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HOW AI SHAPES MUSIC RECOMMENDATIONS AND CONSUMER PREFERENCES

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ABSTRACT
Artificial Intelligence (AI) has changed how people find, listen to, and interact with music. AI-powered recommendation systems are a key part of the personalized experiences that streaming services such as Spotify, Apple Music, and YouTube provide to their users. These recommendation systems match listeners' tastes and interests but also work to influence consumers' preferred behaviour and ultimately reshape the global music industry. Here we have a detailed exploration of how AI operates within music recommendation systems, helps shape consumer behaviour, and the wider implications beyond music recommendation systems themselves. To achieve this, we draw upon some technological fundamentals, real-world examples, and academic literature to analyse the opportunities and challenges posed by AI-driven, personalized experiences. The paper talks about the analytics over the data to perform certain action and then take knowledgeable actions on it. The paper is analysed using machine learning algorithms on different parameters like precision, recall and accuracy scores. Confusion matrix is drawn to understand the implication of data on the consumer preferences.
KEYWORDS: *Recommendation System, personalized, technological perspective, Artificial Intelligence, Digital Revolution.*

1. INTRODUCTION
Artificial Intelligence (AI) has changed the way lives and depicts the life in technology paradigm [1]. Digital revolution is a technology paradigm in the new century. AI is more than a tool to do it did and used to create, distribute and consume in the digital world.

Music has always been a universal communication in day to day life that cuts across cultural, social, and geographical separation. With technology breakthroughs, particularly with the advent of the internet and continued explosion of digital platform revolutions, the way people experience and engage with music has experienced an astonishing amount of change in this new climate. Traditionally, listeners would rely on radio stations, record stores, or recommendations from others to find new tracks or bands. With current music streaming platforms having millions of songs, millions of artists who have produced millions of playlists from every genre imaginable, there is much more than one person could ever discover alone.

Artificial Intelligence (AI) tackles this issue by processing [2] large quantities of data and issuing individualized recommendations. AI systems assess patterns of listening behaviours to anticipate what a user is likely to like. This expands the listening experience and shifts general consumer preferences and industry developments. Here we will explore how AI operates in music recommendation systems, how it shapes consumer behaviour, and its future benefits and limits.

2. AI IN MUSIC RECOMMENDATION SYSTEMS WITH MUSIC EXPOSURES
A recommendation system is a software program that recommends or suggests an appropriate action to take for a certain set of tasks. It also understands and reads the preferences and behaviours of the customer before recommending an action [3]. There are different platforms to read and analyse before taking the optimal decision i.e. dependent on multiple criteria's. There are different types of recommendation systems: -
1. Collaborative Filtering Systems
2. Content Based Filtering Systems
3. Hybrid Recommendation Systems
4. Context Aware Recommendations

Collaborative Filtering: Collaborative filtering [4] relies on the assumption that individuals who share similar listening patterns will also enjoy similar songs. There are two main approaches in collaborative filtering: user-based and item-based collaborative filtering. In user-based filtering systems, the system identifies users with similar listening histories and recommends tracks accordingly. In item-based filtering system, the system finds relationships between songs based on how frequently they are co-listened. For instance, if users who like Song A also enjoy Song B, the algorithm will recommend Song B to other listeners of Song A. While effective, collaborative filtering faces challenges such as the 'cold start' problem for new users or songs, and data sparsity when user-song interactions are limited. The algorithm reads and understands the patterns among themselves.

Content-Based Filtering: Unlike collaborative filtering, content-based filtering emphasizes the attributes of songs themselves [5]. It analyzes musical features such as tempo, key, rhythm, instrumentation, and lyrical content. If a user enjoys slow, piano-based ballads with emotional lyrics, the system will recommend other songs with similar profiles. Content-based methods are effective in reinforcing a listener's preferences but may limit exposure to unfamiliar genres. For example, a listener who primarily enjoys classical music might rarely be exposed to hip-hop or electronic genres unless hybrid or exploratory techniques are used. The algorithm understands the temperament of the listener and accordingly suggests the right music to them. To increase the accuracy of the algorithm for the recommendations content and collaborative filtering works together by yielding efficient and effective results [6].

Hybrid Models or Hybrid Recommendation Systems: Most streaming platforms now rely on hybrid models that combine collaborative filtering systems and content-based filtering systems [7]. These models aim to balance familiarity and novelty of the algorithm by understanding the mechanics of the right music recommended to the listener. The most seen example is Spotify song recommendation. It sees signals from users that blends into suggestion of different songs according to the frequency. Hybrid Recommendation system minimizes the problems of systems suggesting alone as a device and provides user with a richer experience of listening. These systems do proper analytics of the user's data before making the suggestions to the listeners [9].

Context-Aware Recommendations: Artificial Intelligence (AI) is used to provide suggestions based on context-aware recommendations [10] according to the mood, activity and environment of the listeners. For example, when a user is working out, a platform may recommend an energetic playlist, or when studying, music that is calming or soothing. Music recommendation platforms also consider more than just moods and may recommend certain genres at certain times of day. Additionally, sensors on smartphones and wearables could help to refine these contextual recommendations as they could provide relevant contextual signals, such as time of day, activity, location, heart rate and so on. This type of personalization shows the increased level of sophistication from AI in understanding how to personalize music experiences for listeners' lived realities. In the future we may not have to select specific contexts as these platforms will be able to make recommendations simply by understanding our moods and making recommendations for us based on specific artists, genres etc.

In our day to day life we listen songs on Spotify, YouTube music and other song listening platforms that recommend songs according to the streaming history, listening preferences, artist and music exposure and the revenue generation benefits.

3. HOW AI SHAPES CONSUMER PREFERENCES AND IMPACT BUSINESS GROWTH

Artificial Intelligence interprets the processing history of the data, analyzes it and then takes the desired action based on the pre-processed data. Below are the few key features that consumer preferences are shaped or altered in their daily living.

- **Music Discovery and Exploration:** One of the most celebrated benefits of AI-driven systems is music discovery. By analyzing listening habits and cross-referencing them with global data [11], AI can expose users to new artists, genres, and even languages they might not have explored otherwise. This discovery process enhances cultural exchange and broadens the horizons of listeners. For example, the global spread of genres such as K-pop, reggaeton, and Afrobeats has been amplified by recommendation systems that suggest tracks beyond national borders. This form of recommendations adds the effect of personalization irrespective of global diversity.
- **Reinforcement of Tastes:** Artificial Intelligence also reinforces existing preferences [12] by continuously recommending similar songs according to the tastes of the users. This creates a feedback loop where listeners' tastes become more defined and stable over time. While this reinforcement can be satisfying, it also raises concerns about limiting diversity and creating musical echo chambers. For instance, a listener who primarily listens to indie rock may rarely encounter electronic or jazz music, even though these genres might appeal to them if given the chance. So, sometimes this personalized recommendation negatively influences the preference of the listeners.
- **Impact on Consumer Behaviour:** Artificial Intelligence driven personalization influences not only what listeners consume but also how they consume it. Shorter attention spans have led to an increase in track skipping, which recommendation systems analyse to refine predictions. This has also influenced the industry: songs are now being structured to capture attention quickly, often within the first 30 seconds, to avoid being skipped. Thus, AI shapes both consumer behaviour and the very structure of the music they consume. Therefore, the behaviour defines the way people consume and like the recommendations nowadays [13].
- **Globalization of Music Trends:** Recommendation systems promote globalization by highlighting songs that are trending worldwide. A viral hit in one region can quickly become an international phenomenon as AI amplifies its reach. The meteoric rise of hits like 'Despacito' illustrates how AI-fueled recommendations [14] contribute to global music culture. This has positive effects, such as increased cross-cultural appreciation, but may also lead to homogenization where global hits overshadow local artists. The heterogeneous mixings of music lead to greater retention of the artists leading to decreased cross cultural boundaries.
- **Impact on Artists and the Industry:** Artists and producers are increasingly aware of how AI shapes music discovery and consumer engagement. As a result, many now tailor their creative processes to optimize for algorithmic visibility. Features

such as shorter intros, frequent hooks, and consistent beats are designed to align with what AI systems tend to recommend. This has sparked debates over whether AI-driven preferences promote or constrain artistic creativity [15]. This has leads to the continuous debates all over the world that whether AI promotes or degrades the creativity of the music artists.

- **Benefits of Artificial Intelligence in Music Recommendations:** Artificial Intelligence brings significant benefits to both consumers and the music industry. For listeners, AI saves time by curating customized playlists, introduces new artists, and adapts to moods and activities. For the industry, AI increases user engagement, boosts subscription retention, and provides emerging artists with opportunities to reach global audiences. Furthermore, AI enables data-driven insights into consumer behaviour, helping record labels and independent artists make informed marketing and helps in taking creative decisions [16].

Algorithmic biasness is one of the prominent problem in the usage of AI. It streams and learns from a single source of training data and then make recommendations. Some artists have higher visibility whereas other local artists are shadowed and their visibility becomes lower. It results in advantageous favour to a certain set of population and resulting in biased data. Training results and their outputs are the biggest ethical challenge in AI.

4. HOW DATA DRIVES MUSIC STREAMING

AI powered music recommendation system that personalizes song suggestions based on user's sentiment analysis. It contains user-generated text, detected emotions, and corresponding music recommendations with relevant song attributes. The dataset can be used for sentiment classification, music recommendation modelling, and Natural Language Processing (NLP) [17] based on emotion recognition. Artificial Intelligence tries to understand the streams of the data streaming more over the internet and then recommends the right music accordingly to the listener.

Some of the key features of the dataset are: -

Feature	Description
User ID	ID of the user
User Text	Expressing emotions using text input
Song Name	Recommending the name of the song
Artist	Music Artist of the song recommended
Genre	Genre of the song classified
Beats Per Minute (BPM)	Temp of the song
Mood	Emotional tone of the song i.e. Joyul, sad, angry, slow etc.
Sentiment Label	Sentiments of the songs i.e. happy, sad, relaxed, motivated etc.
Energy	Energy level of te song i.e. high, medium, low.
Song Recommended	Unique identification of the song recommended
Dance ability	Suitability for Dancing i.e. high beats, low beats or medium beats.

Further, the data is cleaned, pre-processed and normalized for performing the predictive analytics over the data. The data is processed on Python for making analytics over the data using the standard libraries. Load the data check for the missing values if any. Apply text cleaning operations on the different sentiments of data [18]. If there is any missing value or the out of range value pre-process and correct it i.e. handle any outlier operations. Figure 2 depicts training the model using the machine learning algorithms and then make predictions. The data of music recommendations on different genre, classical or traditional customs is used. Machine learning algorithm is sued and trained. Pre-processed features are trained and tested in order to understand the efficacy of the music.

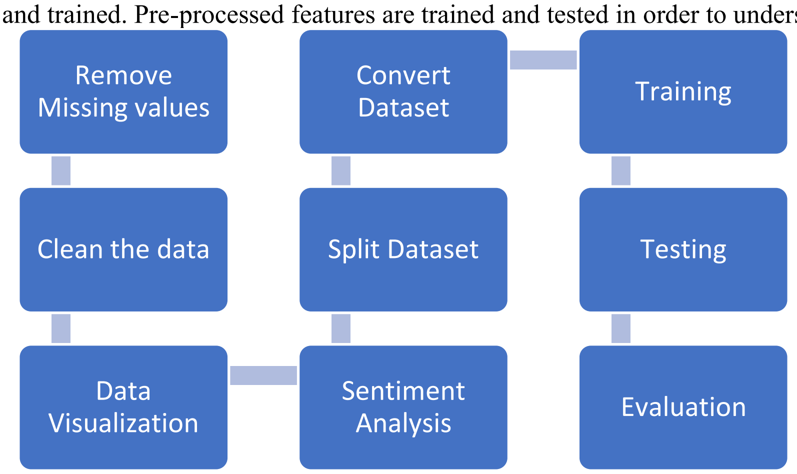

Figure 1: Exploratory Data Analysis

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Confusion Matrix

Confusion Matrix as shown in figure 2 is useful for evaluating the effectiveness of a classification method. It provides a brief summary of the outcomes, categorizing them as true positives, true negatives, false positives, and false negatives. It's a useful tool for determining the model's correctness and detecting certain sorts of flaws.

- True Positives (TP): Instances in which the model predicts the positive class properly.
- True Negatives (TN): Instances in which the model predicts the negative class.
- False Positives (FP) are cases in which the model predicts the positive class when the real class is negative.
- False Negatives (FN): When the model predicts a negative class when the real class is a positive class.

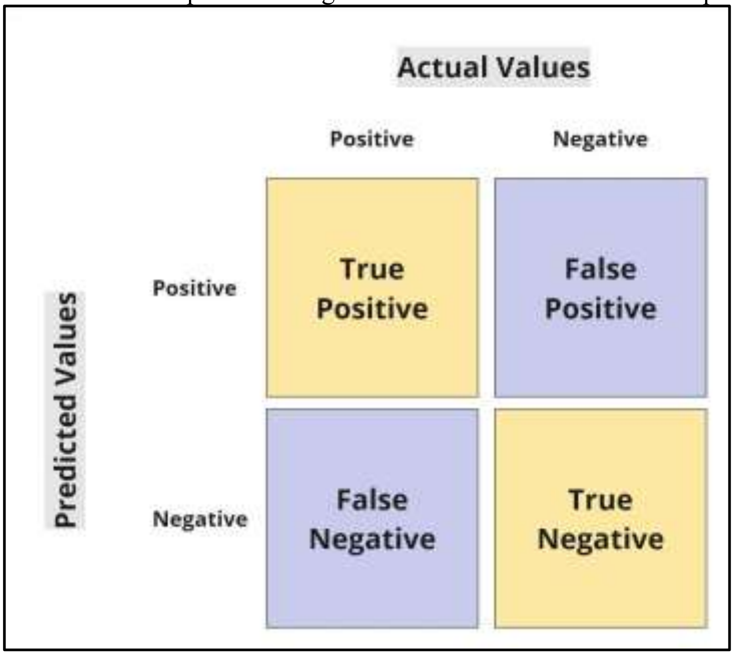

Figure 2: Confusion Matrix

Figure 5 shows that the Exploratory Data Analysis (EDA) to visualize the data. Remove missing values i.e. handle outliers clean the data and visualize it for better understanding. Convert the attributes into numerical attributes [19]. Split the dataset into training and testing and then apply the evaluation parameters.

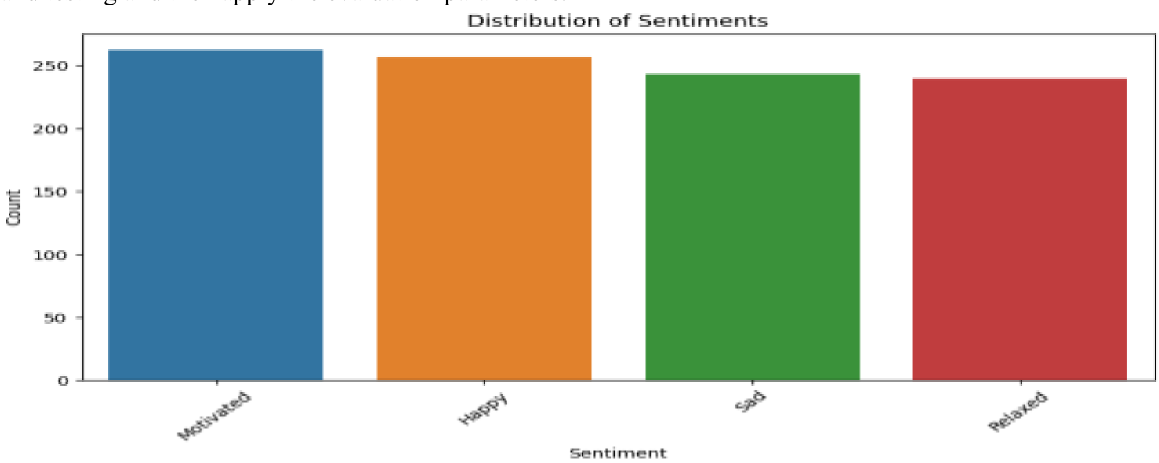

Figure 3: Distribution of sentiments

Figure 3 depicts the sentiments of the people on four different aspects i.e. happy, sad, relaxed and motivated. Measure the performance of the data using the performance evaluation parameters like precision, recall, F1-Score and support values.

- Precision: Precision is the ratio of total predicted positives (TP + FP) to total predicted positives (TP + FP), emphasizing the accuracy of positive forecasts.

$$Precision = \frac{TP}{TP + FP}$$

- Recall: The ratio of TP to total real positives (TP + FN), concentrating on the model's capacity to catch all positive cases.

$$Recall = \frac{TP}{TP + FN}$$

- F1-Score: A balanced metric based on the harmonic mean of accuracy and recall.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

- Support: The number of instances of each class in the provided dataset.

$$Support = \frac{No. Of\ transactions}{Total\ no. of\ transactions}$$

Table 1: Performance Evaluation

Parameter	Precision	Recall	F1-Score	Support
Happy	0.84	0.785	0.74	0.88
Sad	0.83	0.72	0.82	0.80
Motivated	0.81	0.73	0.82	0.84
Relaxed	0.82	0.82	0.81	0.90

5. CHALLENGES AND CONCERNS

Artificial Intelligence has some challenges also; when used in real world applications such as [20]:

1. The foremost risk of AI driven applications is the filter bubbles i.e. users are exposed to similar content repeatedly. This leads to the lack of interest among listeners. Due to which listeners listen to same type of content repeatedly without experiencing different genres. Sometimes, AI driven apps stereotype about certain set of audience choice that reduces the experience of listening.
2. The data of the users gets hacked heavily on the basis of their personal choice like the history of listening, location, the device they utilize their biometric signals and many other traits of the users. This leads to varied concerns among population and the personalization of data.
3. Biasness towards one type of choice of data in music economy. Algorithms are pre-trained over certain set of choice of data while others don't get enough privilege for the same. This is the major concern among musicians also having different diversity of genres.
4. Transparency of data is another biggest concern in AI applications. Users are unaware the way choices are produced before them. XAI comes into the fields that helps unveil the recommendations produced by AI.

6. CONCLUSION

Hence, we can say that AI has changed the way we think, process and live. Recommendations have become the important characteristics of AI. Music industry is greatly benefitted the way AI reads the data makes interactions with listeners by recommending the right choice of song according to their listening preference. AI uses time context and pre-trained algorithms to discover the patterns of the data. AI provides a unique balance between the personalization and recommendation of data to the users. The ethical and cultural diversity are the main core of the data analytics to be preserved. The paper talks about the efficient methods for streaming the right choice to the users and it also develops the right algorithm to be targeted. Data is trained on the several parameters like happy, sad, motivated and relaxed on the parameters such as precision, recall, F1-score and support and their accuracy values are recorded. The future lies in AI showing personalized recommendations, having interactive experiences, having different genres and immersive experience to the users.

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