MUST BE THE MONEY?:
INFORMING BUDGET ALLOCATION STRATEGIES FOR MUSICAL ARTISTS

by

NOAH GOULD

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Approved: *Dr. Innessa Colaiacovo*
Primary Thesis Advisor

The classic story of a band's rise to fame often starts in a smoky dive bar. A music scout sits in the back, inconspicuously watching the band play. They don't know it yet, but he's going to turn them into the next Nirvana. This a fantasy that some musical artists still have: One day – if they are talented enough – they will be "discovered." For better or for worse, this story has largely become antiquated.

Since digital platformization has revolutionized the music industry labels have become increasingly risk averse in their signings and mainly conduct research online (Choicharoon, 2024; Geurts, 2023). Thus, growing an established social media following has become a prerequisite for artist success (Raffa, 2025). Emerging artists must figure out ways to successfully market their music online with limited promotional budgets (Anderton, 2019).

Video accompaniments to songs are an important digital promotional tool because they help develop an artist's visual identity (Anderton, 2019) and are effective at increasing social engagement (Park, 2018). This study looks to discover if higher video budget increases listener enjoyment of and engagement with songs and musical artists, and if so, to what extent?

In April and May 2026, I showed 107 participants 4 music videos each in a controlled lab setting. I randomly assigned participants to listen to each song with either a high budget or low budget visual accompaniment. Using survey procedures, I asked respondents a series of questions aiming to measure the fondness of their perception of the song (enjoyment, quality, and talent ratings) and their engagement with the song (wanting to listen to the artist in the future, wanting to know the name of the song, and if they recorded information).

I find that high budget visuals do not significantly outperform low budget visuals across both fondness and engagement constructs ($p > .05$).

Since this experiment was conducted on college students at the University of Oregon, the generalization of my findings is limited to populations with similar age and demographic breakdowns to my study sample.

I conclude that emerging artists wishing to increase positive perceptions and engagement of their music among an audience of college-aged students should avoid investing in high budget music videos and instead allocate funds elsewhere in their promotional mix.

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Project Overview

The digital revolution (digitization) of the music industry was once predicted by writer Chris Anderson (2006) to grow the market share of smaller musicians, but has effectively done the opposite, exaggerating a "winner takes all" effect on the music market. This is due to market saturation and consumer "tyranny of choice," amplifying the need for developing artists to possess the skills and knowledge required to stand out in a crowded digital landscape (Coelho, 2019).

Since digital platformization transformed how music is consumed, shifting economic power to streaming platforms, labels have gotten more risk averse, overwhelmingly leveraging social media and streaming metrics as critical signals guiding their signing decisions (Geurts, 2023). Consequently, more musicians must find economical ways to self-promote their music online during the early stages of their career before they have the capital for tremendous marketing budgets (Raffa, 2025). This dynamic requires artists not only be talented musicians but also savvy digital marketers.

Music promotion is typically investment intensive, so the relevant choice for emerging artists and their management teams is how to partition marketing budgets most efficiently (Waldfogel, 2019). Music videos are a crucial component of recorded music promotion, and, on YouTube, visual-focused music videos have proven to generate more user engagement than audio-only videos (Oh, 2022).

Performers with active followings are more likely to be signed and this type of social media success can also help artists catch the attention of editorial playlist curators on digital streaming platforms (Choicharoon, 2024, Bonini, 2019). Playlist inclusion on Spotify, especially inclusion on one that Spotify curates itself, has a significant effect on the success of artists and songs. Exemplifying Spotify's gatekeeping power: in 2017, the 24 of the 25 most followed playlists on Spotify were editorially curated, meaning they were created and maintained by Spotify themselves (Aguiar, 2021).

Because traditional music videos often require a more costly budget than many artists can afford at the beginning of their careers, I am asking if low-budget visual accompaniments are effective enough to stand in for high-budget ones and cheapen the costs of promoting new music. The result of this research will will be particularly valuable for rising and independent artists who lack the funding that the highest earners in the industry have.

Literature Review

In their extensive guide to the music industry for future music professionals, *Music Management, Marketing and PR,* Anderton et al (2022) assert that "in some respects, an artist does not fully 'exist' until they have come into contact with an audience and the press – until they have defined themselves through photographs, live performance, and online content."

Creating an immersive brand around a musical artist, a 'discrete world' as they refer to it, is a central goal of any music marketer. Given how important this brand development is, artists spend large amounts on promotion. Marketing budgets reach $100,000+ for typical major-label releases (Waldfogel, 2019). Thus, the decision of how to spend a marketing budget most efficiently is a crucial one for musical artists and their teams/stakeholders to make. Although both independent and major label artists must budget correctly to maintain sustainable careers, this question is particularly relevant for emerging artists without external funding.

The last twenty-five years have seen rapid changes across the music industry, so some context is helpful in elucidating the broader importance of studying the effectiveness of video budget size on promotional performance. The first two sections will cover a brief history of music videos and their importance in music promotion. The second section will review the changes to the music industry caused by digitization, defined as the adaptation of systems, processes, and content to digital forms because of the advent of the internet.

The Dawn of Music Videos

It is difficult for the modern music consumer to imagine a world in which visual media is not an inseparable part of music consumption. Yet, before the astounding popularity of MTV in the 80s, visual accompaniments to music were broadly dismissed as mindless promotions.

The Beatles were early pioneers of the music video concept. Their first feature film "A Hard Day's Night" made a profit three times its costs of production despite being solely music focused and not having much of a central narrative arc. Notwithstanding its success, a New York Times article from May 1966 did not praise the movie without a quip calling film music "long a subliminal (some say insidious) advertising tool." Retrospectively, "A Hard Day's Night"'s profit margin was an indication of an upcoming cultural shift towards the marriage of music and visual media.

In the late 60s, record executive Jaz Holzman worked on marketing for the first Doors album and had helped with the creation of a ~$1,000 video of the band performing. After identifying that this method of combined media was effective at creating buzz around the band, he created the pilot program which eventually became the infamous MTV (Music Television) channel (Anson, 2008).

Yet, when the flag was planted and The Buggles' "Video Killed The Radio Star" played for a national audience for the first time, the new channel were met with widespread skepticism. Skeptics were wrong, of course; MTV became an instant pop culture sensation among America's youth from its onset (Douris, 2021). Though it continued to be labeled by critics as "promoting mindless sensation" and distributing content with "the sole purpose to advertise a band," MTV found increasing success and remained on television sets 24 hours a day, seven days a week (Agger, 2003).

The money quickly followed, with the advent of music videos having a stark effect on record sales. In fact, United States recorded music sales more than doubled in the two decades following MTV's launch (Richter, 2022). Music videos facilitated the ascent of artists such as Cyndi Lauper and cemented the status of others, like Madonna and Michael Jackson, as superstars (Behr 2021).

During this time, music videos flourished, and investment sizes reflected their success. Allegedly, the cost of Michael Jackson's 'Thriller' music video was over a million dollars. These days of colossal video budgets did not last forever. By the early 2000s, music videos had been put on the backburner by the music and television industries but were finding a 'natural home' on internet sites like YouTube (Edmond, 2014).

More recently, on the last day of 2025, MTV finally got its official obituary. The television station shut down their last all-music channels in the UK, reportedly ending with a final broadcast of the quintessential representation of its genesis: Video Killed the Radio Star (Tapp, 2025). Although it failed to adapt its business model to fit a changing industry, MTV left a crucial legacy: it cemented the crucial role of the video in music consumers' consumption habits.

Importance of Visual Accompaniments

Previous research has already identified that music videos provide a clear benefit to record sales. By analyzing an event where music videos were briefly blocked in Germany, researchers Kretschmer, et al (2020) found that restricting access to music videos decreases recorded music sales by an average of five to ten percent. Additionally, they found that YouTube's positive effect on sales is around two-thirds larger for newcomer artists than it is for mainstream artists. Using data from South Korean songs on YouTube, Park, et al (2018) found that user engagement with music visuals (both company and user created) positively influences music sales.

Fan engagement is particularly facilitated by distinct qualities of music videos. Raharjo, et al (2024) explored fan reactions to a music video from a K-Pop group and found that a focus on creative innovation and production quality are common aspects that boost meaningful fan engagement. By holistically analyzing YouTube engagement data, Oh, et al (2022) found that videos with visual, performance, and storytelling characteristics boost engagement more than music that was only accompanied by a static image. They recommended that music stakeholders looking to maximize fan engagement should prioritize creating a diverse set of visual content and live performances including strong storytelling themes. They also found that YouTube users are less likely to engage with audio-only versions of songs than visually accompanied versions.

Music videos have additional benefits beyond promotional strategy. They are also helpful for creating affective resonance with an audience and enhancing an artist's visual identity (Anderton, 2022). Many artists see music videos as an opportunity to further their artistic expression, with some artists also using the format to make political statements or prompt dialogue about societal issues (Smith, 2019).

Additionally, Spotify is betting on the future of visuals by testing music video streaming to their premium users this year. The company stated that this decision was prompted by a survey where 70% of users reported that more music video content would enhance their experience on the platform (Goldsmith, 2025).

Digitization

As society began its transition into an interconnected digital era, researchers theorized how the internet age would affect various industries that had previously centered around physical products. Davidson (2005) heralded "The End of Print," identifying potential benefits and downsides of the digitization of scholarly articles. On the importance of the invention of the internet, he writes that it is "one of the most transformative periods in human history in the realms of person-to-person communication."

Regardless of if his headline statement was correct or not, this quote accurately captures the scale of the changes that many industries faced because of digitization. Dellarocas (2003) wrote about the potential that digitization had to scale word of mouth networks for eliciting feedback on products. These systems evolved to be crucial to a variety of systems. Most pertinently to this paper, they provide the basis for the feedback systems that influence recommendation algorithms that determine content performance on social media.

An Ad Age article from 2000 described an (at the time) new form of internet marketing where agencies recruited fans of artists to promote albums and movies by creating written and visual content and distributing it online (Friedman, 2000). This is an early example of entertainment marketing and online content being mixed, not unlike like the way music visuals and UGC (user generated content) help promote record sales in today's market. Additionally, Shaw (1994) offers an early perspective on how the internet can help facilitate fan engagement by offering a one or two-way communication channel between fans and artists.

The Long Tail Theory

One of the more popular ideas of how digitization could change the entertainment industry was promoted by Wired magazine chief editor Chris Anderson in his 2006 book *The long tail: Why the future of business is selling less of more*. Anderson theorized that digitization would result in an expanded "long tail" of the music market.

His idea was that consumers gravitated towards blockbuster hits and superstar artists mainly because of limited shelf space in physical retailers, and so the introduction of infinite shelf space on the internet would result in an increased demand for niche products. Some preliminary data from Rhapsody (an early digital music marketplace) supported this hypothesis, with the tracks ranked between 25,000 and 100,000 being downloaded at an average of 250

times per month, and accounting for 25% of their business. This was a stark difference compared to Walmart's record shelves, where the top 200 albums accounted for 90% of revenue (Anderson, 2006).

In a study measuring music homogeneity changes from 1990-2015, researchers Bourreau, et al (2022) break the digitization of music into four 'turning points': Napster (1999), iTunes (2003), YouTube (2003), and Spotify (2009). Napster was a website which introduced peer-to-peer file sharing – a (later deemed unlawful) system that allowed the sharing of music between users.

Although Napster's reign was short lived, it was the first time consumers got access to near-unlimited quantities of music on demand. The idea that this was even a possibility readied consumers for Spotify's business model and paved the way for its success (Wainer, 2026).

Napster's quick stint at the top provided economists with the data they needed to quickly dispute Anderson's theory. Page, et al (2009) found that the long tail theory did not apply to peer2peer file sharing. In fact, instead of finding growth in the long tail, they found that the opposite had happened: 95% of the inventory on Napster accounted for only 20% of the P2P file sharing swaps. Only 5% of the total inventory accounted for 80% of the swaps.

In the long tail theory, the lower 95% of inventory is expected to account for 80% of consumption. The reality of P2P file sharing (an uninhibited representation of demand) was far from this.

One answer as to why could be because of "search costs," which are described as the cost of the time spent searching for music that could be better spent elsewhere. This could be a reason that consumers gravitate towards the short tail when they are confronted with unlimited options.

Harvard Business School professor Anita Elberse (2008) wrote an article in which she came to the extensive conclusion that at the point of writing, hits remained dominant in video and music. The tail has lengthened with increased volume but has grown flatter. She pointed out that ironically, Anderson's "The Long Tail" itself was a good example of a blockbuster hit generating a disproportionally large percentage of revenue for its publisher.

The final nail in the coffin: the number of titles in the top 10% of weekly music sales dropped by more than 50% between 2000-2005, a pattern common in winner-take-all markets.

More recent sources corroborate Elberse and maintain that this pattern has not changed (Matthew, 2019). As of 2020, streaming data showed that 90% of streams go to the top 1% of

artists (Blake, 2020). Coelho and Mendes (2019) theorize that this change is because of consumer "tyranny of choice," (i.e., the abundance of choice leads us to familiar options) and dilution of quality. Additionally, platformization (the switch to digital algorithm-based music distribution systems) has exacerbated revenue concentration by using algorithms that recommend music based on previous selections.

Anderson himself admitted in 2008 that "it's hard to make money in the Tail. The revenues are disproportionately in the Head. Perhaps that will never change."

All things considered; digitization has created an increasingly competitive market for emerging musicians to differentiate themselves within.

A Digital Music Industry

Despite increased difficulty to grow and compete as an up-and-coming artist, the emergence of new digital platforms has indeed increased the democratization of music promotion and increased artist control of the fan-artist relationship (Anderton, 2022). Accessible production software and distribution platforms have lowered the barriers of entry to production and promotion for musicians globally, though this has created an over-supplied market. (Guerra, 2024).

This increase of accessibility and disintermediation is a massive flip in a traditionally investment intensive industry (Waldfogel, 2019). Researchers observed a resulting rise in DIY and independent musicians, growing from 1.7% share of revenue in 2015 to 4.1% in 2019[1] (Frenneaux, 2023). Frenneaux also notes that artists who build teams around themselves are better placed in terms of content development.

Social media platforms have become important promotional tools and success indicators for artists. Simon, et al (2023) analyzed paths that various country musicians followed to signing record deals and found that, in their regression model, the number of Facebook followers an artist had explained 32% of variance in net worth.

Fan interactions and UGC have also become a powerful promotional tool for artists on social media (Lingel, 2011).

[1]Here, it is crucial to understand that DIY/independent and long tail are not synonymous terms. Many DIY/independent artists have appeared in the Head. Clairo and Billie Eilish are two prominent examples.

New digital marketing strategies help fans feel more connected to artists but require artists to take on more entrepreneurial labor as digital marketing becomes the standard for music promotion (Wade Morris, 2014).

Maasø, et al (2020) interviewed music industry stakeholders and found that platformization has given them access to more data than ever before. They determined that the skillset of analyzing music industry data is becoming more advanced. Additionally, social media has now become a business analytics tool as well as a vehicle for advertising.

Transition of Power

Record companies, the incumbent music industry titans, failed to capitalize on digital music early, initially seeing digital music sales as financially unattractive (Geurts, 2023). They reacted to Napster's popularity by unleashing a flurry of lawsuits instead of adapting to changing circumstances (Wainer, 2026).

To their credit, selling digital music using the same model that they had followed for most of a century with physical music was financially unsustainable. The dip in global recorded music revenue from 21 billion in 1999 to 13.6 billion in 2009, before the popularity of music streaming services skyrocketed, illustrates this (IFPI, 2025).

Subsequently, the emergence of digital streaming platforms reconfigured value creation and platformized the industry, gaining dominant market position over record labels as the primary industry gatekeepers (Geurts, 2023).

Today, recorded music revenues are higher than ever at 29.6 billion in 2024, with streaming holding a 69% share of the market (IFPI, 2025). The reason streaming services were able to capture a dominant market share is simple: their distribution system benefited consumers the most, offering the closest system to Napster's early 2000's "free music" utopia.

Spotify holds important gatekeeping power as the dominant DSP. Playlist inclusion on Spotify, especially inclusion on one that Spotify curates, has a significant effect on the success of artists and songs. While you used to have to pitch a song to radio shows or music publications to reach the public ear, that power now lies with streaming services. 24 of 25 out of the most followed playlists in 2017 were Spotify-curated (Aguiar, 2021).

Thus, the influence of music curation has shifted from traditional gatekeepers to editorial curators on Spotify and Apple Music. The tastes of these editors are still influenced by traditional

gatekeepers, but the key to success is in their power. An artist's team must pitch to these editors to reach a wide audience. If you land a playlist spot, the DSP's algorithms decide if you stay on it long term (Bonini, 2019).

Risk Averse Labels Front-Load Risk on to Artists

In the period of 1990-2010, major labels became more selective with artists scouting (Benner, 2016). Additionally, resulting from the platformization of the music industry, both independent and major labels have transitioned to relying on pre-existing market validation through digital self-branding in the process of scouting talent. This was a move away from other strategies such as market testing through traditional media and networking through industry relationships.

In this way, labels front-load initial risk onto the artist, only signing them once they have a certain level of momentum. Artists must have digital marketing expertise, or have a team with digital marketing expertise, before they receive any label support – both major and indie (Raffa, 2025).

Modern A&R's consider strength and size of artist social media following and strength of audience engagement to guide their signing decisions (Choicharoon, 2024). In today's increasingly competitive music industry, emerging artists need to create effective digital marketing campaigns with limited resources. My research hopes to provide a valuable piece to this puzzle, aiming to guide artist budgeting decisions for production of the ever-important music videos.

Methods

Survey Design

Using a survey lab experiment at the Insights Research lab at the Lundquist College of Business, respondents viewed 4 clips of music with visual accompaniments, each from a different genre, and answered the same questions for each. Participants were assigned to either the high budget condition or the low budget condition for each of 4 songs. The stimuli alternated between the high budget and low budget videos, so participants either saw a HB,LB,HB,LB or LB,HB,LB,HB pattern for songs 1-4. Which of these two surveys that each respondent received is determined by Qualtrics randomization, keeping roughly a 50/50 split between all subjects. Each subject saw the same songs in the same order. After each song respondents answered a series of questions. The survey questions were the same for each song and between each condition.

I aim to measure two distinct construct variables: Listener perception of the song and the artist and listener engagement with the song.

If listeners rated the songs more highly when accompanied by high budget relative to low budget visuals this would suggest that music videos are a worth investing high percentages of promotional budgets into. This is important for artists in the early stages of their careers who hope to get signed by a label because evaluating a minimum positive audience reaction is one of the first criteria A&R's use to determine whether a talent is even worth a detailed evaluation (Choicharoon, 2024).

Specifically, I am measuring listener perception with questions asking about personal enjoyment of song and artist. These questions, which were asked after respondents viewed each stimulus, are listed below. A question to measure how closely the stimulus aligns with the respondent's taste is also included:

Song Perception Questions + Taste Question
Question (S)7: "Using the stars below, please rate your enjoyment of this song out of 10"
Question (S)8: "Please rate the quality of this song from 1-10."
Question (S)9: "How talented is this musical artist? Please rate their musical talent out of 5."

Table 1: Perception Qs

In addition to fostering listener enjoyment, a critical consideration for artists and their teams is how to encourage fan engagement. Not only does strong engagement on social

platforms directly drive algorithmic growth, but it is also a key sign that music scouts use to evaluate talent (Choicharoon, 2024).

To proxy for fan engagement, I gave participants the opportunity to learn more about the artist within the survey. This was to approximate the experience of listeners searching for more information on an artist they encounter, for example, while searching social media. To engage further with the artist they may have to remember this information, save the video, follow the artist's account, or even leave the social media app to save the song on a digital streaming platform.

I measured engagement with three yes/no questions meant to replicate this discovery process within the limitations of the survey design. Subjects were not provided with any information about the stimulus up front (such as artist/song name).

Engagement Questions
Question (S)13 "Could you see yourself listening to this artist in the future?"
Question (S)14: "Would you like to know the name of this song?" [If the respondent answers "yes," then the song title and artist name will be revealed to them]
Question (S)15 "You should have a sticky note in front of you. You may write information on this sticky note if you wish to remember anything" [*I did not write anything down relating to this music video clip/I wrote something down relating to this music video clip.*]

Table 2: Engagement Qs

In my analysis, respondents received an engagement score from 0-3 based on the number of "yes" answers to the previous three questions.

To incentivize watching each video instead of skipping through, participants were not able to leave the page for each stimulus until a "next" button appeared after 15 seconds. Each stimulus was 30 seconds in length (give or take less than one second). Data were recorded about the length that each participant stayed on the page. This is another variable I analyzed to determine listener engagement.

Additionally, there were three questions evaluating the subject's familiarity with the stimulus:

Familiarity Questions
Question (S)10: "How often do you listen to songs that sound like this?" *[Rarely, Sometimes, Always.*]
Question (S)11: "Were you familiar with this song before participating in this study?"
Question (S)12: "Were you familiar with this musical artist before participating in this study?"

Table 3: Familiarity Qs

Once, at the start of the survey, a series of questions were asked about how the respondent interacts with music.

General Music Questions
Question B1: "How many days a week do you listen to music?" [*1-7*]
Question B2: "Which of the following do you ever use to listen to music? Select all that you use." [Options included: *Spotify, Apple Music, Amazon Music, YouTube, Physical Media (Vinyl/CD), SoundCloud, Radio/Internet Radio, Other*.]
Question B3: "On which of the following have you discovered new music?" [Options included: *TikTok, Instagram, YouTube, Live Performance, Radio/Internet Radio, SoundCloud, Spotify, Apple Music, Amazon Music, Other.*]
Question B4: "When was the last time you went to see live music?" [*This week, Over a week ago, Over two weeks ago, Over a month ago, Over 6 months ago, Over a year ago.*]
Question B5: "Do you consider yourself a musician?" *[Y/N/M].*

Table 4: Music Qs

Three demographic questions were asked at the end of the survey. These were: age, gender, and ethnicity.

Demographic Questions
Age: "What is your age? [In years]." The response box was open-ended, with restrictions limiting answers to only whole integers between 18-99.
Gender: "What gender do you identify with most closely?" The response options for this question were: [*Male, Female, Non-binary / third gender, Prefer not to say.*]
Ethnicity: "What race/ethnicity(ies) do you identify yourself as? Select all that apply" and the response options were: [*American Indian/Alaska Native, Asian, Black/African American, Hispanic/Latino, Middle Eastern/North African, Native Hawaiian/Pacific Islander, White, Other not listed,* and *Prefer not to say.*]

Table 5: Demographic Qs

I chose these response options to roughly match the US Census categories, allowing me to compare the ethnicity distribution of my study's sample to US Census population data to assess the generalizability of my findings (USCB, 2024). However, there are some differences between the 2020 census and the now updated census boxes planned for Census 2030, limiting this overall generalizability (see limitation i).

Treatment Arms

Low budget: Subjects viewed a "low budget" video featuring a ~10 second repeating clip without overlayed text or lyrics. The video must appear to be plausibly made by a person without professional videography training without any of the following:

I. Stage design
II. Hiring of actors
III. Hiring of stylists
IV. Hiring of professional video editors
V. Usage of equipment beyond a consumer-grade camera (e.g., Drones, cranes, dollies, etc)
VI. Any other non-camera expense that would require the hiring of other persons or cost the creator more than $300 USD.

High budget: Subjects viewed a "high budget" video without any repeating elements or overlayed text or lyrics. This video must require the labor of more than one person to record.

Table 6 below describes each stimulus. Links to watch each video are in appendix []. Throughout the results section, I commonly refer to songs by their number (e.g., Song 1 = "Get Back" by Samm Henshaw).

Song	**Low budget video**	**High budget video**
Song 1: "Get Back" by Samm Henshaw	 Description: Man plays guitar in front of an audience.	 Description: Man sings and dances around a room while a band plays around him.

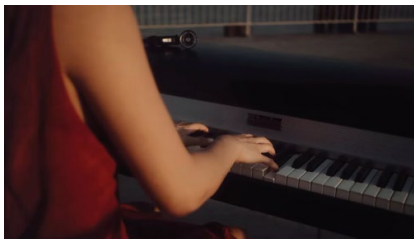
Song 2: “Waiting for Doomsday” by Sunday (1994)	 Description: Guitarist plays while a woman sings behind him.	 Description: Woman dances while a band plays. Woman holds a sign that says “Waiting For Doomsday.”
Song 3: “Triple Nickel” By Mavi	 Description: Man canoes down a river.	 Description: Man dances and raps in a park, and empty room, a subway, against a green wall, and with a skyline behind him, while another man dances behind him.
Song 4: “Lovegod” By Sarah Kinsley	 Description: Woman plays piano.	 Description: Woman plays piano and sings in a plant-filled house. Woman sits and dances with a large blue puppet.

Table 6: Stimuli Descriptions

Recruitment Methods

The Insights Research Lab study pool draws from a requirement for students in UO marketing classes. Students are compensated with research credits. Sona systems are used to organize studies. Only the pool coordinator has access to student information to identify subjects and I (the researcher) do not.

Because I drew participants from Insights Lab subject pool, this study exclusively included students at the University of Oregon. Participants had to be of able sight and hearing to be effectively exposed to the stimulus. There were no other inclusion criteria.

Analysis Methods

I conducted all analyses in the programming language R, using the R studio interface and the tidyverse package. I used the ggplot2 package to generate visualizations. A link to download the full R script is included with my data set in appendix iv.

For the purposes of analysis, I divided the outcome variables into two constructs: Fondness and engagement. Table 2 below summarizes each construct. I compiled the fondness variables into one compound variable that I included in many of the models as a fixed effect for each respondent's proclivity for positive perception across all songs. I used the engagement compound variable as a dependent in two regression models.

Fondness	**Engagement**
Enjoyment rating	Future (*"Can you see yourself listening to this artist in the future?"*)
Quality rating	Name (*"Would you like to know the name of this song?"*)
Talent rating	Sticky (*"You should have a sticky note in front of you…"*)

Table 7: Outcome Variable Categories

I ran T-tests to compare means across conditions for both the continuous dependent variable, time spent on the stimulus page, and the ordinal dependent variables, enjoyment, quality, and talent ratings. For the purpose of descriptive comparison, it is appropriate to treat these ordinal scales as continuous. Similarly, bar charts showing means allow for visual comparison across outcome variables but do not directly reflect answers that respondents could have given (i.e., the mean enjoyment score for Song 1's low budget condition was 7.06 but no respondent could actually have recorded a response of 7.06 because they were given an ordinal scale).

For each song, to compare the relationship between budget condition and the responses to *"could you see yourself listening to this artist in the future?"* and *"would you like to know the name of this song?"* I ran chi-squared tests. This is the appropriate hypothesis test for binary variables.

For the final binary variable, I had to analyze the responses to *"You should have a sticky note in front of you. You may write information on this sticky note if you wish to remember anything"* using Fisher's exact test (opposed to using the chi-squared test) due to small cell counts.

To gain a more accurate answer on if the condition contributes to the variance in the outcome variables broadly, I created models to evaluate data from all the songs. I primarily used an Ordinary Least Squares (OLS) regression to evaluate relationships between the fondness variables and budget condition. This can be denoted as:

$$fondness_{ij} = \beta_0 + \beta_1 HB_{ij} + \beta_2 \alpha_j + \varepsilon_{ij}$$

Where:

- $fondness_{ij}$ is the fondness outcome variable
- $_i$ is participant
- $_j$ is song
- HB is high/low budget variable
- β_0 is the intercept
- β_1 is the coefficient for HB
- $\beta_2\alpha_j$ is the song fixed effect
- $\beta_3 respondent_i$ is the fixed effect for each subject
- ε_{ij} is the error term

Similarly to the T-tests, I treated rating scales as continuous for the simplicity of OLS regression output. Since the discreteness of the ratings scales violates OLS regression's normally distributed residuals assumption, I corrected using robust standard errors.

For the binary engagement variables, I ran models using logistic regression. One important thing to note is that I had to remove the song fixed effect for the "sticky" model due to the small cell counts I previously mentioned. The logistic regression equations are notated like so:

$$\log\left(\frac{p_{ij}}{1 - p_{ij}}\right) = \beta_0 + \beta_1 HB_{ij} + \alpha_j + \beta_2 respondent_i$$

Where P indicates the probability of a yes response to each engagement variable.

In each model, the coefficient for HB indicates to what extent high/low budget visual accompaniments contribute to the variance in the outcome variable.

Results

Sample Characteristics

107 respondents took the survey in the Insights Research Lab between April 30th, 2026 and May 8th, 2026. 105 respondents completed the entire survey. The two respondents who did not complete 100% of the survey completed 99% and 51% respectively. Respondents completed the survey in an average of 339 seconds (five minutes and 39 seconds), and a median of 328 seconds (five minutes and 28 seconds).

Characteristic	**HB:LB:HB:LB** N = 54[1]	**LB:HB:LB:HB** N = 53[1]
Age	21.18	21.13
Gender (Female)	54%	55%
White	76%	74%
Asian	22%	19%
Hispanic	13%	13%
Days Listened Per Week	6.46	6.5
Musician	17%	13%
Listens on Spotify	72%	72%
Listens on Apple Music	35%	42%
Discovers on Spotify	80%	74%
Discovers on Instagram	80%	74%
Discovers on TikTok	69%	77%

Table 7: Balance Table

The balance table above shows relatively even distributions of respondent demographics and psychographics by randomized condition and showed no significant differences in means in T-tests.

Of the total sample, 75% of respondents reported to identify as White, followed by 21% who reported to identify as Asian, and 13% who reported to identify as Hispanic. Black, NHPI, MENA, and AIAN were each selected by less than 5% of respondents. No respondents selected other.

Characteristic	**Sample %**	**U.S. %[i]**	**Oregon %[ii]**
Gender			
Female	54%	50.8%	50.2%
Male	43%	49.2%	49.8%
Non-binary / third gender	2%	—	—
Race / Ethnicity *(select all that apply)*			
White	75%	71.0%	84.8%
Asian	21%	7.2%	6.5%
Hispanic / Latino	13%	18.7%	13.9%

Black / African American	4%	14.2%	3.2%
Middle Eastern / North African	<1%	—	—
Native Hawaiian / Pacific Islander	<1%	0.3%	0.5%
American Indian / Alaska Native	<1%	1.3%	2.1%
Other / Prefer not to say	0%	—	11.5%
i. US Census Bureau national data ii.Us Census Bereau Oregon data			

Table 8: Demographics Summary Table

The distribution of gender responses is charted in figure 2 in appendix ii. While gender identity can differ from biological sex, self-reported gender in my sample is roughly aligned with the binary sex ratio in the broader U.S. population of 50.8% Female and 49% Male (Blakeslee, 2023). 2% of respondents answered non-binary / third gender.

In summary, the percentage of Black and Hispanic identifying respondents in the study sample is representative of Oregon's latest population data (America, 2021) but is far less than the proportions of the overall US's (USCB, 2021). Additionally, the prevalence of respondents who answered White is proportional to the total US population, but less than Oregon's population percentage. Asian identifying respondents are a larger portion of our data set than both the US and Oregon population percentages.

Respondents ranged from 19 to 30 years in age, with a median age of 21 and standard deviation of 1.56. This is certainly a key limitation of my study; Given the sample was drawn from students, my findings are not generalizable to populations with different age distributions (see limitation iii for more detail).

Although responses for *"How many days per week do you listen to music"* varied from 0 to 7, the median response was 7, the mean response was 6.48, and the standard deviation 1.26. Figure 3 in appendix i shows this distribution.

45.8% of respondents reported having seen live music less than 6 months before the time they took the survey, though the most common response was *"over 6 months ago"* which was selected by 33 participants. Following this was *"over a month ago"* and *"over a year ago,"* each selected by 22 participants. Figure 4 visualizes this distribution and can be found in appendix ii.

Spotify was the most selected listening platform with 72% of respondents indicating that they listen to music using the platform. Half of the respondents indicated listening to music using YouTube, while 38% indicated listening via Apple music. Interestingly, the fifth most used listening platform within my sample was radio at 26%. No other platform was listened to at a rate of more than 25%. Figure 5 visualizes these proportions and can be found in appendix ii.

Although population listening data by platform was difficult to find, similar polls of students from other colleges confirm that Spotify is indeed the common leader (Jones, 2020). This makes sense, because Spotify leads all platforms in revenue share (IFPI, 2025).

Respondents most reported using Spotify and Instagram to discover music, with TikTok coming in at a close third and YouTube at a further fourth. It is important to note that three of these four platforms center around visual content. This finding reinforces the importance of this project and aligns with my background research. Figure 6 below visualizes the rate of discovery usage by platform.

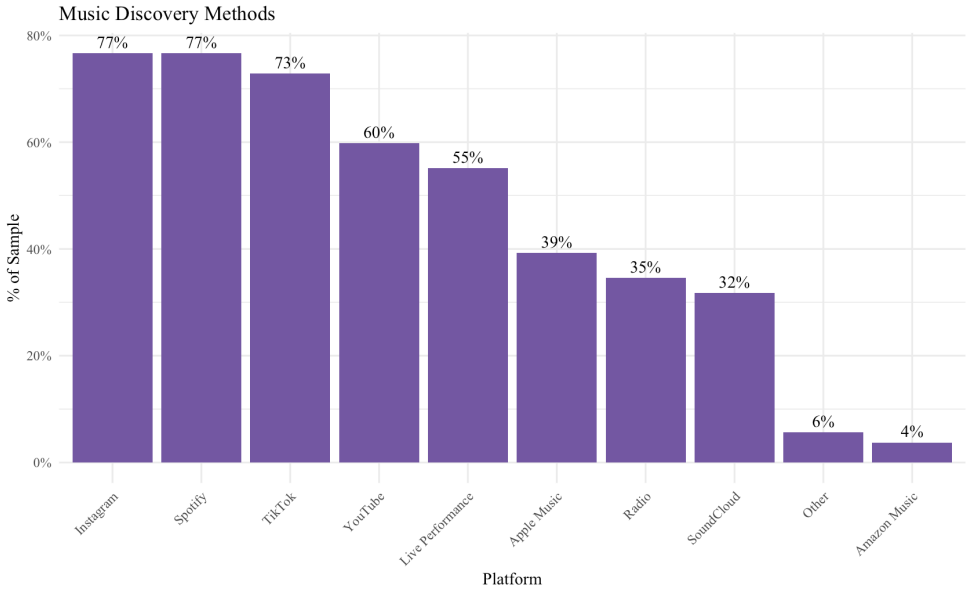


Figure 6: Music Discovery Methods

Finally, only 14.9% of the sample reported considering themselves a musician. An additional 8.4% reported being unsure. Figure 7 visualizes the distribution of responses from this question. It can be found in appendix ii. Respondent self-identification as a musician had no significant predictive power over any of the outcome variables across any model I ran.

Song Performance

Pooling performance across all songs, there was minimal difference between outcomes in both constructs. The histograms in figures 8 and 9 below visualize this.

Figure 8: Pooled Density Plots of Enjoyment Ratings

Figure 9: Pooled Density Plots of Engagement Ratings

It is important to isolate the performance of each song to contextualize the broader analyses. Song level performance could also indicate possible genre differences to be explored with future research. These charts visualize that there was no large difference in outcomes between budget conditions.

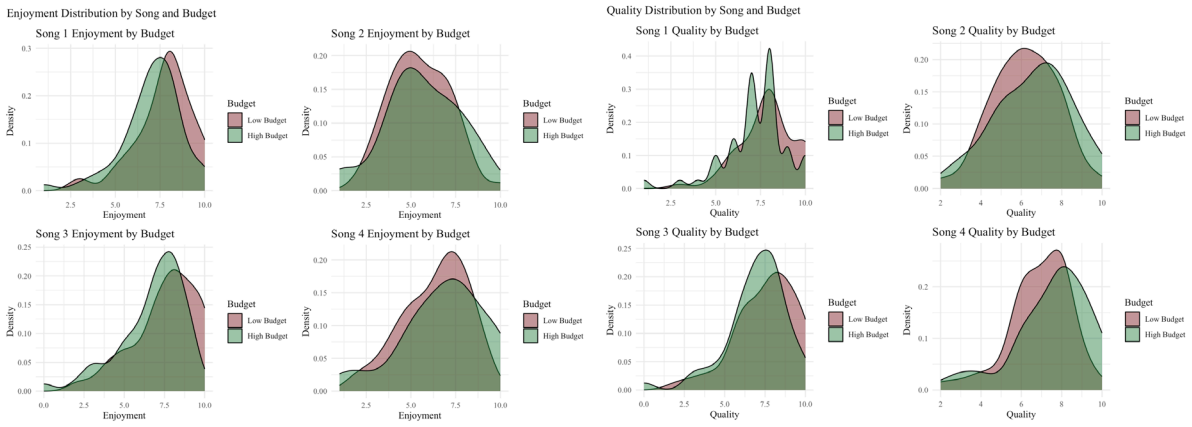


Figure 10: Density Plots of Enjoyment Ratings by Song, Figure 11: Density Plot of Quality Ratings by Song

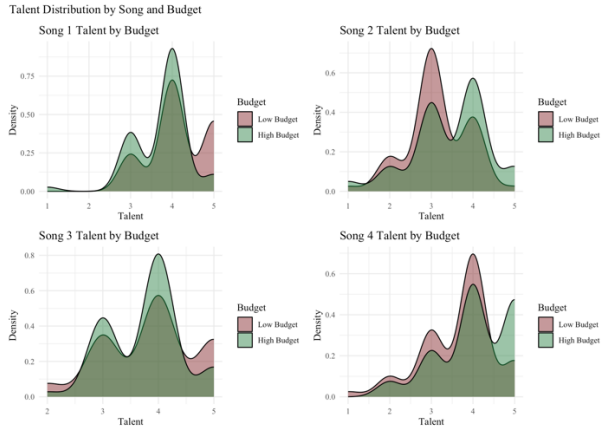


Figure 12: Density Plot of Talent by Song

Engagement rates show a similar picture. The third engagement variable, "Sticky," has an interesting distribution. 9% of respondents reported writing something down relating to song 4, which consistently placed second or third in the other metrics. This could indicate that there was some specific aspect about song 4 that respondents wanted to remember, or it could point to respondent confusion – another possible limitation of the study design (see limitation iv).

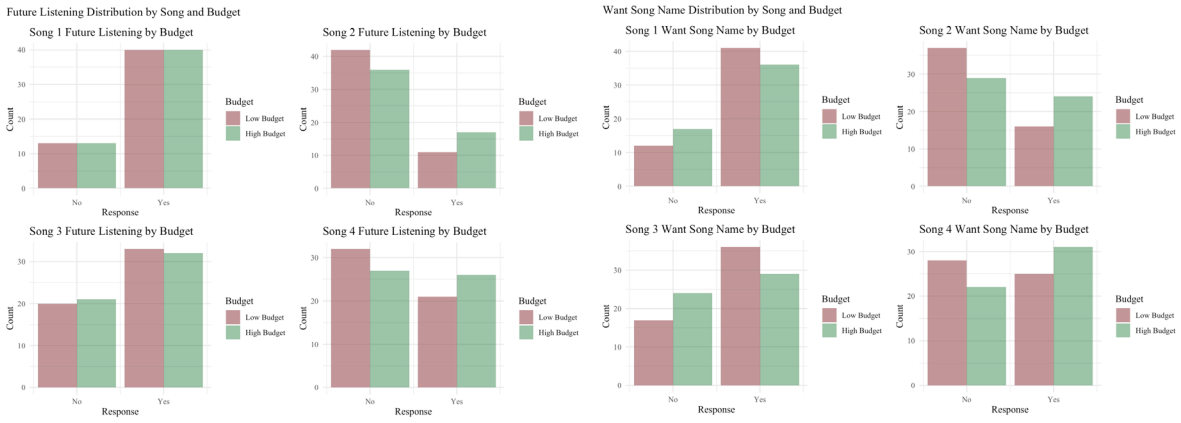


Figure 14: Future Listening Distribution by Song, Figure 15: Want to Know Name Distribution by Song

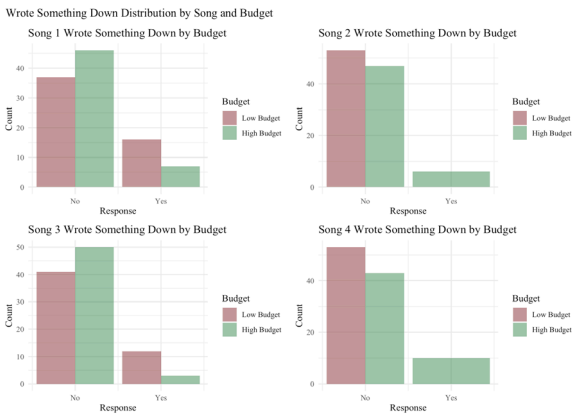


Figure 16: Wrote Something Down Distribution by Song

When picking which songs to use, I attempted to choose songs that my sample was unlikely to know in order to generalize my results to inform the promotion of music to new audiences. However, this proved difficult to ensure. The artists I selected had to be at a certain level of career success to have produced high quality visuals for me to use in the experiment. Listening metric location breakdowns would have helped me search for artists that were popular in other localities but not in Eugene, OR, but those data are sold by streaming services to music statistics companies – who guard it with steep paywalls that were out of budget for this project.

My solution was to seek songs from artists with between 200k and 1M Spotify monthly listeners. The logic behind this is that these artists are successful enough to have high budget visuals, but not yet large enough to be widely known. Spotify is the natural platform to use to track this metric given that it is the largest music listening platform globally (IFPI, 2025). This was consistent with my sample (see Figure 5 in appendix ii). Table 5 below summarizes the chosen artists' Spotify monthly listener counts as of May 16th, 2026, recorded directly from Spotify itself.

Artist	**Spotify Monthly Listeners as of 5/16/2026**	**Sample Artist Familiarity**	**Sample Song Familiarity**
Samm Henshaw	838,446	1.9%	.09%
Sunday (1994)	315,086	4.7%	2.8%
Mavi	701,495	8.5%	3.8%
Sarah Kinsley	921,981	7.5%	5.7%

Table 10: Artists' Spotify Monthly Listeners Counts & Sample Familiarity

The survey results confirm that this solution was successful. No song was familiar to more than 6% of the sample, and no artist was familiar to more than 8%. The distributions of

both artist and song familiarity roughly follow each other, with Mavi and Song 3 being the most known, and Samm Henshaw and Song 1 being the least known. These low rates of familiarity across my sample make the project results applicable to acquiring new listeners (a key focus for emerging artists) but less generalizable to campaigns targeted at existing audiences.

Song 1 consistently outperformed its counterparts across all fondness ratings, while song 2 consistently underperformed. It is possible this difference is due to order in the survey since all respondents heard the songs in the same order. In my regression models, the song fixed effect controls for possible order bias. Figure 8 summarizes fondness ratings by song with red indicating high budget performance and green indicating low budget.

Performance Across All Observations

Respondents stayed on stimulus pages for 1.9 to 73 seconds after the next button appeared, with an average of 21.58 seconds of voluntary time spent on song pages. A histogram detailing voluntary time distribution across all observations (Figure 17) can be found in appendix ii. None of the independent variables tested significantly contributed to the variance in voluntary time spent on the stimulus pages.

I created a compound variable, "engagement," compiled as an average score across all three binary engagement questions for each observation. I used both a Poisson and OLS regression model to investigate if condition had any contribution to its variance and I did not find a significant relationship in either. Table 7 in appendix ii details these coefficients. The mean engagement score across all observations was 1.44 with a standard deviation of .887. Figure 18 is a histogram showing the distribution of engagement scores. It can be found in appendix ii.

Bivariate Tests

I ran a series of bivariate tests to explore differences between condition responses within each song. Table 8 summarizes the output from each test, and the type of test used (as appropriate for each variable type). For the significant p values, an arrow up (↑) indicates a positive relationship with the high budget condition, and an arrow down (↓) indicates the inverse.

Fondness Tests by Song					
Outcome	**Test Type**	**Song 1**	**Song 2**	**Song 3**	**Song 4**
Enjoyment	T-Test	p = 0.042*↓	p = 0.685	p = 0.046*↓	p = 0.288

Quality	T-Test	p = 0.045*↓	p = 0.254	p = 0.112	p = 0.093
Talent	T-Test	p = 0.004**↓	p = 0.068	p = 0.513	p = 0.021*↑
Engagement Tests by Song					
Outcome	**Test Type**	**Song 1**	**Song 2**	**Song 3**	**Song 4**
Future (χ^2)	Chi-Squared	p = 1.000	p = 0.247	p = 0.904	p = 0.387
Name (χ^2)	Chi-Squared	p = 0.310	p = 0.141	p = 0.191	p = 0.285
Sticky (Fisher)	Fisher's	p = 0.013*↓	p = 0.013*↑	p = 0.243	p = 0.001**↑
All Songs Combined					
Outcome	**Test Type**	**p**	**Statistic**		
Enjoyment	T-Test	0.277	t = -1.09		
Quality	T-Test	0.708	t = -0.38		
Talent	T-Test	0.538	t = 0.62		
Future	Chi-Squared	0.481	$\chi^2 = 0.50$		
Name	Chi-Squared	0.939	$\chi^2 = 0.01$		
Sticky	Chi-Squared	0.888	$\chi^2 = 0.02$		

Table 11: Bivariate Test Results

Across all three fondness variables, respondents significantly preferred the low budget condition for song 1. Consistent with fondness, respondents were significantly more likely to write something down for song 1's low budget visual It is uncertain what about this visual led to it performing so well.

Significantly more respondents reported writing down information after viewing song 2 HB compared to its counterpart. The low budget visual for song 3 significantly outperformed its counterpart in enjoyment ratings. The high budget visual for song 4 significantly outperformed its counterpart in talent ratings and rate of writing something down.

No general trend relating to condition can be gained from these song level bivariate tests – only internally valid conclusions about each song emerge. Additionally, I ran bivariate tests for each outcome variable across all songs combined and found no significance.

Outcome Models – Fondness

Across all three OLS models for fondness, no significant variance in the outcomes was explained by budget condition. The most significant contributors to the models were the song and respondent fixed effects. Budget was not a significant predictor of enjoyment, quality, or talent ratings in OLS models. This information is summarized below.

Effect of Budget on Fondness Outcomes

	Enjoyment	Quality	Talent
(Intercept)	8.080***	8.226***	3.952***
	(<0.001)	(<0.001)	(<0.001)
High Budget Video	-0.217	-0.066	0.038
	(0.282)	(0.663)	(0.579)
Num.Obs.	424	424	423
R2	0.576	0.643	0.580
R2 Adj.	0.429	0.520	0.433

p values in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table 12: Fondness OLS Regression Model Results

Outcome Models – Engagement

The table below illustrates predicted probabilities from the logistic regression models for "future," "name," and "sticky." Like the previous models, budget condition did not meaningfully account for the variance in any engagement dependent in these models.

Due to "sticky" being a binary variable with a rare "1" outcome (there were 54 "yes" observations to sticky, totaling 12.7% of outcomes) and that two low budget stimuli had no "1" outcomes, a standard logistic model has a risk of small sample bias.

To eliminate likelihood of bias, I ran a Firth's penalized likelihood logistic regression model. This model is designed for rare binary variables. The outcome of the Firth's model confirmed the logistic regression model's findings that there is no evidence of a significant relationship between budget and writing down something related to the song (p =.857).

Effect of Budget on Engagement Outcomes (Odds Ratios)

	Future Listening	Want Song Name	Wrote Something Down (Firth)
(Intercept)	22.321***	6.059400e+01***	0.295***
High Budget Video	1.374	7.890000e-01	0.918
Num.Obs.	424	424	424

Odds ratios reported. Clustered SEs by ResponseId for future and name models. Firth penalized likelihood Ses for sticky. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Engagement Logistic Regression Model Results

I also ran models including gender response as an independent variable. The results show no significant gender interactions: self-identifying as female is a strong positive predictor of the respondent reporting seeing themselves listening to the song in the future with a p value of .038 and an odds ratio of 1.94. The data reveals no certain answer why female respondents were so much more likely to select yes for this outcome. Table 13 in appendix iii summarizes the outputs of the gender interaction models. There is no evidence of any mixed effects between gender and budget.

Limitations

i. Difference Between US Census Demographic Questions and Mine

It should be noted that the US Census asks "What is your ethnicity" which is a deviation from my question phrasing, though both the census and our survey rely on self-identification. This is a limitation of direct census comparison.

It is also worth noting that although the 2020 census did not include an official option for MENA (Middle Eastern / North African), 3.5 million Americans wrote in a MENA identity in the "white racial category box" (Marks, 2023). It is uncertain, however, how many MENA Americans did not write in an extra identity. This category will be officially included on the next census, in 2030. This difference makes it difficult to compare the MENA population in my sample to the general US population numbers.

ii. Limitations of Ethnicity Models

With respondent counts for MENA, NHPI, AIAN, and Black boxes totaling 1, 2, 1 and 4 respectively, small sample sizes make it impossible for these variables to have any statistical power within my models. Thus, I removed them from the final ethnicity models, and the output p values only include the White, Asian, and Hispanic boxes. There very well could be differences between the way the small sample ethnicities interact with the outcomes, but they would not be able to be revealed in such small quantities. It cannot be assumed that the variance in outcome variables that none of the White, Asian, or Hispanic boxes contribute to would not be impacted by a larger sample of MENA, NHPI, AIAN, or Black identifying respondents.

iii. Average Age of Respondents

As mentioned previously, respondents were drawn from a study pool of UO students. Thus, the average age of respondents was 21 years old. I am unable to create a model to meaningfully test if age of respondents has influence over any of my outcome variables because there was not a respondent in my study over the age of 30.

Although all the findings in this paper can only be generalized to the limited age group of college-aged students, youth are an important demographic for music marketers to target. Recall the story of MTV's beginnings from earlier in this paper: They were able to see what younger

demographics wanted before mainstream consensus had shifted their way and created a cultural icon from it.

Additionally, it is useful to look at this from the perspective of customer lifetime value (CLV). Previous research has shown that song reminiscence and liking often peaks for music that people first encountered at age 14 and continues to steadily decline until at least age 54 (Jakubowski, 2020). So, aside from the theoretical value of a customer acquisition increasing the younger the customer is, people remember music they were exposed to earlier, better.

iv. Sticky Note Confusion

When participating in Insights Research Lab studies, respondents are prompted to write down codes on a given sticky upon the completion of each survey. My survey attempted to utilize the sticky note function to prompt respondents to record information as they wished. Attempting to find deeper insights beyond stated intent, this was a way for me to simulate the action of a listener coming across a song on their preferred discovery platform and saving that song on an online listening platform.

However, because the sticky note had multiple utilities (optionally writing information down during the survey, and mandatorily writing a code down upon completion) it is possible that respondents got confused what the "sticky" question was asking. Although I phrased the answer options to specify *"…wrote something down relating to this music video clip,"* it is possible that respondents were not paying complete attention and misinterpreted the question to refer to their completion code. Because my survey was likely bundled with other studies (students are generally required to complete ~30 minutes' worth of studies for one research credit, my study was completed by respondents in an average of under 6), respondents may have already written completion codes on their sticky note. It is also possible that some respondents ran out of space on their sticky notes and were unable to record information, even if they desired to.

Because the last song in the survey received 2% more *"I wrote something down…"* answers than the second highest song in that category, it is also possible some respondents could have misinterpreted the question as asking if they had written anything down throughout the whole survey. Because of all these potential biases, I am unable to claim conclusive external validity of my findings related to the "sticky" outcome variable.

Discussion

External Validity

Due to the limitations discussed above, I can only generalize my findings to a restricted level. Most importantly, I can only be certain my conclusions are valid for college-aged students. Since I was only able to accuracy assess the relative effects of the most common ethnicity responses in my sample, I cannot generalize my findings to populations with significantly different proportions of the small count ethnicities (AIAN, Black, MENA, and NHPI).

Because the ethnicity models showed that Asian, Hispanic, and White were not significant predictors of study outcomes besides writing something down, findings from all variables except for "sticky" can be generalized to populations with different proportions of Asian, Hispanic, and White identifying people if the small count ethnicities are similar to my sample. Because Asian respondents had 84% lower predicted odds of writing something down, sticky note outcomes cannot meaningfully predict conclusions if the same study was replicated with a sample that included a significantly different proportion of Asian respondents.

As discussed in limitation iv, the sticky note study design itself has potential for bias. Because of this, I would have been hesitant claim any causal relationships involving "sticky" if I had found any significant evidence of such in my models. Nevertheless, I did not find evidence of causal relationships involving "sticky" other than the aforementioned interaction with Asian respondents.

Key Findings and Implications

Conclusively, I find that high budget videos do not increase respondent perceived fondness nor respondent engagement within my study demographics. This is useful and insightful information for artists teams as they develop promotional budgeting strategies.

The first key implication of these findings is that if increasing positive perceptions of an artist among new listeners between the ages of 18 to 22 is the primary goal of a particular campaign – and the artist team is targeting similar demographics to my study – then pouring promotional budgets into professional visual accompaniments is not likely to be helpful. It may even be counterproductive.

Similarly, if increasing engagement among new listeners between the ages of 18 to 22 is the primary goal of a campaign – and the artist team is targeting similar demographics to my

study – then it is not useful to invest heavily in video budgets. That money is best spent elsewhere.

This is not to say that high budget music videos should not ever be made. Since music videos are also an important part of artistic expression and helpful for developing a musician's visual identity, artist teams who can afford to do so may still allocate high budgets to music videos (Anderton, 2022, Smith, 2019).

Because of this, my findings are particularly relevant to emerging artists operating with tight promotional budgets. It is wise for many emerging artists to invest efficiently, target younger listeners to maximize customer lifetime value, and focus on marketing strategies that help boost social media engagement. In summary, I recommend that emerging artists wishing to target my study demographics not invest in high budget visuals, and instead allocate money to tactics with higher returns on investment.

Areas For Further Research

My finding that respondents who viewed a low budget visual were predicted to score that song nearly half a point less enjoyable than their counterparts ($p = .023$) remains unexplained. A following research question could ask "why do respondents (in my demographic sample) rate song quality slightly lower when they view a low budget video versus a high budget video?"

I can imagine the addition of focus group procedures or nominal survey questioning possibly revealing an indication of the deeper cause. It would be informative to hear from respondents themselves why they rated a song a specific way versus another. Within these focus groups, it would be important to avoid leading lines of questioning and allow respondents to answer questions openly to avoid biasing their responses.

Female respondents had almost double the proclivity to want to know the name of the song than Male respondents. This is a significant relationship at $p = .038$. Similarly to the enjoyment finding, investigating respondent motivations behind each score might reveal a deeper trend as to why Male and Female respondents answered the way they did.

Evaluating perceptions beyond fondness is another interesting area to study further. The first iteration of my survey included questions about authenticity. I ultimately removed them because they were a diversion from the narrow focus of this project: outcomes that drive digital

platform performance. It would interest me to ask if authenticity (or any other neutral perceptions) drives performance, and if budget has any mixed effects on those outcomes.

Another key challenge for artist teams is how to break through the noise on social platforms as the music industry's long tail shrinks and competition increases (Coelho, 2019). Since respondents were shown the stimuli without any other options to choose from and were not able to leave the stimuli pages until 15 seconds had passed, the premise of my findings assume that the viewer's attention has already been captured (for 15 seconds at least).

I tried to test this by measuring voluntary time on the stimuli pages (how much time respondents spent on the stimuli pages minus the required 15 seconds), but regressions showed that this metric was most highly correlated with individual songs – with p values below .001 for each song in the time model. Since all respondents were exposed to the songs in the same order, song and song order are collinear by design. Thus, variation in voluntary time could be due to the order the songs were in, instead of or as well as, due to the nature of the songs themselves.

Future studies could potentially use A/B testing methods on social media to assess if budget makes any difference in song performance. This kind of design would be optimal for generalization because sample sizes could be larger, audiences could be more diverse, and outcome variables would be directly aligned with tangible outcomes that artist teams track. However, one limit to this design is that it is unlikely to enable the discovery of a causal relationship due to confounding variables in the lack of a controlled environment.

Additionally, future research could replicate my study with an increased emphasis on the recorded information outcome. Due to limitation iv, it was difficult to control for the actual construct of wanting to remember and record the song information.

The first iteration of my study design had the respondent input their email if they wanted to be sent the song after the study. This may have eliminated the confusion surrounding sticky notes but required a higher degree of IRB approval than I had time to pursue due to concerns over respondent anonymity. Future studies with more flexible timelines can use this design to reveal more significant insights about the recorded information construct.

Appendices

i. Charts

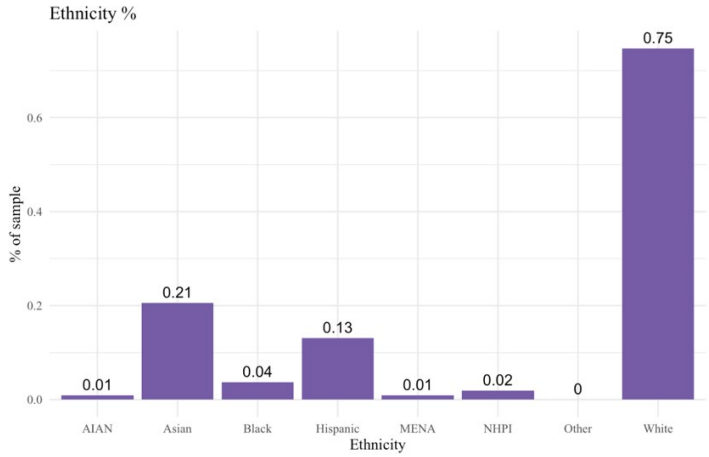


Figure 1: Ethnicity Rate

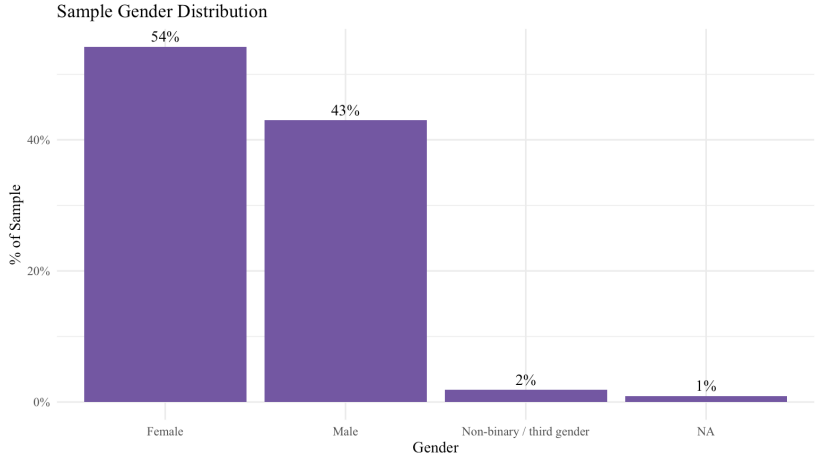


Figure 2: Gender Distribution

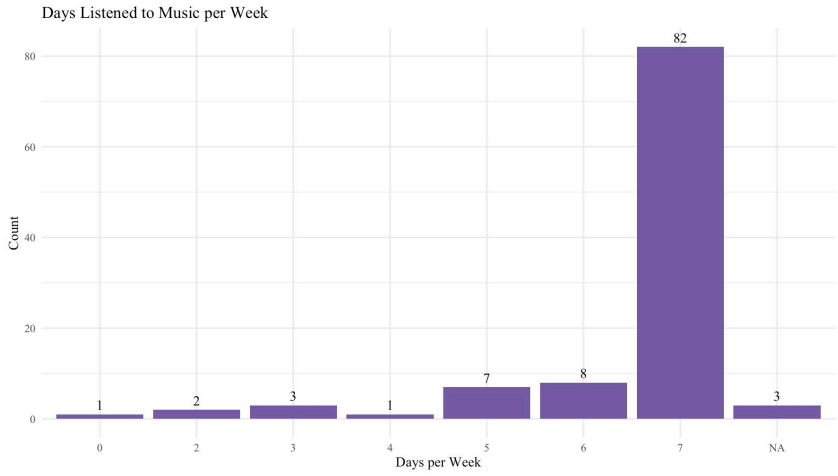


Figure 3: Days Listened per Week

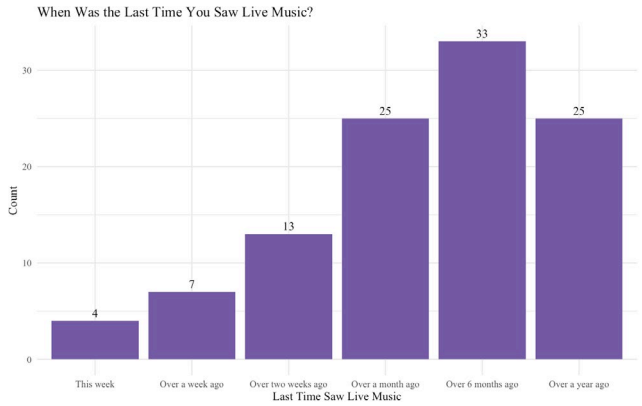


Figure 4: Last Time Saw Live Music

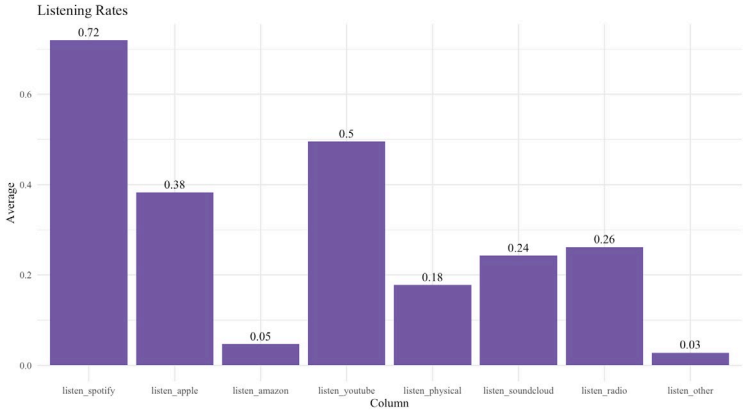


Figure 5: Listening Rates

Figure 6: Music Discovery Methods – Page 28

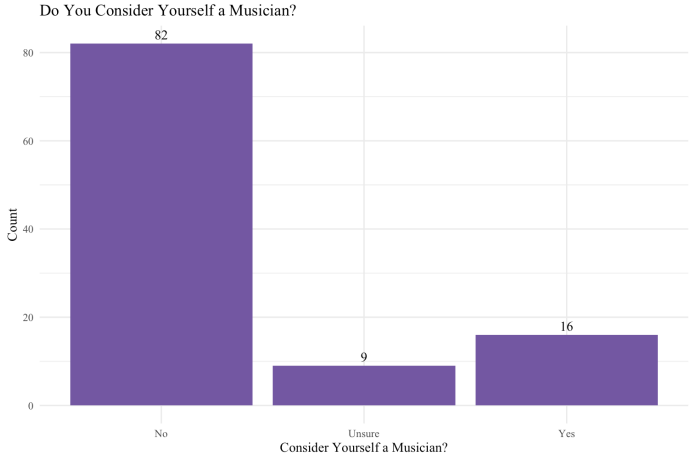


Figure 7: Do You Consider Yourself a Musician?

Figure 8: Pooled Density Plots of Enjoyment Ratings

Figure 9: Pooled Density Plots of Engagement Ratings

Figure 10: Density Plots of Enjoyment Ratings by Song – Page 26

Figure 11: Density Plot of Quality Ratings by Song – Page 26

Figure 12: Density Plot of Talent by Song – Page 27

Figure 13: Future Listening Distribution by Song – Page 27

Figure 14: Want to Know Name Distribution by Song – Page 27

Figure 15: Wrote Something Down Distribution by Song – Page 28

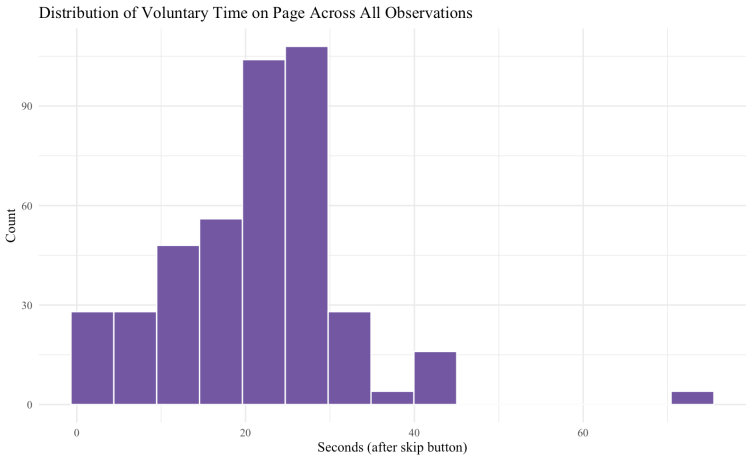


Figure 17: Distribution of Voluntary Time

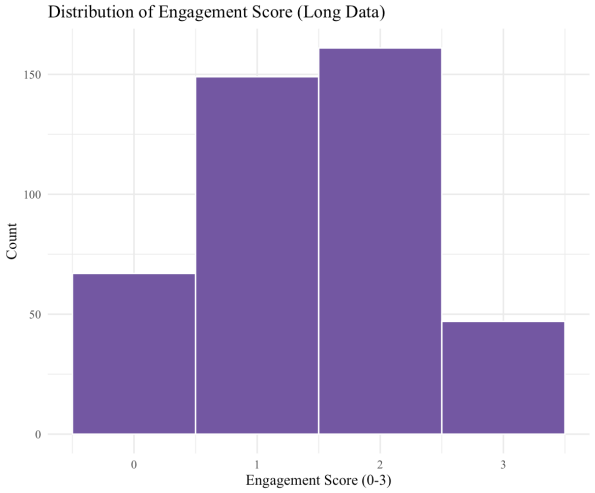


Figure 18: Engagement Score Dist.

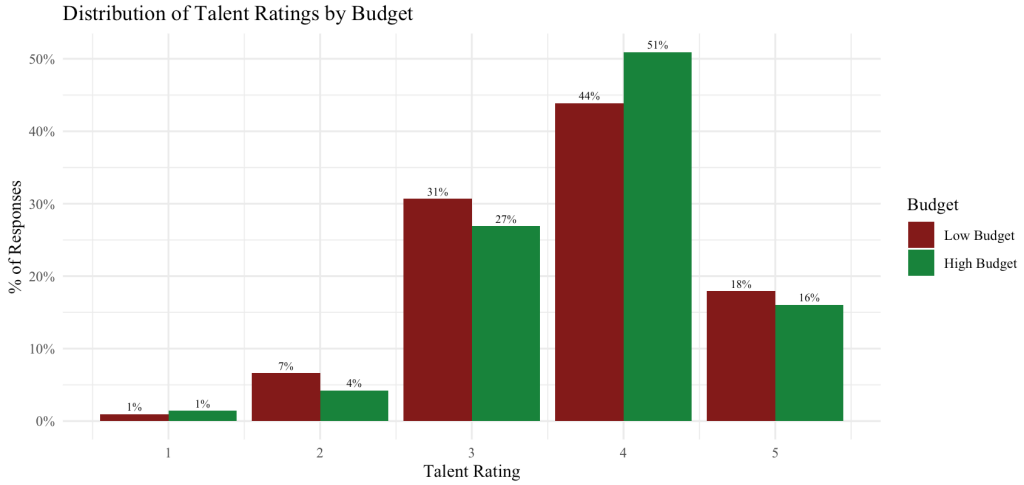


Figure 19: Distribution of Talent Ratings by Budget

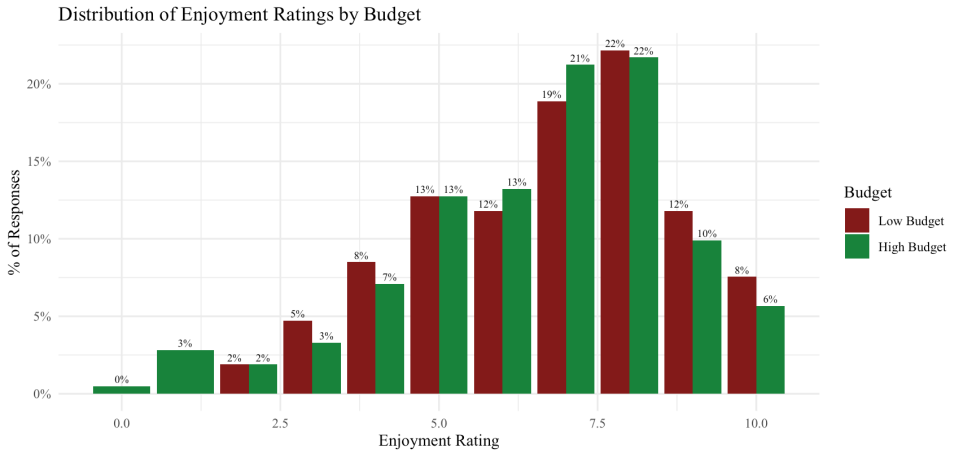


Figure 20: Distribution of Enjoyment Ratings by Budget

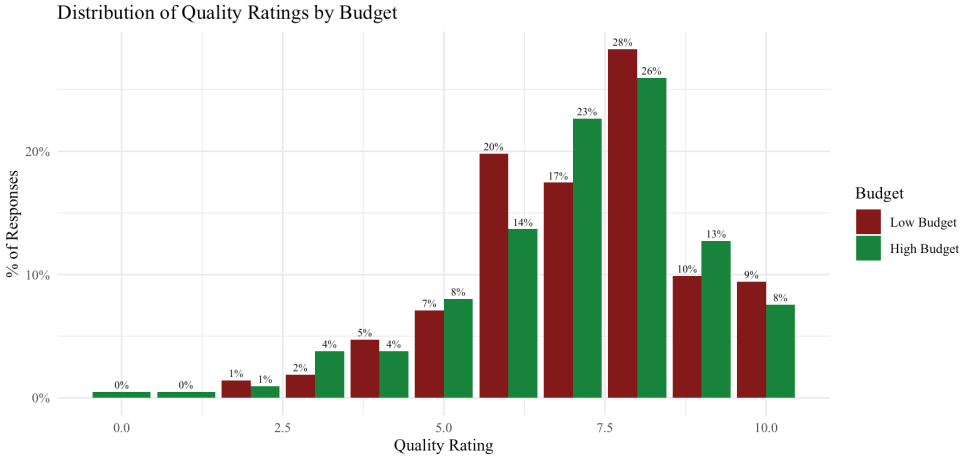


Figure 21: Distribution of Quality Ratings by Budget

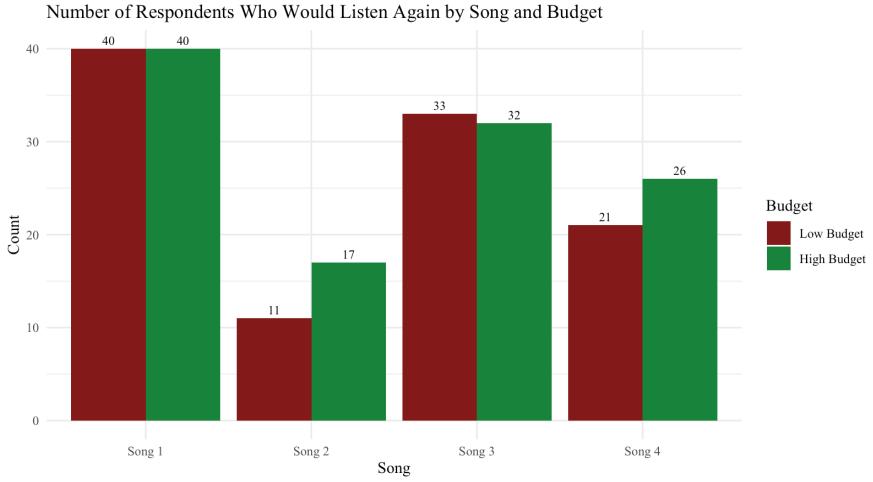


Figure 22: Distribution of Wanting to Listen Again

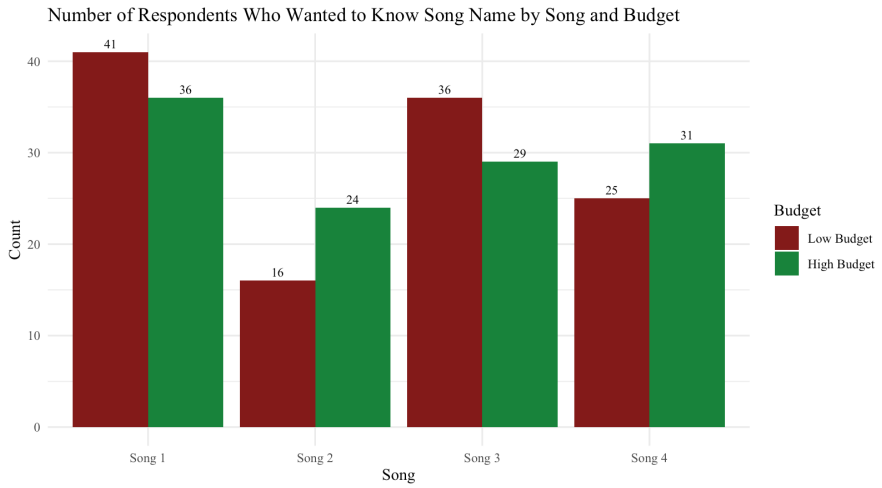


Figure 23: Distribution of Wanting to Know Song Name

ii. Tables

Table 1: Perception Qs – Page 15
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Table 8: Demographics Summary Table – Page 23

Outcome	**White p**	**Asian p**	**Hispanic p**
Enjoyment	0.549	0.531	0.637
Quality	0.286	0.619	0.871
Talent	0.702	0.611	0.276
Future	0.162	0.290	0.717
Sticky	0.204	0.004**	0.403
Name	0.860	0.350	0.482

Table 9: Ethnicity p Values Across Outcome Variables – Page 25
Table 10: Artists' Spotify Monthly Listeners Counts – Page 26

Model	**βHB_{ij}**	**p**
Poisson	-.052	0.54
OLS	-.108	0.16

Table 11: Bivariate Test Results – Page 29
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Table 13: Engagement Logistic Regression Model Results – Page 31

Variable	**Enjoyment (OLS)**	**Quality (OLS)**	**Talent (OLR, OR)**	**Future (Logit, OR)**	**Sticky (Logit, OR)**	**Name (Logit, OR)**
High Budget	-0.333 (0.109)	-0.104 (0.534)	1.18 (0.566)	1.48 (0.240)	0.75 (0.509)	0.87 (0.661)
Female	-0.133 (0.502)	-0.137 (0.392)	1.65 (0.071)	1.94 (0.038*)	0.76 (0.509)	1.22 (0.526)
Budget × Gender	0.213 (0.449)	0.070 (0.758)	0.93 (0.855)	0.52 (0.141)	1.46 (0.532)	1.30 (0.548)

Table 14: Gender Interaction Models

iii. Data and R Script
Download via OneDrive here.
Password: Mustb3th3M0n3y

iv. AI Usage
Claude AI was leveraged to help write and debug R code, summarize R outputs into well formatted tables, and to help ensure references were formatted consistently.

v. Links to Stimuli
Access via YouTube here.
Note: Stimuli are specified via codenames to not reveal condition to respondents. Consult the table below for which stimulus corresponds to which YouTube video.

Codename	**Stimulus**
ClipA1Aqua	Song 1 HB
ClipA1Terra	Song 1 LB
ClipB1Aqua	Song 2 HB
ClipB1Terra	Song 2 LB
ClipC2Aqua	Song 3 HB
ClipC1Terra	Song 3 LB
ClipD1Aqua	Song 4 HB
ClipD1Terra	Song 4 LB

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