creators. Ultimately, the ability to forecast not just virality but virality conversion efficiency could be the next frontier in digital music analytics.

Strengths

In addition to its analytical depth, the study offers several methodological strengths that enhance the credibility and generalizability of its findings. Most notably, the use of a multilevel Bayesian modeling framework enables a principled treatment of random effects, capturing both persistent track-level idiosyncrasies and time-varying dynamics. The three-model structure, binary, ordinal, and continuous, provides a rich, layered understanding of cross-platform success, offering insight not only into whether a song charts but also how high it climbs. Feature engineering was carried out with methodological rigor, employing standardization, splines, and orthogonalized interaction terms to reduce multicollinearity and honor model assumptions. Importantly, the findings are not merely statistical: marginal effect simulations and visualizations translate the results into tangible chart movements, making the study accessible to both academic and applied music industry contexts. Taken together, these strengths reinforce the study's value as a robust contribution to the emerging literature on social media spillover and streaming success.

Limitations

While this paper offers valuable insights into the interaction between TikTok virality and Spotify chart performance, several important limitations constrain the generalizability and precision of

its findings. The first and most significant limitation lies in the scope of the data. By focusing exclusively on the Top 50 charts for both Spotify and TikTok, the dataset captures only a fraction of total platform activity. While Top 50 tracks account for high visibility and often dominate consumption, many songs experience meaningful engagement outside of this threshold. For instance, songs trending just below the Top 50 may still be on an upward trajectory or enjoy significant popularity. The exclusion of songs ranked 51-200 (and even chart positions beyond the top 200) on Spotify or TikTok likely omits a substantial portion of viral phenomena, especially those that evolve slowly or emerge from subcommunities. Consequently, the models may overlook important predictors and underestimate longer-tail dynamics.

A related limitation concerns the loss of data due to platform non-overlap. TikTok and Spotify are fundamentally distinct ecosystems: the former emphasizes short-form, user-generated video content while the latter is structured around sustained audio streaming. As a result, many weekly observations include only a Spotify rank or only a TikTok rank. This misalignment means that a considerable share of otherwise useful observations are excluded from regression models, especially when requiring both lagged TikTok rank and contemporaneous Spotify rank. While efforts were made to preserve sample size by implementing imputed values, such procedures necessarily introduce their own assumptions.

Furthermore, the accuracy of Spotify acoustic feature variables depends on the reliability of Spotify's internal algorithms. Several outliers (e.g., in danceability, energy, or instrumentality) suggest that certain genre-specific or production-specific characteristics, such as vocal distortion or rhythmic variation, may mislead Spotify's classification system. While these were addressed through targeted imputation strategies based on artist and genre medians, such corrections rely on the assumption that stylistic consistency exists within artist-genre clusters, which may not always hold. The data cleaning was also done manually by a single coder, and with the size of the dataset and given time constraints only obvious outliers could be inspected.

Lastly, the lack of longitudinal user engagement data prevents deeper analysis of what happens beyond chart entry. While this study models initial Spotify visibility and relative rank, it cannot speak to questions of retention, playlist inclusion, skip rate, or downstream monetization. These dimensions likely play a central role in the broader platform ecology, particularly for assessing long-term artist success and cross-platform migration.

In sum, the findings presented here should be interpreted within the context of a selective, top-tier chart dataset and with recognition of necessary compromises.

Future Research

Despite its limitations, this paper provides an important foundation for exploring the cross-platform dynamics between social media virality and digital music consumption. As one of the first studies to apply a HSS framework to the context of TikTok-to-Spotify spillover effects, it offers a structured approach to disentangling the multi-stage process of music discovery, selection, and streaming behavior. However, to deepen theoretical understanding and derive

more actionable insights, future research should build on this framework with richer data and extended model design.

A clear next step would involve expanding the scope of the dataset beyond the Top 50. Access to full Top 200 (or even Top 1000) chart data from both Spotify and TikTok would not only increase statistical power but also allow the modeling of more subtle virality effects, those that occur just beneath the surface of major popularity but often serve as early signals of emerging trends. This would allow for a more continuous analysis of rank dynamics across the popularity spectrum.

Furthermore, access to longitudinal user-level or song-level engagement data, such as playlist inclusion, skip rates, time-on-track, or repeat listens, would offer a more nuanced understanding of what constitutes "success" on Spotify. While chart rank is an accessible proxy for performance, it abstracts away much of the underlying engagement behavior. Integrating such micro-level metrics could clarify how initial TikTok virality translates into sustained streaming, and whether certain musical features help convert virality into loyalty.

Another important avenue lies in platform-specific algorithmic exposure. TikTok's For You Page (FYP) and Spotify's playlist ecosystem operate under different logic, but both shape visibility in algorithmically curated environments. Future research might investigate whether TikTok virality increases the probability of inclusion in prominent Spotify playlists (e.g., Today's Top Hits), thereby serving as an indirect bridge between organic discovery and curated prominence.

Furthermore, it would be highly valuable to conduct a study of similar magnitude using data from other music-streaming or social media platforms. Platforms such as Apple Music, YouTube Music, or Instagram Reels offer distinct user behaviors, algorithmic dynamics, and content discovery pathways that may yield different patterns of spillover or feature effects. Investigating whether the same interaction effects between virality and musical attributes hold across these platforms would enhance the generalizability of current findings. Moreover, such comparative analyses could reveal platform-specific nuances in how songs convert short-form content exposure into sustained listening behavior, thereby offering deeper insights for both academic theory and industry practice.

Finally, further research could explore the genre-specific or demographic moderators of spillover effects. Do certain genres (e.g., hip-hop, EDM, acoustic) exhibit stronger virality-to-streaming conversion patterns? Are emerging artists affected differently than established ones? Answering such questions would yield not only academic value but also practical insight for artists, labels, and platform curators.

In summary, while this paper offers a targeted analysis of a narrowly defined cross-platform effect, its findings open up rich terrain for continued exploration. The intersection of social media virality and algorithmic music consumption remains underexplored in academic literature, particularly through the lens of HSS. Expanding this line of inquiry promises to contribute meaningfully to both theoretical discourse and managerial strategies in a rapidly evolving digital media landscape.

Appendix

Table 1

Summary Statistics of continuous variables for model 1 dataset

Variable	Mean	SD	Min	25%	Median	75%	Max	NA Count
tiktok_rank_lag1_centered	-0.126	13.919	-28,045	-11.045	0.955	11.955	20.955	0
danceability_z	0.217	1.070	-3.612	-0.464	0.339	1.070	2.046	0
energy_z	-0.056	1.049	-3.236	-0.734	0.028	0.684	2.131	0
loudness_z	-0.135	0.904	-6.613	-.0556	0.080	0.561	2.017	0
speechiness_z	0.236	1.141	-0.810	-0.639	-0.307	0.889	5.908	0
acousticness_z	-0.038	1.053	-0.968	-0.865	-0.518	0.518	2.773	0
instrumentalness_z	0.210	1.32	-0.265	-0.265	-0.265	-0.260	5.438	0
valence_z	0.056	1.000	-2.018	-0.726	0.079	0.854	2.055	0
tempo_z	0.021	0.904	-2.517	-0.661	0.152	0.661	3.502	0
duration_ms_z	-0.089	1.382	-2.078	-0.708	-0.206	0.376	31.989	0

Note: Values are rounded to the third decimal when appropriate

Table 2

Frequency Table of on_spotify for model 1 dataset

0	1
4,409	1,061

Table 3

Frequency Table of mode_factor for model 1 dataset

Minor	Major
1,875	3,595

Table 4

Frequency Table of key_factor for model 1 dataset

0	1	2	3	4	5	6	7	8	9	10	11
432	1,187	624	119	274	381	367	512	352	442	285	494

Table 5

Summary Statistics of continuous variables for model 2 and 3 dataset

Variable	Mean	SD	Min	25%	Median	75%	Max	NA Count
spotify_rank_centered	0.000	15.0	-32.351	-11.351	4.649	12.649	16.649	0
tiktok_rank_lag1_centered	-0.569	14.4	-28.045	-13.045	0.955	11.955	20.955	0
danceability_z	0.095	1.04	-2.769	-0.721	0.222	0.833	1.931	0
energy_z	-0.088	0.930	-2.893	-0.645	-0.067	0.601	1.964	0
loudness_z	0.034	0.826	-5.482	-0.337	0.160	0.619	1.291	0
speechiness_z	-0.224	0.750	-0.792	-0.690	-0.535	-0.167	3.981	0
acousticness_z	0.052	0.948	-0.969	-0.727	-0.270	0.707	2.612	0
instrumentalness_z	-0.193	0.361	-0.266	-0.266	-0.266	-0.264	5.030	0
valence_z	0.047	1.02	-1.886	-0.792	0.070	0.871	1.993	0
tempo_z	-0.008	0.966	-1.943	-0.794	-0.051	0.795	2.752	0
duration_ms_z	-0.006	0.629	-1.347	-0.488	-0.055	0.426	2.392	0

Note: Values are rounded to the third decimal when appropriate**Table 6**

Frequency Table of mode_factor for model 2 and 3 dataset

Minor	Major
369	692

Table 7

Frequency Table of key_factor for model 2 and 3 dataset

0	1	2	3	4	5	6	7	8	9	10	11
80	206	107	26	61	90	88	76	90	80	66	91

Table 8

Frequency Table of rank bucket for model 3

Top 50	Top 40	Top 30	Top 20	Top 10
122	119	163	179	478

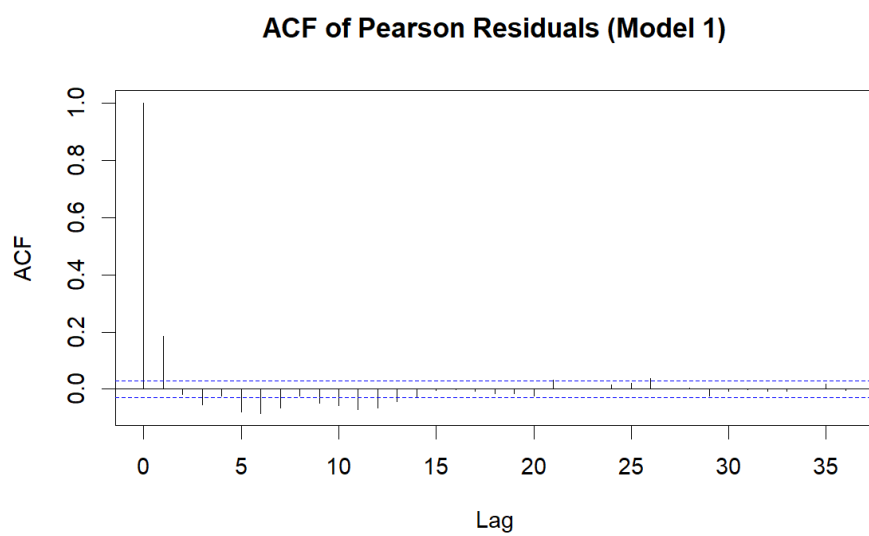
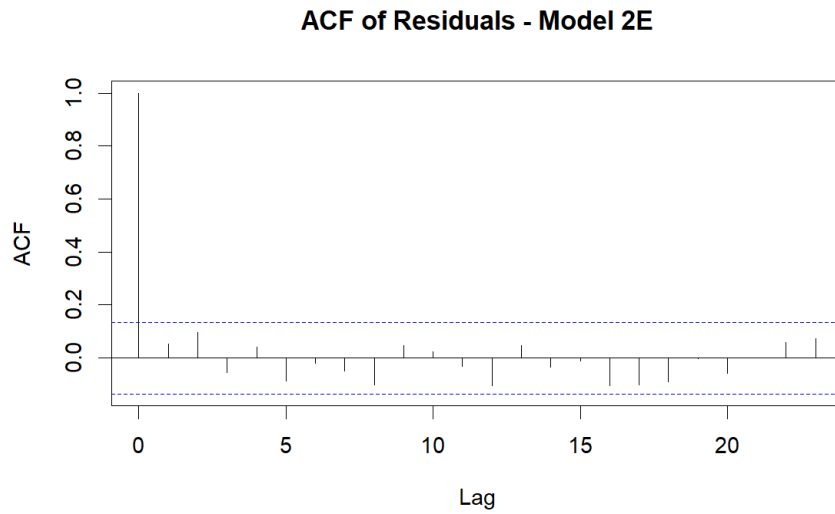
Figure 1

Figure 2**Table 9**

Model 1F Summary

Variable	Estimate	Std. Error	z value	p-value
(Intercept)	-23.1474751	11.97706	-1.932651	0.05328
tiktok_rank_lag1_centered	0.1351206	0.20720	0.652136	0.51431
danceability_z	-0.0385392	0.78467	-0.049115	0.96083
energy_z	-0.5378891	1.06964	-0.502868	0.61506
valence_z	0.4441568	0.82920	0.535646	0.59220
speechiness_z	-1.2345080	0.91990	-1.342002	0.17960
mode_factorMajor	0.3926342	1.33626	0.293830	0.76889
key_factor1	-2.0747493	3.01980	-0.687049	0.49205
key_factor2	0.2458982	2.81985	0.087202	0.93051
key_factor3	-0.6953685	3.97987	-0.174721	0.86130
key_factor4	-4.2828208	6.09945	-0.702165	0.48258
key_factor5	0.4171254	3.12348	0.133545	0.89376
key_factor6	-3.7938522	4.61352	-0.822333	0.41089
key_factor7	0.3450841	3.00553	0.114816	0.90859

key_factor8	0.9823581	2.78255	0.353042	0.72406
key_factor9	0.4675144	2.77429	0.168517	0.86618
key_factor10	-0.1889983	3.48760	-0.054191	0.95678
key_factor11	-8.3836322	7.35330	-1.140118	0.25424
loudness_ns1	18.5454535	20.23867	0.916337	0.35949
loudness_ns2	0.7963026	5.78600	0.137626	0.89054
tempo_ns1	-1.3279604	5.31786	-0.249717	0.80281
tempo_ns2	6.4661343	5.34067	1.210734	0.22600
duration_ns1	-1.7080093	14.48613	-0.117906	0.90614
acoustic_ns1	0.8521996	3.42747	0.248638	0.80364
acoustic_ns2	-2.4547802	4.04689	-0.606584	0.54413
instrumental_ns1	-11.5569458	11.49462	-1.005422	0.31469
instrumental_ns2	-0.5235242	9.81797	-0.053323	0.95747
tiktok_rank_lag1_centered:danceability_z	-0.0204492	0.03200	-0.638992	0.52283
tiktok_rank_lag1_centered:energy_z	-0.0022027	0.03878	-0.056803	0.95470
tiktok_rank_lag1_centered:valence_z	0.0273551	0.03579	0.764336	0.44467
tiktok_rank_lag1_centered:speechiness_z	-0.0002716	0.04423	-0.006142	0.99510
tiktok_rank_lag1_centered:mode_factorMajor	-0.0056357	0.06250	-0.090174	0.92815
tiktok_rank_lag1_centered:key_factor1	0.1863253	0.16450	1.132659	0.25736
tiktok_rank_lag1_centered:key_factor2	-0.1319353	0.14398	-0.916352	0.35948
tiktok_rank_lag1_centered:key_factor3	0.1143880	0.22104	0.517493	0.60481
tiktok_rank_lag1_centered:key_factor4	-0.3024818	0.21061	-1.436238	0.15093
tiktok_rank_lag1_centered:key_factor5	-0.1462692	0.16082	-0.909546	0.36306
tiktok_rank_lag1_centered:key_factor6	-0.1793733	0.17217	-1.041813	0.29750
tiktok_rank_lag1_centered:key_factor7	-0.0166808	0.17083	-0.097646	0.92221
tiktok_rank_lag1_centered:key_factor8	-0.0498842	0.15397	-0.323983	0.74595
tiktok_rank_lag1_centered:key_factor9	-0.0434058	0.15889	-0.273189	0.78471
tiktok_rank_lag1_centered:key_factor10	-0.1495038	0.17366	-0.860921	0.38928
tiktok_rank_lag1_centered:key_factor11	-0.4739781	0.25632	-1.849188	0.06443

tiktok_rank_lag1_centered:tempo_ns1	-0.0552772	0.25037	-0.220784	0.82526
tiktok_rank_lag1_centered:duration_ns1	-0.4640971	0.72779	-0.637681	0.52368
tiktok_rank_lag1_centered:acoustic_ns2	0.0541981	0.16331	0.331882	0.73998
tiktok_rank_lag1_centered:instrumental_ns1	-0.1941236	0.45790	-0.423942	0.67161

Table 10

Model 2E Summary

term	estimate	std.error	conf.low	conf.high
(Intercept)[1]	-4.738505	1.058456	-6.84024	-2.666658
(Intercept)[2]	-3.013241	1.049426	-5.09789	-0.977585
(Intercept)[3]	-1.180413	1.045320	-3.23515	0.849508
(Intercept)[4]	0.694768	1.048120	-1.35303	2.712686
tiktok_rank_lag1_centered	0.098933	0.041000	0.01996	0.181921
dance_ns2	-0.394334	1.123018	-2.57806	1.776709
energy_ns2	-1.066679	1.234101	-3.48565	1.436416
loudness_ns2	0.396634	1.308137	-2.17441	2.945141
tempo_ns1	-0.793457	1.535988	-3.82854	2.123205
duration_ns2	0.260735	1.442129	-2.52828	3.103851
valence_ns2	1.688502	1.022648	-0.35219	3.660838
speechiness_z	-0.644374	0.397877	-1.44091	0.165732
key_factor1	-1.400416	0.880693	-3.09468	0.342645
key_factor2	0.355877	0.975944	-1.54883	2.229186
key_factor3	-0.090500	1.402348	-2.79004	2.665286
key_factor4	-0.222896	1.204918	-2.55275	2.165285
key_factor5	-0.398008	1.022547	-2.39394	1.582874
key_factor6	-0.141348	1.015802	-2.10309	1.944624
key_factor7	-1.916063	1.097816	-4.04283	0.238711
key_factor8	0.309727	1.130530	-1.88546	2.522436

key_factor9	0.581421	1.139110	-1.70227	2.822217
key_factor10	0.445165	1.224739	-1.87109	2.848026
key_factor11	-0.888326	0.980488	-2.80730	0.964514
mode_factorMajor	-0.400826	0.637319	-1.63209	0.840151
tiktok_rank_lag1_centered:dance_ns2	-0.027560	0.036161	-0.09978	0.043902
tiktok_rank_lag1_centered:energy_ns2	0.049953	0.042960	-0.03430	0.135060
tiktok_rank_lag1_centered:loudness_ns2	-0.022744	0.046580	-0.11329	0.067234
tiktok_rank_lag1_centered:tempo_ns1	0.048939	0.062838	-0.07713	0.168694
tiktok_rank_lag1_centered:duration_ns2	0.093245	0.084474	-0.06513	0.264993
tiktok_rank_lag1_centered:valence_ns2	0.007929	0.036590	-0.06399	0.081458
tiktok_rank_lag1_centered:speechiness_z	0.004931	0.009785	-0.01449	0.024014
tiktok_rank_lag1_centered:key_factor1	-0.055496	0.038574	-0.12943	0.022077
tiktok_rank_lag1_centered:key_factor2	-0.046083	0.042376	-0.12978	0.037902
tiktok_rank_lag1_centered:key_factor3	-0.082063	0.080558	-0.23191	0.080368
tiktok_rank_lag1_centered:key_factor4	-0.063292	0.045307	-0.15080	0.029351
tiktok_rank_lag1_centered:key_factor5	-0.036971	0.044589	-0.12398	0.052197
tiktok_rank_lag1_centered:key_factor6	-0.042502	0.045228	-0.13023	0.045192
tiktok_rank_lag1_centered:key_factor7	-0.054049	0.043992	-0.13886	0.034336
tiktok_rank_lag1_centered:key_factor8	-0.066917	0.041792	-0.14793	0.016875
tiktok_rank_lag1_centered:key_factor9	-0.094388	0.038812	-0.17366	-0.018365
tiktok_rank_lag1_centered:key_factor10	-0.083659	0.044286	-0.17087	0.003593
tiktok_rank_lag1_centered:key_factor11	-0.059293	0.038997	-0.14002	0.015352
tiktok_rank_lag1_centered:mode_factorMajor	0.003618	0.019358	-0.03411	0.041781
tiktok_rank_lag1_centered:mode_factorMajor	0.003618	0.019358	-0.03411	0.041781

Table 11

Model 3G Summary

Variable	Estimate	Std. Error	CI Lower	CI Upper
(Intercept)	0.6902173	0.879664	-1.079553	2.3604583

dance_ns1	-0.1960473	0.819906	-1.786775	1.4364121
energy_ns1	0.5759715	0.901998	-1.170364	2.3574391
loudness_ns1	-0.1718996	0.964560	-2.075922	1.7347262
tempo_ns1	-0.2415680	0.714275	-1.631817	1.1580276
duration_ms_z	0.1242252	0.209473	-0.280291	0.5619510
acousticness_z	0.0943915	0.151635	-0.200255	0.3987752
valence_z	0.2771854	0.143774	-0.018045	0.5497828
instrumentalness_z	-0.1589964	0.234949	-0.633147	0.3094884
speechiness_z	-0.3525476	0.149316	-0.632366	-0.0451496
tiktok_rank_lag1_centered	0.0360942	0.006388	0.023741	0.0486507
key_factor1	-0.3182519	0.393294	-1.101357	0.4226304
key_factor2	0.2213221	0.463187	-0.717865	1.0860089
key_factor3	0.1530390	0.611264	-1.004571	1.3480391
key_factor4	0.2042297	0.562245	-0.884260	1.3377581
key_factor5	-0.3589931	0.467677	-1.255894	0.5910589
key_factor6	0.3883746	0.464202	-0.508965	1.3136192
key_factor7	-0.5838824	0.487048	-1.589011	0.3278483
key_factor8	0.1346610	0.488681	-0.778870	1.1048802
key_factor9	0.4186857	0.499195	-0.560729	1.3909496
key_factor10	0.1235437	0.521242	-0.923905	1.1077961
key_factor11	-0.1538090	0.429300	-0.978301	0.6702850
mode_factorMajor	-0.1094164	0.263610	-0.604940	0.4032047
tiktok_rank_lag1_centered:int_dance_ns1_resid	-0.0006565	0.002453	-0.005426	0.0041330
tiktok_rank_lag1_centered:int_energy_ns1_resid	-0.0056648	0.002786	-0.011204	-0.0002823
tiktok_rank_lag1_centered:int_loudness_ns1_resid	-0.0019269	0.004810	-0.011541	0.0073954
tiktok_rank_lag1_centered:int_tempo_ns1_resid	-0.0005378	0.001696	-0.003814	0.0027533
duration_ms_z:tiktok_rank_lag1_centered	0.0145864	0.005566	0.004171	0.0260010
acousticness_z:tiktok_rank_lag1_centered	0.0060627	0.003652	-0.001126	0.0132760
valence_z:tiktok_rank_lag1_centered	0.0080226	0.003325	0.001484	0.0143796

instrumentalness_z:tiktok_rank_lag1_centered	0.0192352	0.008254	0.003419	0.0363962
speechiness_z:tiktok_rank_lag1_centered	0.0029726	0.004358	-0.005669	0.0116027
tiktok_rank_lag1_centered:mode_factorMajor	-0.0078749	0.007356	-0.022019	0.0066771

Figure 3: Influential Outlier Check Model 1E

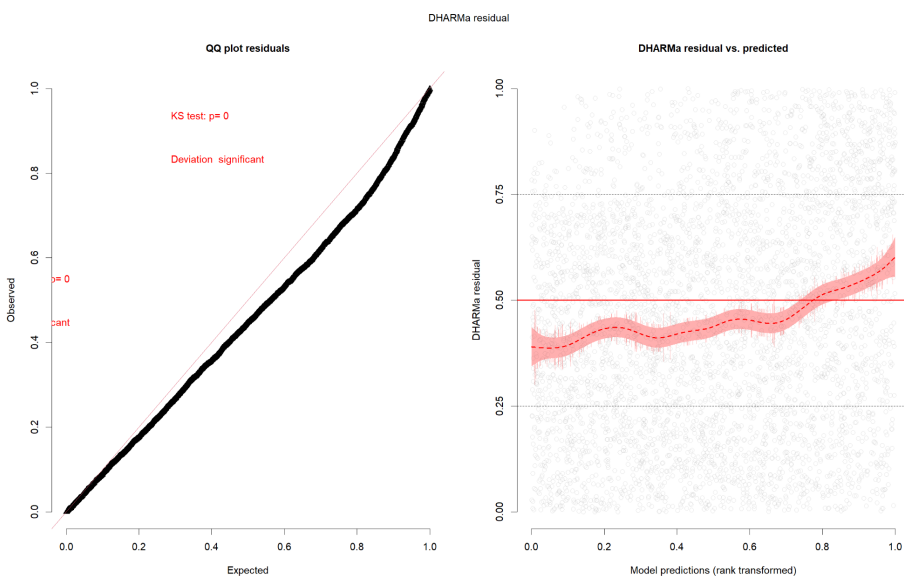


Figure 4:

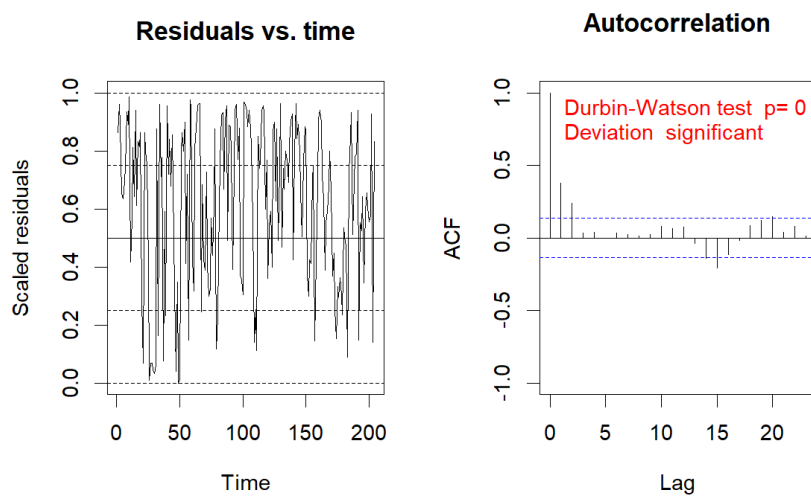
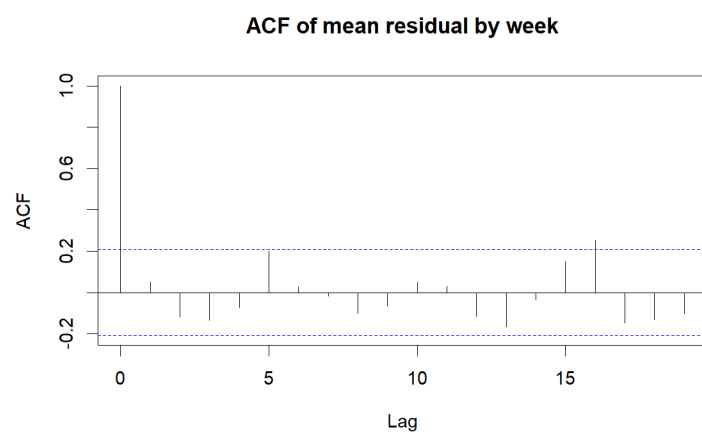


Figure 5**Table 12**

Pareto k range	Diagnostic Category	Count	Pct.	Min. ESS
($-\infty$, 0.7]	good	733	86.0%	94
(0.7, 1]	bad	64	7.5%	
(1, ∞)	very bad	55	6.5%	

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