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Melodic Repetition Shapes Success

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**Abstract**

Music is fundamental part of human existence. But why are some songs, hymns, or other types of music more successful?  While some have argued that success is random, driven by patterns of social influence, this work suggests that melodic repetition might shape success. A multimethod investigation, including automated audio analysis of thousands of songs using cutting-edge audio processing algorithms, as well as two controlled experiments, demonstrates that songs that repeat the melody more often are evaluated more positively and become more popular. Further, the studies illustrate that this effect is driven by processing ease. Melodic repetition makes songs easier to process, which boosts their success. Taken together, these findings shed light on why things catch on, the psychology of music, and how automated audio analysis can be used to provide insight into human behavior.

**Significance Statement**

Why do certain pieces of music succeed while others fail to resonate? While some have argued that success is random, this paper suggests that melodic repetition might help explain what becomes popular. Automated audio analysis of thousands of songs demonstrates that songs that repeat the melody more often are more successful. Two follow-up experiments provide evidence that processing ease drives this effect. Melodic repetition makes songs easier to process, which increases evaluations, and boosts success. Taken together, these findings shed light on why things catch on, the psychology of music, and how automated audio analysis can be used to provide insight into human behavior.

**Main Text**

**Introduction**

Music is a human universal (1). Prehistoric tribes played music to celebrate and mourn and ancient Greeks sang songs to tell stories and honor gods. Today, every culture has some form of music (2-3), and music plays a role in everything from the profound (e.g., religious rituals and coronations) to the mundane (e.g., commuting and team sports). Indeed, music appeals to almost everyone (4), and is used to manage emotions, connect with others, or just relax (5-8).

But while it’s clear that music is an important part of being human, some pieces of music (e.g., songs, hymns, or lullabies) become more popular than others. Why?

One possibility is that success is random. Even experts armed with data have trouble predicting which cultural items succeed and fail (9-11) and patterns of social influence can make popularity unpredictable (12). People often follow others (13-14), so if certain songs get slightly more attention, this could lead to a snowball effect where some songs succeed based on nothing to do with their actual content.

In contrast, we suggest that musical features play an important role in driving success. While some work has begun to explore the role of lyrics in driving evaluations (15-16), there has been less attention to musical features, in part, because of how difficult they are to study. While lyrics are relatively easy to identify, musical features (e.g., melody, harmony, timbre, and rhythm) occur simultaneously, making it hard to isolate and measure them in an objective, automated, and scalable way.

In particular, we examine the effect of melodic repetition. Melody refers to the progression of notes that form a musical tune. Said another way, it is the pitch sequence that listeners might reproduce if asked to whistle or hum a piece of music (17). When Freddy Mercury sings “We will we will rock you!” from Queen’s “We Will Rock You,” for example, he is chanting the sequence of notes “G-F♯-E-D-E-E”.

We suggest that melodic repetition should make music more popular. Some songs repeat the melody only a few times, while others repeat it more frequently (see Fig. 1 for examples of melodic repetition in different songs).

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**Figure 1.** Melodic repetition examples. Sometimes the melody appears when the chorus does (e.g., Queen’s “We will rock you”), other times it appears during the verses (e.g., The Beatles’ “Hey Jude”), and sometimes it appears in both (e.g., Johnny Cash’s “I walk the line”).

We suggest that such repetition should increase success because it makes music easier to process. Stimuli vary in how much cognitive effort they require to parse (18). Fonts that are easier to read, for example, or words that are easy to pronounce, require less cognitive effort to process. This, in turn, can lead them to be evaluated more favorably (19-20).

We suggest that melodic repetition should have similar effects. Frequent exposure to stimuli can decrease the effort required to process them (21), and as a result, encourage positive evaluations. Consequently, we suggest the melodic repetition should increase evaluations and make songs more popular.

**Measuring Melodic Repetition in the Field**

To begin to explore these possibilities, we start by using state-of-the-art automated audio processing techniques to analyze thousands of songs. We transform songs into frequency maps, employ an algorithm to detect the prominent melody (i.e., recurring note sequences), and quantify its occurrences throughout the song. Then, we examine whether, controlling for other relevant factors (e.g., lyrics, artist, and acoustic elements), songs that repeat the melody more frequently are more popular.

First, we convert each song’s raw audio signal into a Mel-scaled spectrogram, or a 2D array where each row represents a different frequency band, and each column represents a different point in time (Fig. 2). We use the Short-time Fourier transform (which breaks down the audio signal into a series of short-time frames) and the Mel-frequency cepstrum (which converts each frame into a representation in the frequency domain). The Mel Spectogram is expressed as follows:

where *H* is the hop length (to define the number of samples between the start of one frame and the start of the next), *f(i)* is the Mel filterbank (to convert the power spectrum of each window into a set of Mel-frequency bands), and *N* is the Fast Fourier Transform (FFT) window size.

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**Figure 2.** Mel Spectrogram from Queen’s “We Will Rock You”. Each row represents a different frequency band, and each column represents a different point in time in the song. Boxes indicate where the melody appears.

Second, to identify each song’s melody, we used the Melody method (22). This state-of-the-art algorithm combines signal processing techniques and music theory knowledge, looking for patterns of pitches that repeat throughout the audio signal and detecting the prominent melody (23). To do so, it computes a Pitch Activation Function (PAF), which represents the likelihood of a pitch being present at each time in the spectrogram (e.g., 24; see *SI Appendix* for details). This is done by comparing the spectrogram to a pitch template generated based on the properties of the typical musical notes. Then, the algorithm applies a post-processing step to the PAF to extract the most likely pitch at each time frame, considering the continuity of the melody over time. The resulting pitch sequence represents the predominant melody and is represented as a vector ***v*** with dimensions (*nmel*, 1), where *nmel* is the number of Mel frequency bins in the Mel spectrogram. Each element ***v*** corresponds to the average value of the Mel spectrogram across all frames for that particular Mel frequency bin. The algorithm includes some additional processing to remove noise and other non-melodic elements from the pitch content, to ensure that only the melody is detected. Note that the Melody method is capable of detecting melody in complex musical textures that can pose significant challenges for the human ear.

Third, we identified how many times the melody appears in a given song. A sliding window *w* was used across the Mel spectrogram, and we compute the dot product between the prominent melody vector ***v*** and the corresponding section of the Mel spectrogram, which is denoted as ***S***. This dot product is a measure of the cosine similarity between the prominent melody and the current window of the Mel spectrogram.

Specifically, for a window with Mel spectrogram ***S*** with dimensions (*nmel*, *w*), the dot product between the prominent melody and the window is computed as:

where is the dot product operation, “| |” denotes the L2 norm, and the division ensures that the similarity measure is normalized to be between 0 and 1. A window was considered to contain an instance of the melody if the similarity score equaled 1. Said another way, to measure the number of times the melody appears in each song, we slide the window across the entire Mel spectrogram and counted the number of windows where the similarity score was equal to 1 (M= 5.33, SD= 4.51). Looking at Fig. 2, for example, the melody of Queen’s “We Will Rock You” appears between 0:30 and 0:35, and in seven other places (e.g., from 0:36 to 0:41, 0:53 and 0:58, and 0:59 and 1:04). Results are the same using a range of less conservative cuts (i.e., 0.8 or 0.9; *SI Appendix*, Table S1) that allow for slight melodic variations. See Table S2 for a sample of songs that the algorithm classified based on their degree of melodic repetition.

Fourth, we examined song success (i.e., ranking on the Billboard charts, see Materials and Methods for more details).

**Results**

Analysis of thousands of songs finds that songs which repeat the melody more often are more popular (*b* = .672, SE = .212, *t* = 3.16, *p* = .002; Table 1, column 1).

One could wonder whether the relationship is driven by other factors (e.g., the lyrics or other aspects of the music), so to address this possibility, we measured a range of aspects of the lyrics, music, and other factors that might play a role. This included things like the topics discussed, word repetition, language complexity, second-person pronoun, and major psychological features of language, key, loudness, mode, tempo, time signature, duration, danceability, energy, speechiness, acousticness, instrumentalness, liveness, and valence of music, and artist, genre, membership in multiple genres, times charted, radio airplay, and time of release; see *SI Appendix* for details. Even controlling for these dozens of other factors, however, results remain the same (*b* = .714, SE = .237, *t* = 3.01, *p* = .003; Table 1, column 2).

Note that the relationship between melodic repetition and success is not somehow restricted to highly popular songs. Comparing two songs by the same artist, released at the same time, appearing on the same album (see Materials and Methods for details) finds that those that became more popular use greater melodic repetition (M= 5.33 vs 4.54, *F*(1, 5073) = 23.32, *p* < .001). Using the main linear regression model and treating less popular songs as rank 51 finds the same results (*b* = .716, SE = .221, *t* = 3.23, *p* = .001) as does using propensity score matching (25) to further test robustness to selection (*b* = .826, SE = .384, *t* = 2.15, *p* = .032, see *SI Appendix* for details).

**Table 1. Melodic repetition and song success**

|  |  |  |
| --- | --- | --- |
|  | (1) Base Model | (2) With Controls |
| **Melodic Repetition**  Controls  *Music*  Key  Loudness  Mode  Tempo  Time Signature  Duration  Danceability  Energy  Speechiness  Acousticness  Instrumentalness  Liveness  Valence  *Lyric* | **0.67\*\* (0.22)** | **0.71\*\* (0.24)**  Included  –0.45\*\* (0.33)  0.10\*\* (0.51)  –0.24\*\* (0.23)  –0.06\*\* (0.21)  –0.46†\*\*(0.25)  –0.13\*\* (0.30)  0.07\*\* (0.39)  –0.08\*\* (0.27)  0.56\*\* (0.28)  0.28\*\* (0.24)  –0.29\*\* (0.23)  0.27\*\* (0.27) |
| Word Repetition  Second-Person Pronoun  Six-Letter Words  Topics  LIWC dictionaries  *Others*  Radio airplay  Artist Fixed Effects  Genre Fixed Effects  Multigenre Count  Times Charted  Quarter Fixed Effects  Year Fixed Effects  Intercept | 25.50\*\* (0.22) | 0.38†  (0.22)  0.54\*\* (0.28)  –0.05\*\* (0.20)  Included  Included  10.94\*\* (0.52)  Included  Included  2.59\*\* (0.30)  1.94\*\* (0.24)  Included  Included  22.19\*\* (1.09) |
| N | 4,200 | 4,200 |

Note that all independent variables for which coefficients are reported are standardized. The dependent variable is not standardized. Parameters are estimated using an ordinary least squares regression. The dependent variable is the Billboard chart rank (1-50). Chart ranks are reverse coded so that positive coefficients reflect a positive relationship with song success.

†*p* < .10, \**p* <. 05, \*\* *p* < .01.

Following (15), we also tested lexical repetition a second way. One could wonder whether songs that repeat the melody more often also repeat the words in the chorus, and that is driving the effect. The melody often occurs beyond the chorus (Fig. 2), however, but to further test this possibility, following (15) we counted the number of times the chorus repeats in each song (M = 3.03, SD = .99; see *SI Appendix* for details). Melody count and chorus count are uncorrelated (*r* = .01), though, and when chorus count is included in the model, the effect of melodic repetition persists (*b* = .714, SE = .238, *t* = 3.00, *p* = .003). This casts doubt on the notion that chorus count could be driving the effect.

One might also wonder whether more repetitive songs feature melodies that are simpler or easier to sing, and this, rather than melodic repetition is driving the effect. To test this possibility, coders rated a random sample of 40 songs’ melodies (20 repetitive and 20 less repetitive; see *SI Appendix* for details) based on how simple and easy to sing they were. More repetitive melodies are neither simpler (MHigh repetition = 4.81; MLow repetition = 5.06, *F*(2, 37) = .21, *p* = .582) nor easier to sing (MHigh repetition = 3.85; MLow repetition = 4.48, *F*(2, 37) = 4.88, *p* = .117), though, casting doubt on these alternative explanations.

**Experimentally Manipulating Melodic Repetition**

While the results of field study are consistent with the notion that melodic repetition increases success, one could still wonder whether the relationship is truly causal. Controlling for a variety of factors (e.g., lyrical repetition) casts doubt on alternative explanations, but to provide an even stronger test, two follow up experiments take the same song, manipulate melodic repetition, and examine whether this leads the song to be evaluated more positively. In addition, the experiment also tests the hypothesized mechanism, examining whether melodic repetition is beneficial because it makes songs easier to process.

In Experiment 1 participants were exposed to an excerpt of a pop song, composed for the study. The only difference between conditions was the number of times the melody was repeated. In the low melodic repetition condition, the melody appeared once, while in the high melodic repetition condition it appeared three times. As predicted, and consistent with the field study, melodic repetition led the song to be evaluated more favorably (MHigh repetition = 4.76; MLow repetition = 4.38, *F*(1, 238) = 3.93, *p* = .048, η2 = .016). Further, consistent with our theorizing, melodic repetition also made the song easier to process (MHigh repetition = 5.16; MLow repetition = 4.09, *F*(1, 238) = 38.48, *p* < .001, η2 = .139). Finally, mediation analysis (PROCESS model 4; 26) found that processing ease mediated the effect of melodic repetition on liking (*b* = .44, 95% CI = .24, .67). Repeating the melody made the song easier to process (*b* = 1.07, *SE* = .17, *t* = 6.20, *p* < .001), which boosted evaluations (*b* = .41, *SE* = .07, *t* = 6.11, *p* < .001).

While the results of Experiment 1 are consistent with our theorizing, and the field data, one could wonder if they are somehow limited to the specific song or genre studied. Consequently, to test generalizability, Experiment 2 uses the same setup but explores multiple songs across multiple different musical genres (i.e., pop, rock, dance, and R&B). Consistent with our prior studies, melodic repetition still led songs to be evaluated more favorably (MHigh repetition = 4.79; MLow repetition = 4.58, *F*(4, 1266) = 4.89, *p* = .017, η2 = .015). It also made songs easier to process (MHigh repetition = 4.95; MLow repetition = 4.33, *F*(4, 1266) = 27.79, *p* < .001, η2 = .067). Mediation analysis found that processing ease mediated the effect of melodic repetition on liking (*b* = .27, 95% CI = .20, .35). Repeating the melody made songs easier to process (*b* = .62, *SE* = .08, *t* = 8.15, *p* < .001), which boosted evaluations (*b* = .43, *SE* = .03, *t* = 14.67, *p* < .001).

Ancillary also casts doubt on the notion that simplicity or ease of singing is driving the effects. Rather than being driven by melodic repetition, per se, one could wonder whether the effects are somehow driven by the nature of the melodic part and non-melodic part it replaces in the low repetition conditions. If the melodic part is simpler, or easier to sing, maybe that drove the effects. To test this possibility, we isolated the melodic and non-melodic sections and asked participants to rate them on how simple and easy to sing they are. The two parts, however, were rated as equally simple (MMelody = 4.48; MNon-melody = 4.52, *F*(4, 77) = .48, *p* = .716), and easy to sing (MMelody = 4.53; MNon-melody = 4.58, *F*(4, 77) = .45, *p* = .549; see Material and Methods for further details), casting doubt on these alternatives.

**Discussion**

Music is an integral part of human existence. From tribal chants and religious hymns to childhood lullabies and pop radio, music serves many important functions. But why are some pieces of music more successful than others?

Results of three studies suggest that melodic repetition increases success. Music that repeats the melody more frequently is evaluated more positively and became more popular. Further the studies demonstrate processing ease’s role in driving these effects. Repeating the melody makes music easier to process, which makes people like it more. Demonstrating these effects across thousands of real songs, as well as two controlled experiments, provides causal evidence for the effect and its importance in the field.

This work contributes to understanding music, culture, and why some things catch on. Researchers from a variety of disciplines have long been interested in cultural success, or why some things become more popular than others (27-31). But while automated textual analysis has uncovered some important linguistic features (32-33), there has been less attention to auditory or visual features. Further, these dimensions are particularly important given many cultural items’ (e.g., songs, movies, and art) multi-modal nature.

We contribute to this emerging area, demonstrating how automated audio analysis can shed light on cultural success. Future work might also explore other musical features. Songs vary on harmony (i.e., underlying chords), pitch (i.e., highness or lowness of the notes), timbre (i.e., tonal quality or color of the sound), rhythm (i.e., pattern of beats and accents), and tempo (i.e., speed or pace), and all these aspects may shape whether songs succeed or fails. More upbeat songs, for example, can stimulate movement or dancing, which may increase enjoyment (34).

Harmony, or the chords progression supporting the melody, may also shape popularity through its influence on emotions (35-36). Indeed, some harmonic features or expedients can evoke specific feelings (e.g., make people feel happy or sad). Many songs (e.g., Whitney Houston’s “I Will Always Love You”), for example, leverage the dominant seventh chord to create a sense of tension (i.e., because the minor seventh note of the chord seeks to resolve to the major third of the tonic chord) that resolves in stability (e.g., physiological pleasure; 37) when the chord resolves on the tonic. The type of scale used can also elicit various emotions (38). The Phrygian scale (i.e., minor mode that has a flat 2nd interval), for example, gives it a dark and menacing sound, the Lydian scale (i.e., major mode that has sharp 4th interval) evokes dreamy or mystical feelings, the Dorian scale (i.e., minor mode that has a natural 6th interval) communicates hopeful, and the Mixolydian (i.e., major mode that has a flat 7th interval) provides a bluesy and soulful sound. Similarly, while minor modes tend to convey sadness or melancholy, major modes are often associated with happiness or excitement, which may shape how enjoyable songs are to listen to (39). Songs like Adele’s “Someone Like You”, for example, start with a minor mode (e.g., A minor) for an intimate mood and then resolve to the relative major key (e.g., C major) for a sense of uplift, making the song more engaging.

Cultural or genre differences might also be worth exploring. We focused on western music, but Indian music often emphasizes improvisation and variation rather than repetition. Indian musicians aim to create unique melodic phrases and explore different aspect of the “raga” (melodic framework) they are performing, rather than repeating the same melodic material over and over again (40). Classical music also approaches repetition differently. While pop music uses repetition to create a catchy theme, classical composers use repetition to create theme variations within a longer piece of music. Consequently, success in these, and other domains, may rely less on melodic repetition and more on other features.

Melodic repetition’s effect on processing ease could also be helpful in other domains. Music therapy has been shown to benefit a range of conditions, including anxiety and chronic pain (41). The fact that melodic repetition facilitates processing ease suggests that such songs might be useful in improving cognitive functions for patients with cognitive impairments (e.g., dementia, Parkinson’s, and Alzheimer’s; e.g., 42). Similarly, they could be used to facilitate learning (e.g., memorization) for children affected by developmental disabilities (e.g., autism spectrum disorder; 43) and make the environment more familiar and relaxed, supporting social interactions.

Finally, work might explore how melodic repetition affects other outcomes (e.g., reviews or awards). While processing fluency increases liking, positive affect, and aesthetic pleasure, it may also make things seem more familiar, less innovative, and sometimes less interesting (44; see 45 for a review). Hence, while repeating a melody might boost popularity, it could hurt critical reviews or odds of getting avant-garde awards.

In conclusion, these findings shed light on how melodic repetition shapes song success, and why things catch on. Emerging automated audio analysis tools should allow researchers to study a range of interesting questions related to cultural analytics and human behavior more broadly.

**Materials and Methods**

**Measuring Melodic Repetition in the Field**

**Data and Empirical Approach**. To gather data on songs and song success, we sampled Billboard's digital download rankings every 3-months over two years for seven major genres (i.e., Christian, country, dance, rock, pop, rap, and R&B). Digital downloads were chosen because they are more likely to be influenced by consumer preferences than by institutional actors (e.g., radio DJs). We analyzed all songs that appeared in each ranking and recorded their position in the chart (1-50). These rankings represent downloads on more than 90% of major paid song services (e.g., Apple iTunes, Google Play, and Spotify). Then, we reverse-coded the chart ranks so that positive coefficients reflect a positive relationship with song success. Overall, the dataset includes 4,200 song rankings for 1,736 unique songs from 1,187 artists.

Given the large number and fixed range of ranks, the rank dependent measure is treated as continuous, and we test the relationship between melodic repetition and song success using an ordinary least squares regression. Results are the same using an ordered logistic specification or a log transformation of the rank dependent measure (*SI Appendix*, Table S1).

**Exploring less popular songs**. We also collected an alternative set of less popular songs that were as similar as possible to the popular ones (i.e., same artist, time of release, and album). For three of our ranking periods (i.e., 1,050 ranked songs), we took each artist with a song on the chart in that period, and a research assistant (blinded to hypotheses) randomly selected another song from that artists’ album that did not make the top 50 in any period.

**Experimentally Manipulating Melodic Repetition**

In Experiment 1, participants (*N* = 240, Prolific, https://aspredicted.org/YX7\_HXY) were randomly assigned to a condition in a 2 (melodic repetition: low vs. high) between-subjects design. See *SI Appendix* for exclusion and demographics. Stimuli for all experiments are available at https://osf.io/5p8ud. First, everyone was exposed to 16-seconds excerpt from a song, created for the purposes of this study. Second, they evaluated the song (“how much do you like this song?”, “how much do you enjoy listening to this song?”; 1 = don’t like at all, 7 = like a great deal; *r* = .90; 46). Third, following prior work (e.g., 47-48), they completed measures of processing ease (i.e., “how easy was it for you to remember the melody of the song?”, “how easy was to you to hum or sing alone with the melody of the song?”; 1 = not at all easy, 7 = extremely easy; *r* = .77). Finally, participants completed a manipulation check, attention check, ancillary measures to test an alternative explanation (i.e., typicality; *SI Appendix*), and demographics.

In Experiment 2, participants (*N* = 1360, Prolific) were randomly assigned to a condition in a 2 (melodic repetition: low vs. high) x 4 (genre: pop vs. rock vs. dance vs. R&B) x 2 (different songs in each genre) between-subjects design. See *SI Appendix* for exclusion and demographics. The study set-up and measures were the same as Experiment 1. The analysis includes fixed effects for genre. In an ancillary analysis, participants (*N* = 40, Prolific) listened to musical excerpts from the songs in the study. Specifically, for each song, they listened to the prominent melody (that appeared in both conditions) and the non-melodic part (that appeared instead of the melody in the low repetition condition). The analysis includes genre fixed effects and cluster standard errors at the participant level.

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Descrizione generata automaticamente

Melodic Repetition Shapes Success

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Supporting text

Table S1

Table S2

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**Supporting Text**

**Measuring Melodic Repetition in the Field**

**Pitch Activation Function.** The Pitch Activation Function (PAF) measures the likelihood of a pitch being present at each time and frequency bin in the spectrogram. It does so by comparing the the onset strength function (OSF) at that bin to the OSF values at neighboring time bins for the same frequency, taking into account the continuity of the melody over time by subtracting the maximum OSF value at the frequency across all time bins except for the current time bin. The resulting PAF is a representation of the predominant melody in the audio signal (22).

The PAF is expresses as follows:

where PAF(*t, f*) is the pitch activation function at time *t* and frequency *f*; C(*t, f*) is the onset strength function (OSF) at time *t* and frequency *f*, which measures the presence of a note onset at time *t* and frequency *f* in the audio signal; max(C(*t', f*)for *t'* *t*) is the maximum onset strength function value at frequency *f*, excluding the value at time *t*.

In *librosa*, the PAF is computed using the Constant-Q Transform (a type of time-frequency representation), which is then converted to a chromogram representation. The chromogram is a 12-dimensional representation that summarizes the strength of each pitch class (i.e., the 12 notes in the Western musical scale) across time. The PAF can then be derived from the chromogram by summing the strength of each pitch class across octaves.

**Controls.** The full model accounts for a number of alternative explanations, including aspects related to the music itself, lyrics, and other factors.

*Other musical features*. Rather than being driven by melody repetition, one could argue that the results are driven by some other aspect of the music itself. So, following prior work (49), we used the Spotify API to measure a range of acoustic features capturing the physical aspect of the song (i.e., *key*, *loudness*, *mode*, *tempo*, *time* *signature*, *duration*) and the listening experience (i.e., *danceability*, *energy*, *speechness*, *acousticness*, *instrumentalness*, *liveness*, *valence*). We account for these thirteen variables as controls.

*Lyrical content*. Alternatively, one could wonder whether song success is driven by aspects of the lyrics. First, repetitive lyrics can make songs more fluent, and thus more successful, so we control for individual words repetitiveness (*words repetition*). Following prior work (15), we ranked words in the lyrics according to their frequency, and computed the Hirsch-Popescu-point (50) for each song. The smaller the Hirsch-Popescu-point, the less repetition and greater a song’s lexical richness.

Second, some words can be more complex to process, which may hurt song success, so we control for the proportion of *six-letter words* (15) using Linguistic Inquiry and Word Count’s (LIWC; 51).

Third, second-person pronouns (i.e., “you”) increase song popularity because they make listeners to think of someone in their own lives (46), so we control for the proportion of *second-person pronoun*.

Fourth, beyond individual words, certain topic or themes might make songs more popular, and maybe this, rather than melody repetition, is driving the effects. To address this possibility, we control for the *topics* in each song using latent Dirichlet allocation (LDA; 52). LDA captures the mixtures of words that co-occur within and across songs to identify the main topics (e.g., love, family, dance), and the prevalence of each topic in each song (e.g., 30% about love, 40% about dance). We identified the lowest number of topics that maximize predictive power (i.e., 11 topics as identified by perplexity), and control for the proportion of each topic in each song. In addition, we also control for LIWC categories capturing major social or psychological constructs (i.e., *LIWC dictionaries*: social, drives, conversation, cognition, affect, perception; 53).

*Other factors*. Beyond other musical features, and lyrics, maybe songs whose melodies repeat more often are more successful not because of consumer preferences, but because radio stations play them more, and this drives their success. To test this possibility, we control for whether the song appeared on the Billboard radio airplay list as one of the songs most played on the radio during that period (*radio airplay*).

Alternatively, maybe some singers are just more popular than others, and they also tend to repeat melodies more frequently. So, to control for this, we include fixed effects for artist (*artist fixed effects*).

Finally, maybe the genre the song appeared in (*genre fixed effects*), how many genres it charted in (*multigenre count*), how many times it charted (*times charted*), or when it charted drive the effect (*quarter* and *year fixed effects*), so we control for all these aspects.

Note that multicollinearity does not seem to bias the estimates (variance inflation factor = 1.96).

**Audio Features from Spotify API**

* Acousticness: indicates whether the track is acoustic. Its confidence ranges from 0 to 1 (i.e., high confidence the track is acoustic).
* Danceability: describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0 is least danceable and 1 is most danceable.
* Energy: represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy. It ranges from 0 to 1.
* Instrumentalness: predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.
* Key: indicates the key the track is in. Integers map to pitches using standard [Pitch Class notation](https://en.wikipedia.org/wiki/Pitch_class) (e.g., 0 = C, 1 = C♯/D♭, 2 = D, and so on). If no key is detected, the value is -1.
* Liveness: detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.
* Loudness: describes overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between -60 and 0 db.
* Mode: indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. Major is represented by 1 and minor is 0.
* Speechness: detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g., talk show, audio book, poetry), the closer to 1 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.
* Tempo: is the overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.
* Time signature: is a notational convention to specify how many beats are in each bar (or measure). The time signature ranges from 3 to 7 indicating time signatures of "3/4", to "7/4".
* Valence: describes the musical positiveness conveyed by a track, ranging from 0 to 1. Tracks with high valence sound more positive (e.g., happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g., sad, depressed, angry).

**Chorus Detection.** Natural language processing was used to measure the chorus count. We used the Python *lyricsgenius* library to access lyrics data from the Genius API, tokenized the lyrics into separate lines, and identified sections starting with “chorus,” “refrain,” or “hook” (these terms are used interchangeably). Using this, we counted the number of times the chorus is repeated throughout each song.

**Melody simplicity and ease of singing**. Two research assistants rated 40 songs on how simple (1 = very difficult, 7 = very simple; *r*intercoder = .65) and easy to sing (1 = very difficult to sing, 7 = very easy to sing; *r*intercoder = .68) they were. To isolate the melody and reduce song recognizability, melodies for each song were extracted and recorded on the piano. Research assistants were also asked whether they were able to recognize the song and results are similar whether or not this was included as a covariate.

**Addressing selection bias**. Propensity score matching (PSM) was used to account for differences between the two groups (i.e., more and less popular songs). PSM assumes that there are control variables capable of identifying the selection into treatment and control groups, and uses these controls to estimate a score such that the distribution of all the observed variables and behaviors among the treated units is similar to that among the control units (54). In other words, the PSM “adjusts” for the differences in the treatment and control group which may bias the inferences about the treatment effect. When the propensity scores for two observations are close enough to each other, the treatment is considered random. Thus, the biases in the comparisons between treated and control units are eliminated.

In our case, the propensity score is the predicted probability that a unit receives the treatment (i.e., a song belongs to the top 50) conditional on the value of covariates. To create a matching sample, musical characteristics (e.g., danceability, tempo, duration), lyric features of the song (e.g., words repetition, LIWC dictionaries, second-person pronoun), and other factors (e.g., year, quarter) were included in the matching model.

To estimate *p*kt, the probability of belonging to the top 50 as a function of the covariates, a logistic regression model was used as follows:

where *T*k is the treatment status which indicates whether the song *k* at time *t* belongs to the top 50, and *X*kt includes all the covariates.

To calculate the propensity score for each post in our sample, we adopted a 1:1 nearest-neighbor matching algorithm without replacement to match a song that belongs to the top 50 with a song that does not, with the closest propensity score. The first-stage logit model replicated the relationship between melodic repetition and membership in the top 50 (*b* = .182, SE = .073, *t* = 2.48, *p* = .013). The resulting matched sample contains 1,740 songs, half of which are in the top 50 and half are not.

**Experimentally Manipulating Melodic Repetition**

**Experiment 1: exclusion, demographic information, and manipulation check**. 248 US people were recruited from Prolific to complete the study. Following the preregistration (<https://aspredicted.org/YX7_HXY>), participants (*n* = 8) were excluded if they failed an audio listening pre-experiment task (asking to transcribe 4 words spoken in a one-second audio clip) or an attention check (asking, “the song was for: radio, advertisement”). The final sample consisted of 240 participants (50.8% male, 48.3% female, 0.9% other; mean age = 38.2 years). As expected, a manipulation check revealed that songs including melodic repetition were rated more repetitive (*M*High repetition = 4.95; *M*Low repetition = 4.10, *F*(1, 238) = 20.05, *p* < .001, η2 = .109)

**Alternative Explanation*.*** One might wonder whether the song including melodic repetition is somehow more typical, and this, rather than processing ease, drove the effect. To test this possibility, we adapted a three-item measure of typicality from prior work (55; “this melody is typical of a song”, “this melody is usual for a song”, “I have often encountered such kind of melody in a song”; α = 0.88). Typicality did not vary by condition (*F*(1, 238) = 1.42, *p* = .235, η2 = .006), however, casting doubt on this alternative.

**Experiment 2: exclusion, demographic information, and manipulation check**. 1360 US people were recruited from Prolific to complete the study. As in Experiment 1, participants (*n* = 89) were excluded if they failed the audio listening pre-experiment task or the attention check. The final sample consisted of 1271 participants (54.5% male, 43.5% female, 2% other; mean age = 39 years). As expected, a manipulation check revealed that songs including melodic repetition were rated more repetitive (*M*High repetition = 4.95; *M*Low repetition = 4.09, *F*(1, 1269) = 119.26, *p* < .001, η2 = .086).

**Table S1: Robustness Tests**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **(1)**  **Similarity Score of 0.8** | **(2)**  **Similarity Score of 0.9** | **(3)**  **Ordinal Logit** | **(4)**  **OLS with log DV** |
| **Melodic Repetition**  Controls  *Music*  Key  Loudness  Mode  Tempo  Time Signature  Duration  Danceability  Energy  Speechiness  Acousticness  Instrumentalness  Liveness  Valence  *Lyric* | **0.66\*\* (0.24)**  Included  –0.44\*\* (0.33)  0.10\*\* (0.51)  –0.23\*\* (0.23)  –0.06\*\* (0.21)  –0.45†\*\*(0.26)  –0.13\*\* (0.30)  0.07\*\* (0.39)  –0.08\*\* (0.27)  0.56\*\* (0.28)  0.28\*\* (0.24)  –0.29\*\* (0.23)  0.26\*\* (0.27) | **0.68\*\* (0.24)**  Included  –0.44\*\* (0.33)  0.10\*\* (0.51)  –0.24\*\* (0.23)  –0.06\*\* (0.21)  –0.46†\*\*(0.26)  –0.14\*\* (0.30)  0.07\*\* (0.39)  –0.08\*\* (0.27)  0.57\*\* (0.28)  0.28\*\* (0.24)  –0.29\*\* (0.23)  0.27\*\* (0.27) | **1.11\*\* (0.34)**  Included  0.92†\*\*(0.04)  1.01\*\* (0.06)  0.98\*\* (0.03)  0.99\*\* (0.03)  0.94\*\* (0.03)  0.98\*\* (0.04)  1.03\*\* (0.05)  0.99\*\* (0.03)  1.09\*\* (0.04)  1.03\*\* (0.03)  0.96\*\* (0.03)  1.04\*\* (0.04) | **0.06\*\* (0.01)**  Included  –0.04\*\* (0.02)  0.01\*\* (0.03)  –0.02\*\* (0.01)  –0.01\*\* (0.01)  –0.04\*\* (0.02)  –0.01\*\* (0.02)  0.03\*\* (0.02)  –0.01\*\* (0.02)  0.03†\* (0.02)  0.02\*\* (0.01)  –0.01\*\* (0.01)  0.01\*\* (0.02) |
| Words Repetition  Second-Person Pronoun  Six-Letter Words  Topics  LIWC dictionaries  *Others*  Radio airplay  Artist Fixed Effects  Genre Fixed Effects  Multigenre Count  Times Charted  Quarter Fixed Effects  Year Fixed Effects  Intercept | 0.38†  (0.22)  0.55\*\* (0.28)  –0.03\*\* (0.20)  Included  Included  10.95\*\* (0.52)  Included  Included  2.58\*\* (0.30)  1.95\*\* (0.24)  Included  Included  22.17\*\* (1.09) | 0.38†  (0.22)  0.54\*\* (0.28)  –0.04\*\* (0.20)  Included  Included  10.95\*\* (0.52)  Included  Included  2.59\*\* (0.30)  1.95\*\* (0.24)  Included  Included  22.18\*\* (1.09) | 1.05†  (0.03)  1.07†  (0.04)  1.01\*\* (0.03)  Included  Included  4.24\*\* (0.31)  Included  Included  1.40\*\* (0.05)  1.31\*\* (0.04)  Included  Included | 0.03\* (0.01)  0.01\*\* (0.02)  –0.01\*\* (0.01)  Included  Included  0.58\*\* (0.03)  Included  Included  0.15\*\* (0.02)  0.11\*\* (0.01)  Included  Included  2.39\*\* (0.28) |
| N | 4,200 | 4,200 | 4,200 | 4,200 |

Note that all independent variables for which coefficients are reported are standardized. The dependent variable is the Billboard chart rank (1-50). Chart ranks are reverse coded so that positive coefficients reflect a positive relationship with song success.

†*p* < .10, \**p* <. 05, \*\* *p* < .01.

**Table S2. Algorithm Classification Example**

|  |  |
| --- | --- |
| **Songs with more melodic repetition** | **Songs with less melodic repetition** |
| “Happy” by Pharrell Williams | "How To Save A Life" by The Fray |
| “Thunderstruck" by AC/DC | "Boyz-N-The Hood" by Eazy-E |
| “Roar” by Katy Perry | "Hold Up" by Beyonce |
| “A Thousand Years” by Christina Perri | "She's Out Of Her Mind" by Blink-182 |
| "Mirrors" by Justin Timberlake | "Campaign Speech" by Eminem by Prince |

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