Manufacturing “Hits”: A Data-Driven AI Approach to Releasing a Pop Song in 2022

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Abstract - Technology is radically transforming the music industry through the use of big data, artificial intelligence and machine learning algorithms. This paper presents a pilot study that examines the impact of data-driven approaches in creating, predicting, and marketing music. A machine learning algorithm is used to determine the optimal characteristics of the most popular songs and is used as the basis for creating the next song. Next, an AI technique is used to generate the inspiration of the instrumentation and lyrics of the song. Finally, a listener survey is used to determine the trend which includes the mood, preference, and context for the song. The song is then released on Spotify. The success of the song is determined by comparing the number of streams to two songs released the previous without the use of data. The results show that creating and marketing a song using AI models, Spotify listener data analysis, and listener questionnaires strongly positively impact a song’s streaming success. While this is a pilot study, the findings of this study can be used more extensively to determine success of music videos and releases and serve as a guidance to artists with more quantitative insights.

Keywords - Music marketing, AI Techniques, RNN Model, Characteristics of a Song

Relevance to Marketing Educators, Researchers and/or Practitioners – A new song inspired by AI and created by a young artist is released on Spotify. Will the music perform better or worse than those created purely by inspiration? A pilot study investigates the role of AI in music creation, production, and release.

Introduction

The Music Industry is a $61.82 billion dollar industry, as of 2021 (Götting, 2021). Yet analysts at Goldman Sachs predict that it will more than double in size by 2030 to an astounding $131 billion in size (*Goldman Sachs Report on Music in the Air. Insights* 2016). Many factors can be attributed to this growth: increased demand for music, more robust digital streaming services, technological advancements, and a more democratized environment that allows for independent artists to enter into it as well. Thus, this rapid growth offers a unique opportunity to get into the industry and make significant money. Data and Artificial Intelligence (hereafter AI) can be the tool to leverage to do so.

Prior to 2000, songs were largely made and marketed based on the ‘gut instinct,’ of the producer. The process was very subjective and less than 0.9 percent of musicians became mainstream artists (Menyes, 2014). Additionally, music industry executives followed a traditional business model that overlooked the musicians. Since music was in physical vinyl or CD form, musicians were “not able to collect a decent rate from sold copies, because record labels would take most of the profit” from physical sales (Hujran, Alikaj, Durrani, & Al-Dmour, 2020). One of the first disruptors in changing the way music was marketed, shared, and played was Apple. In January 2001, they launched iTunes and the first iPod soon thereafter ("A&E Television Networks. Apple launches iTunes, revolutionizing how people consume music. ," 2019). iTunes was revolutionary in that it was the first online music marketplace that allowed customers to buy songs digitally on one consolidated platform. Within eleven years, “75% of all music-related transactions were digital sales” (Liao, 2019). This new ‘pay per song download’ business model disrupted traditional music distribution models of CDs, vinyl, and other physical disks. The digital music format further paved the way for streaming services like Spotify and Apple Music. As of 2021, 99% of Generation Z and 98% of Millennials actively use streaming services (Smith, 2022) and the trend is on a rise in both the younger and older demographics. Thus, the industry has seen seismic shifts in how music is consumed, from CDs and vinyl to iTunes to Streaming Services.

The inclusion of big data and machine learning in music is opening up the next chapter of disruption in the music space. Use of analytics and insights based on quantitative data has changed the way for measuring success and reach of music. Many streaming platforms already use data analytics and algorithms to recommend listeners new songs. Spotify has grown its active user base to more than 29% in 2020 alone (Stone, 2020). Additionally, social media platforms like Tik Tok and Instagram use algorithms to curate their content streams and recommend new profiles for users to follow. Users can see data analytics displayed on a page in their profile with Engagement metrics such as video views, profile views, likes, comments, and shares, as well as follower count and number of posts created in the last week. Several AI (Artificial Intelligence) algorithms have proven successful in creating a recommendation and collecting listener feedback.

With the success of AI technologies in the recommendation and review space, AI is now being tested in content creation. While this is arguably the most “creative” step in the process, songwriting follows clear patterns and musical conventions that can be learned. It is important to note that while Big Data and AI algorithms are being used in the industry for more targeted marketing and streaming predictions, they have still not replaced the traditional techniques. There is still a level of distrust in products recommended with no human intervention. Thus, the intent of this study is to focus on the question - How effective is it to use data-focused quantitative and qualitative constructs to create and market songs? This study is a pilot study that will focus on AI techniques that use the salient music characteristics, the physiology of the human brain along with the psychology of the listeners to determine if AI techniques have a future in song creation and marketing.

Literature Review

The constructs in this study are based on understanding conventions and emotions of music and its interaction with the brain, previous data driven AI approaches in the music industry and current trends in the marketing practices in the industry. Each of these areas are detained in this literature review section.

Music and the Brain: Understanding Conventions and Emotions

To understand the science behind music, music can be thought of as vibrations that our ears can perceive, evoke the auditory brain, and elicit an emotional response(Zatorre, 2018). The brain gravitates towards certain songs and away from others, due to the inherent musical preferences we have. A study led by researchers from Cambridge University found that music listeners can be broadly grouped into three categories depending on how their brain processes music in the limbic region (part of the brain involved in our behavioral and emotional responses): Type E (Empathizers), who “focus on people’s thoughts and emotions,” Type S (Systemizers), who “focus on rules and systems,” and Type B, who focus on the two areas equally(Wassenberg, 2019). Type E listeners prefer slow, sad songs with well-written lyrics, while Type S prefer more up-beat, intense, and repetitive songs. Type B listeners tend to listen to both(Wassenberg, 2019). This phenomenon for musical preferences can also be seen in brain images as suggested by a brain imaging study that showed that most musical processing happens in the Broca’s area of the brain, the same area where the brain processes language. People’s brains are as fine-tuned in “recognizing musical syntax, just as they are for verbal grammar” (Holden, 2001). This means that peoples’ brains are as sensitive to musical tastes and quick to judge, as they are to normal speech conventions.

A further study showed that this musicality seems to appear in humans innately, as an intimate form of communication and bonding. Studies show that babies as young as six months can follow musical patterns and recognize when small shifts or deviations occur in the music (Manning-Schaffel, 2019). Lullabies and songs that teach, such as the ABCs or ‘Head, Shoulders, Knees and Toes,’ are built into early childhood education. We rely on music as a way to teach, motivate, and relax children. As children grow into adulthood, they switch to different genres of music such as hip hop, country, or pop. But their joy from music remains. Researchers believe that this joy comes from our interaction with two distinct systems: first, the system that “allows us to analyze sound patterns and make predictions about them” and second, the system that “evaluates the outcomes of these predictions and generates positive (or negative) emotions depending on whether the expectation was met, not met, or exceeded” (Zatorre, 2018). It is this anticipating and setting of a musical expectation, followed by the breaking or following of this expectation, that allow us to elicit an emotional response and ‘feel’ the music.

The oldest known instrument is a vulture wing bone flute, found in Germany’s ‘Hohle Fels cave (Stanborough, 2020). It dates back more than 40,000 years. Researchers and evolutionary scientists think that music has always played an important role in creating feelings of social connectedness and mood regulation (Stanborough, 2020). Today, listeners listen to music for the same reasons and more. They continue to seek out songs to “regulate arousal and mood, to achieve self-awareness, and as an expression of social relatedness” (Schäfer, Sedlmeier, Städtler, & Huron, 2013). According to research presented by Front Psychol, the functions of music can be defined into four specific categories: emotional functions, such as inducing happiness, cognitive functions, such as escapism, arousal-related functions, such as relaxing, and social functions, such as self-expression and connectedness(Schäfer et al., 2013).

Music works as an emotional regulator by releasing dopamine and oxytocin, while simultaneously lowering cortisol, which is the stress hormone in the human body (Stanborough, 2020). A similar study found that listening to songs after a stressful life event will allow a person’s nervous system to recover significantly faster. Thus, music can help us deal with difficult times on a neurological level. But music does not only help us in terms of stress and anxiety. A further study showed that jazz music can help lessen mental illness symptoms, specifically depression, by engaging our reward systems and deactivating the stress systems (Chanda & Levitin, 2013). Thus, music has a strong influence over our emotions. It’s important to note that Americans spend more money on yearly music consumption than they do on prescription drugs (Rentfrow, Goldberg, & Levitin, 2011). One can argue that millions of Americans are prioritizing music as their form of therapy over medications. This makes music an incredibly powerful, yet understated, form of mood and emotion regulation. Secondly, music works as a cognitive function by stimulating dream-like brain activity and improving memory. In one study done on music therapy as a potential intervention tactic for people suffering from Alzheimer's Disease, the results showed that music could act to slow cognitive decline. While it had only minimal effects on patients suffering from strong dementia, people with mild to moderate dementia reported a significant uptake in the remembrance of many episodes from their lives (Fang, Ye, Huangfu, & Calimag, 2017). Similarly, data from a second similar experiment showed that texts that were sung with a melody and rhythm were significantly better remembered than the texts that were only spoken (Fang et al., 2017). Tens of other studies demonstrate these same findings, reinforcing the power of using music to improve memory. Thirdly, music works in arousal-related functions to calm and relax people. A research paper published in 2015 by Shanghai University looked into the efficacy of relaxing music on reducing fatigue and increasing muscle endurance when employees were busy with a mundane, repetitive task (Guo, Ren, Wang, & Zhu, 2015). They found that relaxing music "alleviated the mental fatigue associated with performing an enduring cognitive-motor task" (Guo et al., 2015). Thus, it can be deduced that listening to relaxing background music has a positive effect on reducing fatigue. Lastly, music works as a social function by emphasizing unitedness and self-expression. In one study, participants responded to certain phrases. Popular ones included "Music helps me think about myself" and "Music adds meaning to my life" (Schäfer et al., 2013). Music forms our social identity and strengthens our connections with others, particularly when they are fans of a certain artist that we love as well. Interestingly, responses here indicated that to most people, listening to music is a very private exchange between the listener and the song. This is important to keep in mind when performing research on the topic, as participants may be less open or likely to divulge information they deem as highly personal. Finally, a further study used self-reported mean answers to rank the self-awareness, social relatedness, and arousal/mood regulation functions of music for participants. They found that most people listen primarily for arousal and mood regulation, followed closely by self-awareness. Social relatedness scored lower, as seen by the graph above, but it was still seen as a critical component of the listening experience (Schäfer et al., 2013). Thus, music functions in many beneficial mental health-focused ways in our society.

Another topic to cover cognitive neuroscience is the importance of lyrics in influencing human behavior and generating emotion. Lyrics can be defined as "the words of a song" ("Merriam-Webster: Lyric Definition & meaning,"). Lyrics encompass anything that was sung or rapped or spoken in a song. Songs broadly fall into three emotional categories, as defined by Zentner et. al: vitality (power), unease (tension), and sublimity (wonder or nostalgia) (Zentner, Grandjean, & Scherer, 2008). While lyrics were key to defining unease and sadness in songs, instrumentation was much more important in defining vitality and sublimity in songs (Williamson). This means that strong, well written lyrics matter a lot more in invoking feelings of tension and despair in sad songs compared to happier songs. They matter more in the first instance. And activate the area of the brain responsible for "music chills" (Williamson). Whereas in happy music, lyrics did not matter because the limbic region of the brain was triggered more, which focused on the instrumentation and chordal information (Williamson). Additionally, while clear research supports that lyrics "have the ability to foster meaningful relationships and bring about positive social change," they are increasingly becoming more negative and violent (Jones, 2018). Modern lyrics use fewer instances of collectives such as 'us' and 'ours' and more instances of negative, violent words such as 'kill' and 'hate' (Jones, 2018). Popular topics include misogyny, drugs, sex, and money, however, listeners tend to 'sweep the true meaning under the rug.' However, recent studies show that listening to misogynistic lyrics change men's behavior. One study by Fischer and Greitemeyer studied two groups of men. One group was exposed to music with misogynistic lyrics, and a second group was exposed to neutral lyrics(Jones, 2018). Then the men were asked to squirt hot sauce onto sandwiches for women and men. The men who listened to the misogynistic lyrics squirted more hot sauce onto the sandwiches for women than men (increasing the spice level and thus the discomfort), whereas the men who listened to neutral lyrics were most inclined to squirt an equal amount for both genders (Jones, 2018). This study demonstrates that listening to certain types of lyrics can drastically alter behavior, even if the person is not consciously aware of the change. Thus, although they are frequently overlooked, lyrics have a fundamental effect on emotion and human behavior.

Previous Data-driven AI Approaches in the Music Industry

Over the years, there have been several approaches to apply science to music in the form of algorithms, models, and software. The current approaches fall into three distinct categories: 1) to create music, 2) to market music, and 3) to analyze and predict a song's success.

Creating Music

Alan Turing was the first to build a simple machine in 1951 that "generated three simple melodies" (Chow, 2020). While Turing was arguably most famous for his Turing machine, he was also a great innovator in the Music AI space. His music generating machine was built in the Computing Machine Laboratory in Manchester, England. It was so large that it filled most of the lab's ground floor (Gage, 2016). Soon thereafter, two researchers at University of Illinois called Hiller and Isaacson created the first musical work completely written by AI (Li, 2019). It was called 'The Illiac Suite' and consisted of a four-part string quartet. This name came from the computer behind it, the Illinois Automatic Computer, which "was the first supercomputer to be housed by an academic institution" (Gage, 2016). It emulated different classical music styles such as Baroque and Renaissance. The machine worked by manually entering code on paper tape and "waiting for it to blurt data back out," which took the form of musical song notation (Gage, 2016). As the machine got more refined, Hiller decided to incorporate Markov Chains. This is a probability based mathematical system that bases the current note only on the preceding note. One important thing to mention is Hiller's desire for purity in his machine and experiment. He did not touch what the computer composed, despite how unnatural sounding it could get, and requested that "very few people get to interact with [the machine]" (Gage, 2016). This secrecy only added to public awe in their perceptions of the truly landmark piece. Following this breakthrough, Russian researcher Zaripov created the first AI-based algorithm for music creation called the URAL-1 computer in the 1960s. It used a simple algorithm, binary arithmetic, and vacuum tubes to generate frequencies (Urnev, 2012). The hardware consisted of vacuum tubes, three memory storage devices, rack cabinets, magnetic tape, a fixed length of clock-rate, and Electron valve circuits (Urnev, 2012). While it worked successfully, it was difficult to use, expensive, and extremely large in size. It would also frequently break due to the delicate nature of its vacuum tubes.

Musicians and researchers alike built off of these initial attempts with more advanced algorithms. In the 1980s, University of California's David Cope developed Experiments in Music Intelligence (EMI). This was a generative model system, coined Emmy for short, that analyzed existing songs, and created new pieces of music based on them (Li, 2019). His computer was revolutionary in that it combined the previously seen "rule-based" methods of learning with an element of surprise. To do so, "Cope developed 'a little analytical engine' that could insert some randomness within the predictability" (Adams, 2010). It was this inserted randomness that made the songs more convincing and helped drive the narrative of the song forward. It was the missing piece of the puzzle - a way to incorporate a suspenseful storytelling aspect to it. Cope ended up pushing one button on Emmy and returning to find that she had "produced 5,000 original Bach chorales" (Adams, 2010). He took these pieces, filtered them for the most enticing, and released them on an album called "Bach by Design." Public sentiment was overwhelmingly positive. They admired Cope's work because it was "far more than copying, it carries the recognizable DNA of the original style and fashions it into something recognizable but entirely new" (Adams, 2010). This was the first time an AI had not just emulated based on the songs it was fed. It had created something indistinguishably new and different. This field started to pick up in the 1990s, with David Bowie creating many random synthesizers and a lyric generating app called Verbasizer that garnered public attention. It was during this decade that researchers began using Random Forest Algorithms for classification and regression models and utilizing the recent invention of long short-term memory recurrent neural networks (LSTM) by Sepp Hochreiter and Jürgen Schmidhube to create better models (Jakupov, 2021). Slowly with time, the AI got more accurate. In the 2000s, professors once again trained computers to emulate Bach and compose songs in his style called DeepBach-generated (arXiv, 2020). They then asked listeners to decipher whether a piece that was being played was written by Bach or AI His model was so effective at imitating Bach that around half of listeners from the 1,600-sample group could not tell the difference between a real Bach piece and his emulated piece (arXiv, 2020). It's important to note that only 75% of participants guessed correctly whether or not it was a Bach piece to begin with. Thus, this model was extremely effective.

Today, most AI music creation algorithms rely on a deep learning network, a type of machine learning that uses multiple layers to transform the inputted data (Moolayil, 2020). This works similarly to early algorithms that were used to train machines, but differently in that it allows for a high degree of complexity. For example, if a researcher feeds the AI algorithm a C Major chord, it will break this chord down into its individual notes C, E, and G and then predict another chord from it. This network benefits from a large amount of data, so in order to create a successful model, you must "feed the software tons of source material, from dance hits to disco classics" (Deahl, 2018). Additionally, in order for the algorithm to pick up on musical patterns, it must have many examples so it can learn these patterns and use them to form its own music. The four current initiatives highlighted in the next section are the IBM Watson Beat, Google Magenta, AIVA, and Boomy which appear to have successful results.

The first revolutionary AI technology being used to create music is IBM Watson Beat. This model uses 26,000 Billboard Hot 100 songs to learn how to compose music through Reinforcement Learning (RNN) and a Cognitive Color Design Tool to synthesize album artworks (Gredler, 2019). It then analyzes the "composition of those songs to find useful patterns between various keys, chord progressions and genres completing an emotional fingerprint of music by year" (Gredler, 2019). Instead of thinking about AI replacing humans making music, the team behind IBM Watson Beat thought about it as an augmentation of humans (Gredler, 2019). Watson Beat is a tool that can be leveraged to make music faster and easier to create. It is designed to inspire and push the boundaries of reality. In one experiment, the team at T3 fed IBM Watson a MIDI file with sounds from three different instruments at 60 beats per measure. The instruments were a vibraphone, strings, and bass. Then they left it to learn and create for 100 minutes. When they came back, it had synthesized an impressive one minute 47 composition using the input as inspiration. It added a beat, unique effects, and different chord progressions. It would not be possible to tell if a person or AI created this piece.

The second AI technology being widely used in the Music Industry is AIVA Technologies. AIVA stands for Artificial Intelligence Virtual Artist. This startup was founded by a team of researchers who wanted to provide a technical solution for film directors, advertising agencies, and game developers (Kaleagasi, 2017). Similar to IBM Watson Beat, AIVA uses Reinforcement Learning (RNN) to "understand the art of music composition… and achieve the best sound quality possible" (Kaleagasi, 2017). Interestingly, AIVA was the first AI to officially get the worldwide status of Composer in official documentation (Kaleagasi, 2017). The unique value proposition of AIVA, however, is its focus on the cinematic style used in many films or video games. To get this sound, they use classical music from Bach and Beethoven to train it, which also avoids copyright infringement, since their music is in public domain. AVIA's unique musical soundprint lies in its use of cinematic strings and soft piano, combined with wondrous, dream-like chord progressions.

The third AI tool helping musicians create music is Google Magenta. This is a research project by Google AI that seeks to explore "the role of machine learning as a tool in the creative process" (Synced, 2018). It consists of an open-source Python library powered by TensorFlow and also uses Reinforcement Learning algorithms (RNN) that generate songs based on a given input and pattern ("Magenta: Music and art generation with machine intelligence. ," 2020). Many tools it contains manipulate source data and then use this data to create, test, and train models. These include *Continue*, *Generate*, *Drumify*, *Interpolate*, and *Groove*. Musicians can input their musical choices, which it will use to create MIDI Files in their directory of choice that they can drag into Logic Pro, Pro Tools, or a similar DAW (Synced, 2018). This AI tool is incredibly effective for musicians who want a seamless working setup between a Machine Learning program like this and their DAW. It is the best tool that complements a musician's already existing setup, because it can simply be exported from Magenta and dragged in as a file into a musician's project.

The last revolutionary AI based software helping musicians create music is called Boomy. This is the most user-friendly option to create music and does not require programming or machine learning skills. It consists of a website with a simple UX that allows users to pick a music style from the list. Then "algorithms create a full instrumental track that can be manually rearranged and fine-tuned" (Roettgers, 2021). After the song is complete, users can go in and manually add vocals, edit the composition, and edit the production before saving it to their account. To date, Boomy users have created an astounding 5,331,192 songs, equivalent to around 5.6% of the world's recorded music (Boomy, 2022). Thus, its power lies in the speed at which it can compose. Instead of training their algorithms based on "hit" songs, which could implicate them in serious copyright infringement lawsuits, engineers at Boomy decided to take a "bottom-up approach by leveraging previous experience in artists and repertoire (A&R) research to train the system to build organic, original compositions from scratch" (Ramage, 2021). This takes the form of "advanced algorithms that are doing automatic mixing, deciding what sound should go together—what are the features of those sounds, how do those fit together, what is the perceived loudness rate of those sounds" (Ramage, 2021). Boomy encourages users to release their songs on streaming platforms such as Spotify and Apple Music, but, thus far, no hits from this website have been created (Tarantola, 2021). Thus, this is an incredibly user-friendly and time efficient method to generate thousands of songs in a short amount of time, that a person can then go in and manipulate or customize to their liking.

Marketing Music

Big data helps music companies understand user's listening preferences and push certain social media channels over others for different artists, resulting in more efficient and targeted ways to reach consumers. The first way data can be used to market music better is through aggregating streaming data and examining demographics, consumer behavior, and tastes. This gives an artist a better understanding of their listeners, where they are located, and their age. This, in turn, helps them target their live shows. For example, if we have an R&B artist whose listeners live in Texas, Arizona, and New Mexico, it will make more sense for them to play a show in Dallas, Texas than Missouri or Vermont. As one executive notes, "if you are really asking questions as you're looking, you can see patterns and movements of audiences and how consumers are behaving" (Setaro, 2021). While there may be too much information for a person to clean and see these patterns, computers can find them very quickly. For example, after visualizing the data, one group saw that "Latin artists overperform on Facebook" (Setaro, 2021). Thus, they quickly started using their resources more effectively and pushing Latin artists on Facebook, focusing their marketing efforts there. Additionally, if an artist sees that his or her Twitter page has low engagement and minimal positive effect on streams generated or tickets bought, they may choose to delete this page and instead focus on another platform that does a better job of promoting their music. All of this can be learned from listener or platform analytics through the cleaning, sorting, and grouping of data.

A second way data has helped market music is through social media analytics. This is done by tracking post likes, mentions, reposts, and followers on Instagram, Facebook, Twitter, Tik Tok, and other similar platforms. I would like to focus on Tik Tok Analytics, because Tik Tok's influence on music cannot be understated. In the last year, 175 trending songs on Tik Tok made the main Billboard Charts and seven from the Top 10 Rising Artists in December 2021 were pushed up there from Tik Tok (Charmetric, 2021). Tik Tok allows for sponsored video advertisements, and more importantly, a space for viral trends to take off using songs. As these trends and songs become more viral, people often navigate back to Spotify and Apple Music to add them to their playlist. One example of this is Ankit Desai's work on analytics for Universal Music. He saw that Tik Tok was reviving Logic's song "1-800-273-8255" and that millions of people were adding it and playing it obsessively. He asked Universal to invest Tik Tok marketing dollars into it, resulting in the song rising to No. 3 on Billboard Top 100 (Setaro, 2021). Thus, by investigating social media analytics, they were able to capitalize on a song's Tik Tok popularity which resulted in millions of streams.

Understanding and Predicting a song's success

Another advantage of applying data in the Music Industry is the ability to forecast the success of a song before its release. This is accomplished by understanding and measuring key features of successful songs and aggregating customer's preferences together. A successful application of such an approach was the creation of the "Hit Potential Equation" in 2012. This was an equation, created by a team of scientists from University of Bristol's Intelligent Systems Laboratory under Dr. Tijl de Bie, that tried to predict if a song would make it into the Top 5 UK Charts using a machine learning algorithm (Brown, 2011).

Score = (w1 x f1) + (w2 x f2) + (w3 x f3) + (w4 x f4), etc.

Where: w = weights and f = features of a song

In simplest terms, songs were first scored according to their audio attributes, such as loudness, energy, length, and tempo using the above equation ("Can science predict a hit song?," 2011). These scores were then taken and compared to a database of UK Top-40 singles charts for 50 years using a machine learning algorithm. This allowed the scientists to predict whether the scored songs would "hit" and make it into the Top 5 or "miss", obtaining a striking 60% accuracy rate doing so ("Can science predict a hit song?," 2011). One reason for its higher accuracy rate was that it took into account that musical tastes evolve by slightly tweaking the "Hit Potential Equation" for each era, setting different weights to different features. For example, they found that "low tempo, ballad-esque musical styles" were more popular in the 80s, while louder, higher energy, and more danceable tunes flourished in the 90s (Brown, 2011). Acknowledging these musical differences and accounting for them in the algorithm helped the model to achieve more refined predictions.

While this equation was a revolutionary attempt to deploy a machine learning approach in music, it lacked in several ways. Firstly, it only mined data from the United Kingdom, choosing to ignore the unique music tastes of the rest of the world. Thus, if artists from the US or Germany or South Korea try to apply the equation and machine learning algorithm to their songs, they would find that it is not as accurate or appropriate. Secondly, it only achieved a 60% accuracy rate (Brown, 2011). While this is better than the 30 to 50% accuracy rate achieved by scientists at Tel Aviv working on a similar music data project, it is still good enough at predicting whether a song will make it into the Top 5 in the UK charts slightly more than half of the time. Thirdly, researchers only took into account twenty-three total features when scoring the songs. While twenty-three features is certainly better than merely a handful, data-driven approaches are normally more accurate with more data points and there are clearly some meaningful features still missing from consideration.

Apps such as Shazam can identify music by "listening" to a snippet of it using a complex Music Recognition Algorithm. The app is used by more than one billion people across the globe and is incredibly powerful because it represents peoples' current preferences and tastes (Whalen, 2019). People use it when they listen to a song they like but do not know or cannot recollect the title. They can simply open the app, record a small snippet of the song in question, and wait for the app to tell them which song they are currently hearing. Shazam works by "marrying the audio fingerprint of millions of songs to a small snippet sampled out of the air in a noisy bar or restaurant" (Whalen, 2019). In simplest terms, it first picks up the song being played into it. Then it captures the sound waves and converts it to Frequency Domain, which "acts as a type of fingerprint or signature for the time-domain signal, providing a static representation of a dynamic signal" (Jovanovic, 2015). Next, Shazam takes this unique fingerprint and compares different sections and hashtags of it to its database. Finally, it stores the collected data in its database, which will be used by Shazam engineers to draw insights regarding current song popularities. By analyzing the data of song requests in aggregate, Shazam was able to predict two Grammy winners in 2014 "Macklemore & Ryan Lewis" and their album "The Heist" for Best New Artist and Best Rap Album, respectively (Hujran et al., 2020). It was also able to predict many viral, up-and-coming songs from new artists, who were then picked up by major labels before they made it mainstream.

Current Music Industry Trends

In order to create a successful song, it is also important to closely monitor and study current Music Industry trends data. Songs exist in context of the ecosystem that the listener resides in. Each decade has a unique soundbite. For example, 1920's was renowned for their jazz sound and the 1970's focused heavily on a more up-beat disco sound. Songs that did well in one decade might not do as well in another decade. Thus, social listening and looking at aggregate time-sensitive industry data are imperative. I have taken this into consideration when creating my own song to help guarantee that it appeals to listeners in the 21st century.

Researchers studying trends and the predictability of success in contemporary songs used random forest, a type of AI classification algorithm, to find that songs are becoming more ‘sad’ and less ‘happy’ or ‘bright’ (Interiano et al., 2018). They also found that successful, charting songs sounded more ‘female’ than other released songs that did not do as well. A second Midyear 2021 study done by Billboard and MRC Data found that rock, indie, and disco are making a comeback. Additionally, Korean and Afrobeat influences cannot be understated (*MRC Data's 2021 U.S. Midyear Report, presented in collaboration with Billboard*, 2021). Thus, using this preliminary industry data, we see that we might find success creating a darker, sadder song featuring our vocals. We should utilize streaming platforms to publish our songs, given the immense popularity of streaming. Lastly, we might also want to include rock, indie, and disco influences to ride on the current popularity of these genres in the 2020s.

The Fallacy of the “Perfect” Pop Song

While the use of data and AI have worked to democratize music and make it faster, cheaper, and less complex, there are limitations to their uses. Numbers and statistics cannot explain everything regarding a song’s success. Listening to music is a highly personal and subjective experience. Thus, instead of striving to create the “perfect” song the goal of this study is to understand if analytics from AI techniques can create a song leading to more streams which is a close predictor of success or failure.

Methodology

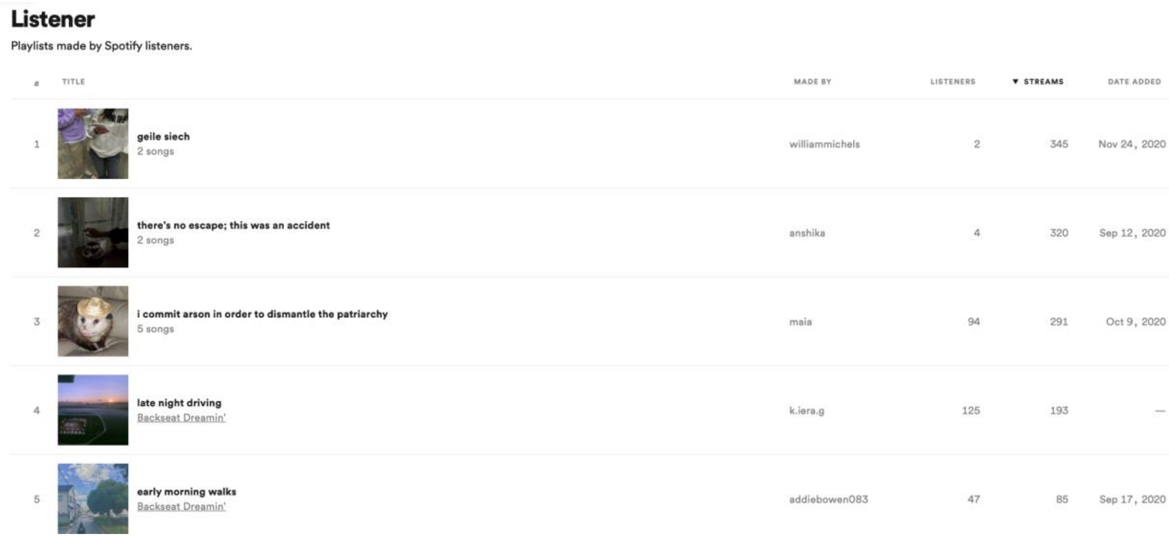
The first author of this paper is a musician who has her own spotify channel (görl) which has been used to complete this study. To set a control or a benchmark, the two latest songs released on the *görl* were chosen. The first song titled *I Messed Up(Birk, 2021a)* and the second song was titled *Ready for Your Love (Birk, 2021b)*. Both the songs were released in 2021.

In order to manufacture a successful song based on analytics and insights, a three-pronged approach was used. Firstly, a data scraping of the playlist in Spotify was done to generate the optimal characteristics of the most popular songs and would serve as parameters for creating the next song. Secondly, an AI technique was used to generate the inspiration of the instrumentation and lyrics of the next song. Thirdly, a listener questionnaire was created to better capture the trend which included the mood, preference and context for the song. Each of these approaches are detailed below.

Spotify Playlist Data Scraping

The Spotify data was collected to analyze the listeners’ Spotify playlists to discover characteristics in songs that they enjoy making the songs successful. The different characteristics collected included the optimal song length, tempo, time signature, loudness, and liveliness for the audience. Spotify for Artists’ built-in tools and Spotify’s Web API powered by a Python code was used to extract these features. The Spotify Artists tools helped analyze the listener playlist to which the “**görl**” playlists were added by the listeners. The top 50 playlists were used to retrieve the metadata and feature data for the all the playlists’ songs. The output of this process is shown in Figure 1.

Figure 1: Spotify Artists Tool view



The metadata included 1,260 rows of data that included features such as Song Name, Album, Artist, Release Date, Length, Popularity (in playlist), Acousticness, Danceability, Energy, Instrumentalness, Liveness, Loudness, Speechiness, Tempo, and Time Signature as shown in Figure 2.

Figure 2: Metadata of Top Playlists that include görl songs

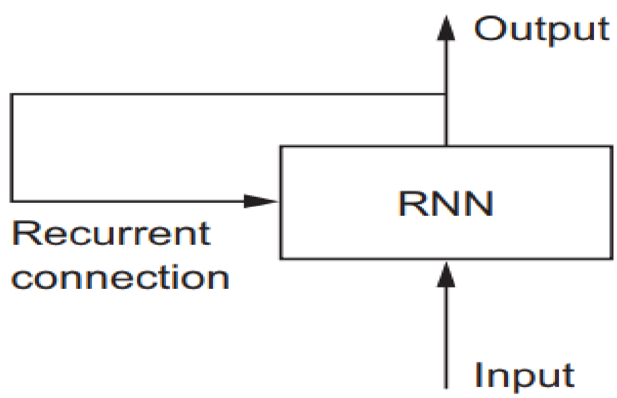
1	song name	album	artist	release_date	length	popularity	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	time_signature
2	Backseat Dreamin'	Backseat Dreamin'	gvðrl	5/11/20	162580	6	0.98	0.62	0.253	0.0278	0.14	-15.268	0.0281	93.534	4
3	Apricot Air	Apricot Air	gvðrl	10/9/20	212700	3	0.952	0.409	0.193	0.0534	0.28	-15.006	0.0347	87.392	1
4	Backseat Dreamin' (Remastered)	Absent-Minded	gvðrl	8/15/20	189304	0	0.952	0.563	0.327	0.119	0.095	-13.565	0.0292	93.491	4
5	Do Not Disturb	Do Not Disturb	gvðrl	11/16/20	158000	0	0.761	0.802	0.664	0.00761	0.128	-10.049	0.313	104.981	4
6	I Think You're Obsessed	Absent-Minded	gvðrl	8/15/20	118153	0	0.104	0.785	0.422	0.00587	0.252	-13.869	0.0448	129.99	4
7	Every Time	Absent-Minded	gvðrl	8/15/20	198000	0	0.128	0.634	0.617	4.32E-05	0.344	-10.64	0.0382	75.987	4
8	Home	Absent-Minded	gvðrl	8/15/20	179999	0	0.953	0.569	0.192	0.369	0.34	-17.112	0.0307	136.008	4
9	Move	Absent-Minded	gvðrl	8/15/20	169354	0	0.53	0.816	0.269	0.069	0.116	-16.545	0.0342	124.02	4
10	I Messed Up	I Messed Up	gvðrl	4/30/21	180705	0	0.939	0.669	0.232	0.000355	0.165	-13.564	0.049	85.028	4
11	Ready for Your Love?	Ready for Your Love?	gvðrl	5/21/21	178834	0	0.87	0.786	0.307	0.000973	0.0907	-10.594	0.0456	103.022	4
12	thor	woah	push baby	9/27/19	194426	48	0.892	0.556	0.278	0	0.0827	-10.196	0.223	104.168	4
13	Straight Face	Straight Face	Younger Hunger	8/2/19	164026	43	0.00659	0.61	0.809	8.08E-05	0.378	-4.475	0.0353	87.996	4
14	Don,Äôt Call Me When You're Lonely	Don,Äôt Call Me When You're Lonely	Fox Royale	3/6/20	161906	0	0.000117	0.462	0.904	1.09E-05	0.347	-3.942	0.0407	117.004	4
15	Ego	Ego	Koren Grace	5/18/18	243018	38	0.353	0.741	0.443	0	0.205	-6.677	0.0304	89.996	4
16	New Banger	I.D.'s and Late Teens	Obungus	3/25/20	215388	19	0.00249	0.463	0.716	5.70E-05	0.0848	-9.871	0.043	164.996	4
17	Sunrise	Sunrise	Kenny Elrod	4/17/20	238524	0	0.4	0.617	0.64	1.07E-06	0.161	-7.28	0.175	125.049	4
18	Two	Atlas: Enneagram	Sleeping At Last	7/11/19	258609	61	0.902	0.504	0.327	7.63E-06	0.445	-9.49	0.0367	132.803	4
19	Daisies	Daisies	Elise Road	6/5/20	238915	25	0.184	0.612	0.516	0	0.329	-7.159	0.129	90.089	4
20	Beach Boy	The Road Back Home	Wxlli	6/19/19	166389	10	0.511	0.765	0.656	0.894	0.196	-9.262	0.0382	119.966	4
21	Excited	Excited	Cory Walker	5/28/20	156814	14	0.134	0.591	0.509	0.000857	0.152	-12.726	0.0298	123.936	4
22	I Wanna Go	Rags 2.0	Jackson Barrett	5/19/20	139075	15	0.958	0.518	0.213	0	0.509	-12.425	0.0917	108.549	1
23	Home for the Summer	Home for the Summer	Sara Kays	6/25/20	155271	0	0.785	0.682	0.531	0.000266	0.102	-9.865	0.0466	126.981	4
24	Backyard Boy	BeVerly Hills BoYfRiEnd	Claire Rosinkranz	6/8/20	129240	1	0.336	0.819	0.642	0	0.0735	-7.037	0.189	138.026	4
25	The One to Blame	The One to Blame	c a n d i d !	2/14/20	289134	24	0.544	0.643	0.449	0.00296	0.112	-8.172	0.0301	114.912	4
26	Backseat Dreamin'	Backseat Dreamin'	gvðrl	5/11/20	162580	6	0.98	0.62	0.253	0.0278	0.14	-15.268	0.0281	93.534	4
27	Sunset Wife	Sunset Wife	Emmett Mulrooney	7/17/20	179431	49	0.5	0.565	0.505	0.000138	0.136	-12.612	0.0445	90.109	4
28	Summer Daze	Summer Daze	RoseAngel	7/15/20	227906	0	0.824	0.645	0.322	0.615	0.101	-13.458	0.0362	123.663	4
29	I Fade Away	I Fade Away	Tulips Ballad	7/10/20	161725	4	0.761	0.602	0.32	0.000269	0.187	-13.902	0.06	87.972	4
30	Burn	Burn	Eliot Merrill	7/25/20	231946	24	0.947	0.61	0.39	0.117	0.0884	-11.888	0.0384	148.926	4
31	Ruby	Rose Colored Glasses	Geskle	7/28/20	201986	0	0.256	0.423	0.588	0.044	0.172	-12.6	0.0312	146.039	4
32	Keep on Walking	Keep on Walking	Liz B	7/21/20	207962	41	0.825	0.689	0.193	3.09E-05	0.113	-17.636	0.0382	74.994	4
33	Stuck in the Middle	Stuck in the Middle	Tai Verdes	5/29/20	196000	0	0.574	0.844	0.429	0	0.0949	-9.308	0.0448	119.989	4
34	$CARY	$CARY	DellaXOZ	12/20/19	133846	31	0.479	0.846	0.177	4.80E-05	0.0834	-13.916	0.0961	103.892	4
35	Looking Back	Looking Back	CAT DAD	3/27/20	332227	6	0.133	0.699	0.404	0.293	0.0888	-11.16	0.0281	133.037	3
36	Mr Loverman	Montgomery Ricky	Ricky Montgomery	4/8/16	216880	0	0.243	0.641	0.527	2.51E-05	0.25	-6.697	0.0256	130.018	3
37	Heart of Gold	Heart of Gold	Anya Gupta	6/8/19	133636	20	0.672	0.682	0.445	0.162	0.156	-9.995	0.106	120.711	4
38	LEMONS - Demo	LEMONS (Demo)	Brye	3/20/20	193207	60	0.901	0.501	0.168	0	0.134	-13.682	0.304	82.574	4
39	Fly in My Room	Fly in My Room	Kerrin Connolly	8/1/20	151462	41	0.167	0.772	0.504	5.37E-05	0.266	-11.4	0.0606	135.048	4
40	Cloudmind	At Dusk	SANJ	8/6/20	211200	15	0.296	0.389	0.658	0	0.0813	-7.702	0.0777	148.625	4
41	Wishful Drinking	Bad Ideas	Tessa Violet	10/25/19	195110	57	0.549	0.809	0.35	4.58E-06	0.117	-7.818	0.305	68.015	4
42	Focus	Focus	Thomas Headon	7/24/20	199350	43	0.79	0.618	0.417	1.46E-05	0.103	-13.238	0.107	76.524	4
43	Loving You	Loving You	Thomas Headon	6/19/20	207000	45	0.512	0.511	0.708	0	0.0778	-5.876	0.0654	79.643	4
44	Happiness In Liquid Form	Happiness In Liquid Form	Alfie Templeman	4/7/20	212824	0	0.00181	0.692	0.854	0.00762	0.333	-4.543	0.0672	124.008	4
45	Two Seasons	Actors	Slow Hollows	10/23/19	224572	38	0.733	0.414	0.478	0.00947	0.125	-10.023	0.0799	88.065	4
46	Flower Picking	Flower Picking	Katie Bug	4/24/20	154540	34	0.897	0.722	0.326	0.000264	0.103	-9.884	0.0718	82.993	4
47	Thursday Afternoon	Thursday Afternoon	Ella Faye	1/28/19	137599	0	0.758	0.759	0.347	0	0.135	-10.274	0.0511	111.12	4
48	I Walked These Streets in November	I Walked These Streets in November	Caroline Manning	10/28/19	192626	48	0.966	0.731	0.291	0	0.461	-10.506	0.0412	125.98	4
49	God in Jeans	Boy in Jeans	Ryan Beatty	7/20/18	172210	51	0.506	0.58	0.772	0	0.236	-6.722	0.0757	74.865	4
50	Thinking of You	Thinking of You	Smoothboi Ezra	3/14/18	159032	0	0.939	0.784	0.231	0.0302	0.0822	-16.679	0.227	79.978	4

A separate Music BPM Dataset (https://www.bpmdatabase.com) was used to find the average BPM of similar songs which included a dataset of 10,000 songs listed by genre, filtered by the genres of “chill out”, “dance pop”, and “power pop”, and then queried for the mean song tempo which came out to be 132 (131.99) beats per measure. This data helped provide the overarching structure of the new song.

AI Machine Learning Models

Two machine learning models that were used to inspire the instrumentation and lyrics for new song were Magenta from TensorFlow and the Recurrent Neural Networks (RNN) Lyric Generation Model. Magenta is a popular AI tool that has been frequently used in this area ("Magenta: Music and art generation with machine intelligence. ," 2020). Magenta Studios is built in with macros which can be used directly or using standalone applications, such as Drumify, Generate, and Groove. For this study the model was created using Python code and macros. This helped inspire the main melody and the bassline of the new song.

Figure 3: A Simplistic RNN Model (F. Chollet, 2017)



This RNN model works by processing sequences, such as words in a sentence or daily stock prices, “one element at a time while retaining a memory of what has come previously” (Koehrsen, 2018). Unlike other machine learning models, such as the bag of words model which goes word by word, an RNN model considers the whole sentence together and the context of each word before making a decision. A simplistic view of an RNN model is shown in Figure 3. These models are incredibly effective for application with the English language. Sometimes important context can only be inferred from the entire sentence, not singular words. Figure 3 (Chollet, 2021), demonstrates the different input, recurrent connection, and output components. Building the Lyric Generation Model using RNN and Python was a little more challenging. It was based on an article from Active State written by Nicolas Bohorquez (Bohorquez, 2021). The data sources were slightly modified to adapt to the desired song outcome. Since this model works extremely well in creating lyrics and poetry because of its structure and focus on generating an emotional response rather than an intellectual one in the reader [or] listener (Bohorquez, 2021). To build the model a dataset from Million Song Dataset, which contains millions of song lyrics from current popular songs was combined with another dataset of popular dark academia, indie pop, and dark pop lyrics from the author’s existing repository was used. Since lyrics follow a lot of conventional patterns, they are easier to learn and emulate than other forms of written work. To improve the accuracy of the model, the data set was filtering for uncommon words, determining a fixed length for words in the training set, creating the Long Short Term Memory (LSTM) functions, and varying the temperature throughout the model's iterations. Running this RNN model took about 12 days in total, due to the sheer volume of data. The final accuracy score of the model was 0.87.

Listener Questionnaire

The third and final approach was to understand the listener choices regarding the trend which included the mood, preference and context for the song. This was accomplished by asking the listeners to fill out a questionnaire to collect the preferences of the segment of the listeners who follow the Spotify channel. The questionnaire consisted of eight questions and asked respondents to share their thoughts, feelings, and opinions on görl's current music. Some sample questions included: *What is your favorite/least favorite song and why? What emotions do you associate with our songs? What instruments do you associate with our songs? When do you listen to our music? What do you want to hear with our new music?* Apart from Spotify, data was also collected by placing the survey on Instagram and Tik Tok. The survey ran for a week and 22 data points were collected. The findings from the three approaches are presented in the next section.

Findings

The findings of the study are being presented under the same sections of Spotify playlist data scraping, AI machine learning outcome and Listener Questionnaire.

The Song Characteristics

The first set of indicators for a successful song was derived from this list as an mathematical average of each of the dimensions. Interestingly, as shown in Figure 4, the listeners enjoy songs that are an average of 3 minutes 18 seconds in length, very danceable, extremely vocal heavy, slightly electronic sounding over acoustic sounding, and an average of 118 beats per measure.

Figure 4: The "mean" Characteristics of a Hit Song

The Table 1 shows the comparative characteristics of the two benchmark songs and the final song. The Acousticness of the song was lowered to 0.41, the instrumentalness was raised to 0.07, tempo was raised to 118, energy was raised to 0.52 and the speechiness was raised to 0.08. The other characteristics were not changed as the recommended values after analysis were close to the average of the benchmarked songs. The final song was created to the exact specifications recommended by the AI algorithm.

Table 1: Comparative Characteristics of the New Song with the Benchmarked Songs

Songs	**Benchmark1**	**Benchmark2**	**AI Based Song**
Song Characteristics	**I Messed Up**	**Ready For Your Love**	**Dancing with Ghosts**
Length (min)	3.00	2.58	3.18
Acoustic-ness	0.76	0.87	**0.41**
Instrumental-ness	0.05	0.01	**0.07**
Loudness	-10.8	-8.6	-9.71
Tempo	86	104	**118**
Danceability	0.67	0.79	0.61
Energy	0.23	0.31	**0.52**
Liveness	0.16	0.09	0.18
Speechi-ness	0.05	0.05	**0.08**
Time Signature	4/4	4/4	4/4

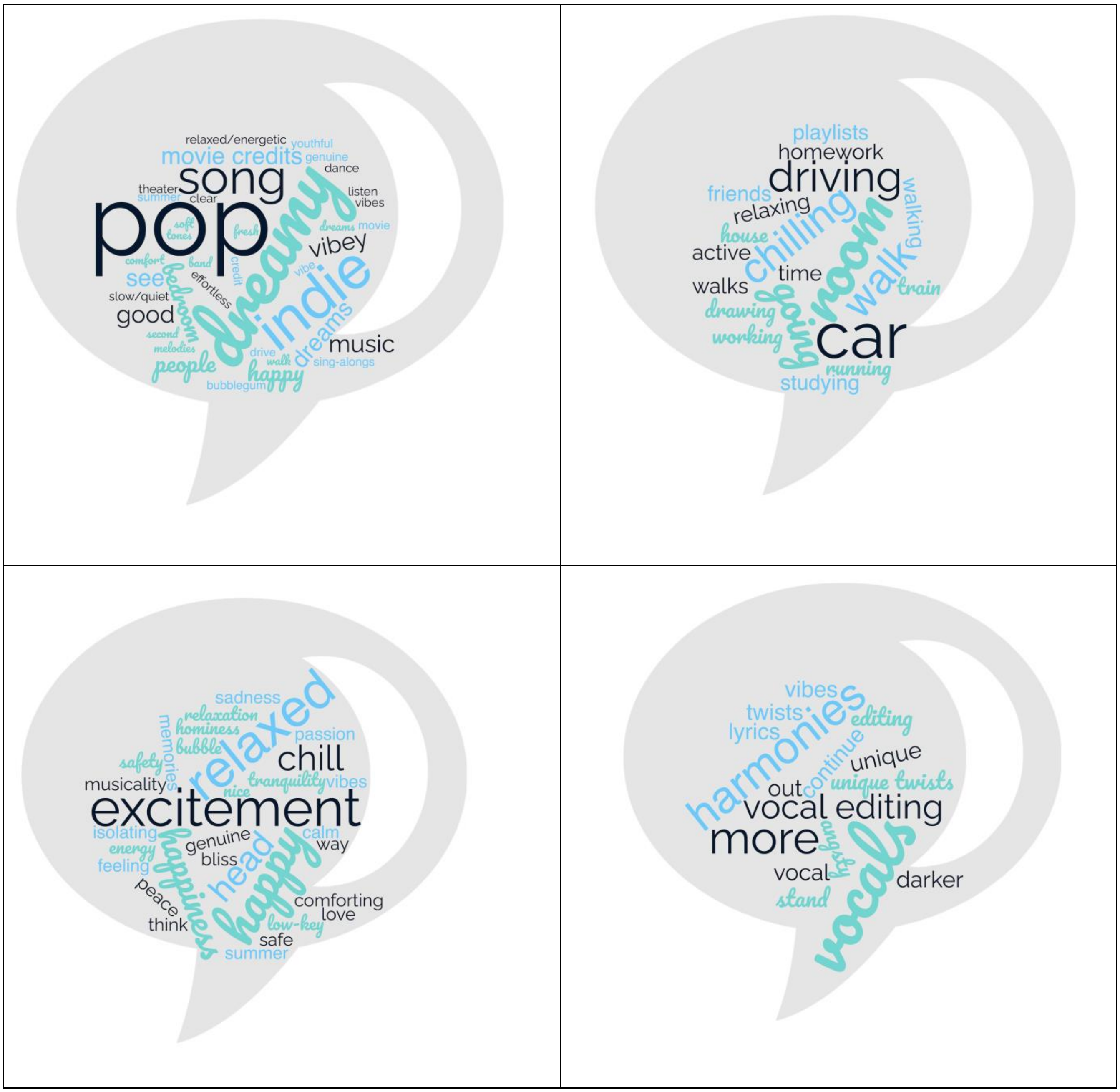
AI Machine Learning Models

The model was very valuable in informing the possible lyrics of the new song. The outcome of the model helped by offering lyrical phrases, thoughts, and ideas. The first epoch generated nonsensical phrases such as "*I'm on the edge of wine and I can see*" and "*I can't say my name, I want to know my name.*" Yet as the model got more accurate, it started generating phrases such as "*I think about you*" and "*I've got a chance to treat you this way.*" After the model finished and reached Epoch 20, the author extracted certain phrases that came across as "extremely clever". These included: "*In the rain on our own*", "*Never been one to believe*" and "*Like only a dream.*" The author used these snippets as her creative cues to determine a melody. The final result was the story of a girl dancing with ghosts in the rain on her own who then tries to bring a friend with her, but the friend can't see the ghosts (Birk, 2022). Since this is a study, the author documented the song creation time. It ended up taking four hours and 30 minutes to finish, which was significantly faster than the usual 20+ hours it takes me.

Listener Questionnaire

The raw data for each questionnaire is provided in the Appendix. In identifying their favorite görl song/s, respondents overwhelmingly chose "Backseat Dreamin'", "Apricot Air", and "Do Not Disturb". Reasons included: they "flowed well", "loved the production", "like the vocals, harmonies, and vibes of the overall songs", "the themes are relatable", and the songs are "catchy and easy going". Respondents noted that they didn't have a least favorite song, for the most part. They also noted that the two instruments they most associated with the songs were vocals and piano. Figure 5 shows the words that the listeners used to describe their favorite songs and when they listened to these songs. These findings helped to understand how listeners value the görl channel and when they listen to this channel.

Figure 3: Words to describe the vibes of the songs and the places they are likely to listen to these songs, emotions evoked by the songs and expectations from future songs.



Based on the summary of the questionnaire, it was found that the listeners enjoy the chill, happy, low-key, safe, relaxed, and excited feels of the songs and associated the music of görl with dreams, indie, pop, and movie credits, and looked forward to hearing more angsty, darker song with better vocal editing. In order to see if data-driven methods to create and market a song lead to more streams, the number of streams of the new release was compared to the streams of the benchmarked songs.

The baselines songs “I Messed Up” and “Ready for your Love?” garnered 187 streams and 33 streams in their first two weeks, respectively. Averaging the two songs together gets us a baseline of 110 streams in the first two weeks without the use of data. In the first two weeks upon its release, “Dancing with Ghosts” garnered 318 streams on Spotify. This is almost three times more streams compared to the baseline. Since there was no additional promotion for this music, it is safe to deduce that this increase in streams came from the data related components.

Table 2: Görl Song Streams for Two Weeks

Song Name	**Streams for 2 weeks**
I Messed Up	187
Ready For Your Love	33
Dancing with Ghosts	318

Discussion

To create the final song informed with the three-pronged approach mentioned above, the musical information from AI Magenta, lyrical information from my RNN Model, and listener input from the questionnaire. The resulting song was 3:19 minutes in length, 130 beats per measure, and in the scale of B minor to add darkness. The voice is light, high, and breathy, whilst adding more reverb and EQ than we usually would for a better vocal edit. In terms of instrumentation, we kept it simple with bass, drums, synths, a choir, and piano. After recording each instrument and vocal take, the final song was mixed and mastered.

Distributing, and Marketing the Generated Song

All the songs including the benchmarked songs and the final recommended songs were placed on Spotify and Apple Music was submitting it for distribution through CD Baby. This is one of the many tools that allow anybody to create and submit music. A release date of Thursday, February 24th was chosen because Thursdays have the highest number of listeners and streams, compared to any other weekday. By collecting listener data from our questionnaire and incorporating their listening preferences into our song, the AI recommended song resonated more strongly with the audience. We can also deduce that building our RNN Lyric Generation model made the lyrics feel familiar yet enticing. Many listeners reached out and complemented the lyrics, noting that they told a dark love story and were emotionally enticing. Additionally, combining these methods with a Spotify playlist data analysis and overarching Music Industry research guaranteed that our song was relevant and musically similar to other songs our listeners enjoyed.

Limitations of the Study

The first limitation encountered was the fact that it was only performed with one song and one band. Hence this study can be considered a successful pilot study that could form a basis for a more robust study. However, this study is the first of its kind where the three-pronged approach of recommendations of the characteristics of the song, recommendations of the lyrics and the trend from a survey were considered as a whole to create a new song. The results of the pilot are very promising and in line with the directional results in each of the individual ideas. In order to draw more widely applicable and accurate insights, this experiment would have to be performed on a much larger sample of 500-600 musicians. However, this would be extremely difficult and involve many moving parts. Even when controlling for the majority of elements such as genre or release dates, there would still be uncertainties of human and procedural errors and a large variety of listeners with different behaviors, tastes, and preferences.

Additionally, the logistics behind having every musician creating and running RNN models, spreadsheets, and Python data analysis would be nearly impossible to run smoothly. Thus, alternative proposals should be considered. If future research were to be conducted, it would be beneficial to create one singular data analysis and AI platform that musicians could use to customize to their liking and deploy and measure its success. This platform would be an all-in-one SaaS (software as a service) platform where users could link their Spotify Artist profile data, fill out questionnaires about their artistic visions, and input their previous songs. Then an AI Machine Learning algorithm would look through this data and predict certain song snippets, tempos, melodies, chord progressions, and lyrical information, among others. It would also have a separate page solely dedicated to song promotion.

It is also important to note the immeasurable component of music. Songs are creative processes at their core. Sometimes there are forces that cannot explain why one song does better than another. When artists try to replicate the success of one song, they often find it impossible to do. Some songs simply come at the right time with the right sound. Additionally, ranking songs is a subjective process that no two people do the same. Since musical tastes are incredibly varied and dependent on personal experiences, the meaning of a song resonates more strongly with one person over another, even if the song itself is not as well-written or well-produced. There is a personal connection that trumps the song composition itself that makes the song so alluring to that person. Even using chart information to determine whether one song does better than another can lead to Thus, the difficulty in comparing one song to another due to the emotional, personal, and subjective elements makes it incredibly hard to define what a "good" song is. This, in turn, makes it hard to tell AI how to write music beyond feeding it patterns, conventions, and lyrical ideas that people find appealing.

Interestingly, some music executives do not condone using any data in the music-making process. They argue that data "shouldn't enter the equation until after the music is made" or we'll end up hearing song after song that only emulate what's already popular and do not differentiate themselves (Setaro, 2021). While this is an interesting stance, it's important to note that current AI and data-driven models do not merely take the popular sounds of today and use them to create more of the same-sounding music. Instead, they go one step further and learn from these trends to forecast and create the sounds of tomorrow. While it can be argued that solely depending on data to make every decision can lead to uncreative, similar-sounding music, that is not how these tools can be used to their full potential. Data is yet another tool to help us to succeed, and it should definitely have a place in the entire creative song-writing process because it helps us make better decisions.

Some executives even went as far as to note that they “have an adverse reaction to trying to use data to change content” (Setaro, 2021). This is an interesting, albeit naive point. We are always using data when creating content, whether it be the qualitative input of a friend, advice of a family member, or view count on our music videos. If we have created two songs, one with 50,000 streams and another with only five streams, human psychology dictates that we try to emulate the more popular song. Whether we are actively realizing this or not, data is always an input into our creative process.

Conclusion

The use of data-driven AI approaches to making and marketing a pop song in 2022 directly led to higher stream counts on Spotify. It was an effective method because it allowed us to better understand our listeners’ preferences, similar song structures and melodies, meaningful lyrical phrases, and the structure of a successful song. While it is difficult to say if an AI will ever fully replace a composer or musician, the exponential growth in AI advancements does point to a world where this could be possible. AI technologies are now capable of creativity. They can take an idea and add a unique spin to it. Whether or not one believes they are capable of replacing humans comes down to the definition of creativity and if they believe it can be taught and learned. While as of right now AIs are not generating completely original ideas, since their creations are based on input, there will probably come a time where they can be defined as creative because they get so advanced that they start to generate new ideas based off of their previous ideas. This would cut out the human input component. One researcher on this topic is “very fond of Cope's remark that ‘Good artists borrow, great artists steal’” (Adams, 2010). Thus, he believes, as do many, that creativity is rooted in taking different ideas from others and combining it to make original creations. This is exactly what AI is doing. Thus, with AI advances showing no signs of slowing down, it won't be long before a computer can be used to make new versions of every musical genre that are indistinguishable from human-composed pieces. AI can work creatively and even innovate, by creating new concepts and exploring new sounds that have never existed before. While many feel that there will always be a human component to making music, it is hard to ignore that AI technologies will improve to the point that the outcome of a human process will be indistinguishable from an AI informed process. AI is already doing it faster, but with more time, it has the potential to also increase its quality of music to the human level and beyond.

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Appendix
Questionnaire Raw data