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ANALYZING THE RELATIONSHIP BETWEEN INTERNATIONAL MUSIC SALES, AUDIO ATTRIBUTES, AND NATIONAL CULTURE

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ABSTRACT

Musicology refers to the study of music. As an interdisciplinary topic, the use of technology in the study of music is an emerging area of interest to marketers, IS/ISA professionals, music entertainment managers, and musicians. For instance, music streaming services provide an excellent opportunity to recommend songs, artists, and genres to listeners, based on prior listening habits and the listening habits of others who are similar. While the current listener recommendation systems have shown some success for within-country recommendations, they have proven inadequate when providing recommendations for songs foreign to a listener's home country. This study explores audio musical attributes, including key, tempo, average pitch, and song length, and examines relationships with Hofstede's cultural values and associations towards wider recommendation systems. We found strong correlations between tempo and both Power Distance and Uncertainty Avoidance; average pitch and Masculinity; key and Indulgence, and song length and Individualism. Culture may thus provide additional predictive capabilities for current recommendation systems, particularly for locations beyond the home country. Our work provides preliminary insights towards music streaming recommendation systems that may help record labels, artists, and other owners of intellectual property predict commercial success of their music across different cultures around the world.

Keywords

Musicology, International music, Audio attributes, Recommendation systems, National culture, Hofstede's culture

INTRODUCTION

Emerging from the ashes of the shaken music industry and the dismantled peer-to-peer illegal websites were new ad-supported streaming services such as Pandora, Spotify, and Apple Music. These streaming services allow listeners to unlimited amounts of music for free, in return for viewing targeted advertisements, revenue from which compensates for the musical IP rights. More recently paid streaming alternatives emerged, with the user paying a monthly fee for unlimited listening and compensating the lawful owners of music intellectual property (IP) rights. Streaming dominates the music market today, contributing to the tune of 80% of total revenue (Halperin, 2021). Users now have easy access to almost any song that has ever been recorded. Thus, subscribers face virtually unlimited options for the music they choose to stream. While search and personalization both are efficient with today's technology, music listeners often enjoy hands-off listening where likable songs are recommended or offered in queue. As a result, intelligent customization of song streams is an efficient way to create brand value and exercise competitive superiority in the market. Thus, streaming services needed a way to differentiate their products from other, almost identical products. With large amounts of music data available, streaming services began to develop methods to improve recommendations; the better the recommendation, the happier the users would be (Xu, 2020). Schrage (2021) notes: "Superior recommendations measurably build superior loyalty and growth; they amplify customer lifetime value" (p. 18). However, creating an accurate recommendation system is challenging. Researchers have tried content-based genre classification recommendation systems, with mixed results, particularly for beyond-mainstream users (Kowald et al., 2021).

One way to create superior streaming strategy is to include music from diverse geographical origins when there are musical factors bearing similarities to local music attributes. The choice typically enriches streaming music at a lower cost per incremental unit, when chosen from niche or low-cost music rights: long tail marketing opportunities in e-commerce have been shown to offer attractive and successful strategies (Oestreicher & Sundararajan, 2009). However, international music recommendations have poor track record. This research uses an alternative lens to analyze how international music can enrich music streaming and recommendation and focuses on the listeners bearings and countries of origins rather than the songs and their genres. Specifically, this research attempts to integrate Hofstede's culture attributes, which are country-level variables, in concert with musical attributes of songs, to explore expanded opportunities towards improving international music recommendation systems. More accurate listener recommendation systems for global consumers of music, streaming service providers, and owners of IP rights have implications for technology, marketing, and musicology.

SUBMISSION TYPE

Completed research – Information systems in society

LITERATURE REVIEW

Music Information Retrieval

While experts do not always agree on the definition of music information retrieval (MIR) (Cottrell, 2018), it generally refers to any technology used to recognize patterns in recorded music (ISMIR, 2019). While some data scientists have studied big music data (BMD) simply for musicological purposes without any business application (Leung & Zhang, 2019), there is a clear need for new and improved MIR technology to solve business problems, especially with the rise of BMD.

Listener Recommendation Systems

One business problem is how to recommend good music options to globally diverse users. Listener recommendation systems (LRSs) typically use collaborative or content-based filtering techniques-. Collaborative filtering groups customers into clusters based upon which songs they choose and how much they enjoy the songs, making new music recommendations for users in the same clusters (Boyd, 2019). By contrast, content-based filtering analyzes individual-level variables, basing future music recommendations on similar choices that the user enjoyed in the past (Ecemboluk, 2020). Content-based LRSs are effective, but adequate training data is needed, along with up-front costs and access to detailed user listening history (Rodriguez-Hernandez et al., 2020). Two content LRSs are Pandora's Music Genome Project and Musimap.

Utilized proprietarily by the internet radio service Pandora, the Music Genome Project uses a complex algorithm to classify recorded songs based on over 400 musical attributes (Pandora, 2021). Pandora Radio selects what songs it will play to its users based upon the principle that if users like a particular song, they should also enjoy songs with similar attributes.

Another effective content based LRS is a technology product called Musimap (https://www.musimap.net/home). Musimap's algorithms have been designed to link musical attributes to emotions and moods; for instance, the technology could select a song to play in places of business based on the desired emotional response for customers.

Content Based Variables Selected for the Study

While selecting audio attributes to utilize for this study, we began by analyzing the main elements of music itself. Many musical scholars provide a similar set of elements of music, including rhythm, meter, pitch, melody, texture, tone color, and form. Cottrell (2018) suggests a smaller set of musical elements that comprise BMD: tempo, key, pitch, and meter. When deciding which elements to include, we identified the difficulty of quantifying the variable and the variable's potential relevance in the global music market. We selected the following four variables for our study, all of which were derived from the elements of music: tempo, key, pitch, and length.

Representing the musical element of texture is *tempo*. Although there are other aspects of texture (such as a musical work's monophonic vs polyphonic nature), music tempo is more easily quantifiable (by beats per minute) and varies amongst different cultures' popular music groups.

Melody and harmony are represented in our study by the musical concept of *key*. Variations of preferred musical key seem evident in songs from different cultures; however, it is difficult to quantify musical key. We resolved this issue by using the Camelot Key System (CKS), which attaches a numerical value from 1-12 for each potential key a song may possess. We found a tangible connection between the ordering of keys in the CKSs and the preference for those keys by different cultures.

The musical elements of pitch, and by extension, melody, are represented by the attribute of pitch. Pitch refers to the listener's perception of a particular note being higher or lower than other notes. Derived from the concept of frequency and measured in hertz, pitch is easily quantifiable. Further, Trafton (2019) suggested that pitches can be perceived differently by culture.

Representing the musical element of form is length. Length, in contrast to other sub-elements of form such as arrangement, is easily quantifiable, as measured in second for our study. Differing song lengths are seen often amongst popular music from different nations, making it a potentially good choice for our research.

Culture and International Business Applications

While helpful, LRSs are not without limitations. Bauer and Schedl (2019) demonstrate that content based LRSs tend to fare poorly when moving beyond a listener's home culture. Further, Schotanus et al. (2018) suggested that musical attributes may be linked to a song's popularity in each culture. Thus, we sought to analyze if a new form of LRS would be a better predictor for suggestions beyond a user's home culture. The new content based LRS focuses on musical attributes and national culture.

Widely accepted Hofstede's model of culture, which analyzes how values are influenced by culture (Hofstede Insights, 2020) may assist in developing models based on culture. Culture in this context is defined as "the collective programming of the mind distinguishing the members of one group or category of people from others" (Hofstede Insights, 2020). Liu et al. (2018) found a positive relationship between Hofstede's cultural factors and countries' favorite musical genres. Integrating culture with audio attributes to determine listener musical tastes may lead to better recommendation models in international contexts.

Cross-cultural Listener Recommendation Systems

The use of data analytics to create engaging LRSs for streaming services has great applicability to global contexts. Bauer & Schedl (2019) suggested that music that is not mainstream to a particular culture would be poorly recommended to music listeners with current methods that fail to rely on heavy data analytics. Zhou (2020) concurs and suggests the use of advanced data science methods, such as neural networks and artificial intelligence, to identify trends in listener habits from disparate countries and cultures. Without access to large music databases for all countries, Schotanus et al., 2018) showed that trends in a song's musical attributes can be directly linked to the song's commercial success in a particular culture. Armed with this knowledge, producers may recommend changes to music or decide to market to a more culturally receptive audience.

METHODOLOGY

We developed a 2-phase process to gather data.

Phase 1

We identified the top eight music-consuming nations in the world (International Federation of Phonographic Industries (IFPI), Yearly Music Sales Report, 2020). The US is the largest market, followed by Japan, Germany, and the UK (Music Production & Distribution, 2016). Although China is one of the world's top music consuming nations according the to the IFPI, we had great difficulty finding accurate music charts; therefore, we ultimately excluded China from the analysis.

Next, we identified the top 20 commercially successful songs by year (2018-2020) from the eight nations selected. The top songs were identified through various international music charts. For each nation, we created a musical profile, See Figure 1 for the Japan musical profile as an example.

	A	B	C	D	E	F	G
1	Japan Profile	Tempo (BPM)	Key (Camelot Harmonic System)	Average Pitch (Mean Hz)	Song Length	**Aggregate Average Tempo**	**126.9924242**
2	**2020 Average**	**127.9393939**	**7.333333333**	**63.19387879**	**241.0606061**	**Aggregate Average Key**	**7.166666667**
3	I Promise (King & Prince)	124	7	58.319	266	**Aggregate Average Pitch**	**64.03982576**
4	Nobody's Fault (Sakurazaka46)	110	10	64.63	270	**Aggregate Average Song Length**	**246.780303**
5	Step and a Step (NiziU)	116	8	63.773	221		
6	New Era (SixTones)	172	7	71.462	195	Unobtained charting songs	5
7	Homura (LiSA)	152	10	59.304	274		
8	Kissin' My Lips (Snow Man)	110	4	59.386	201	**Hofstede's Cultural Dimensions**	
9	Your Song (Hey! Say! JUMP)	96	9	59.919	238	Power Distance	54
10	Yoru ni Kakeru (Yoasobi)	130	5	60.316	281	Individualism	46
11	Endless Summer (Kis-My-Ft2)	132	8	62.512	186	Masculinity	95
12	Omoidaseru Koi wo Shiyo (STU48)	124	8	69.436	308	Uncertainty Avoidance	92
13	Oh-Eh-Oh (JO1)	133	7	69.736	184	Long-Term Orientation	88
14	Re:Live (Kanjani Eight)	153	11	61.766	192	Indulgence	42
15	Smile (Twenty Twenty)	110	8	60.854	343		
16	Run (Sexy Zone)	130	10	62.362	230		
17	Kite (Arashi)	89	12	59.065	283		
18	Navigator (SixTones)	145	4	64.138	186		
19	Fanfare (Twice)	115	3	66.382	256		
20	Last Mermaid (Hey! Say! JUMP)	155	10	66.717	232		

Figure 1. Musical Profile for Japan

Then we obtained MP3 versions of the 480 songs identified. Tempo is measured through beats per minute (BPM). To identify BPM, we uploaded each song's MP3 to the Tunebat online MIR software. BPM ranges from 60-200 for popular music.

Next, we identified the song key. We used the CKS, which numbers 1-12 for keys. Keys were determined by uploading the MP3 to the Tunebat MIR; once the key of each song is identified in Tunebat, it is converted using the CKS.

Then we collected the average frequency, measured in Hz. To obtain frequency, we used Nyquist code, developed by computer engineer Riley Shaw (https://rileyjshaw.com), and used with permission. Song length (in seconds) was easily obtainable. After collecting the data, we computed overall averages for the attributes for the years 2018-2020, resulting in four overall average values (pitch, tempo, key, frequency).

Phase 2

In Phase 2, we completed a series of statistical corrections comparing a country's overall musical profile with its Hofstede cultural dimension scores. In all, 24 individual correlation analyses were conducted (6 cultural dimensions x 4 musical attributes). Other statistical methodologies were conducted as well. Based on the results, we determined potential impacts and business ramifications for LRSs and international music marketing and made suggestions for future research.

ANALYSIS AND RESULTS

Two main analyses were carried out upon the collected international musical data: A correlation analysis (to determine if linear relationships exist between Hofstede's cultural dimensions scores and the quantifiable musical attributes of a nation's popular recorded music) and a logistic regression (to discover if audio musical attributes can be used as predictors of a song's commercial success in a foreign culture). The results of the analyses are detailed below.

Correlation Analysis

Several significant correlations were identified, as shown in Table 2.

	Hofstede's Culture Variables					
Audio Attributes	**PDI**	**IDV**	**MAS**	**UAI**	**LTO**	**IND**
Tempo	0.81			0.82		
Key						-0.71
Pitch			0.89			
Length		-0.73				

Table 2. Significant Correlations Between Audio Attributes and Hofstede's Culture Variables (p-values<0.05)

Logistic Regression Analysis: Predicting Song Success in Foreign Cultures

We used logistic regression analysis to see how accurate a hypothetical system might predict in which nation(s) a particular song would likely be commercially viable.

We ran a logistic regression with the RapidMiner statistical software. We used song attribute data taken from two nations in the study: United States and Japan. The results, shown in Table 3, indicate that a logistic regression model utilizing audio musical attributes could predict whether a song would be most successful within the United States or Japan with an accuracy of 77.43% (+/- minus 12.98%) overall. Other metrics of fit (precision and recall) were also high. Predictive capabilities were higher at 81.67% for the United States, with Japan trailing at 72.73%.

Country	**True 1**	**True 0**	**Class Precision**
Japan	11	40	76.56%
United States	49	15	78.43%
	81.67%	72.73%	
Accuracy = 77.42% +/- 12.98%; micro-average = 77.39%			

Table 3. Results of Logistic Regression

DISCUSSION

This analysis provides initial results of a hybrid LRS, using musical attributes and cultural dimensions from Hofstede's framework to predict whether a song may be commercially successful across a range of countries. We then test the model using two countries; we find strong predictive capabilities in the initial model. These results offer insights into the potential relationships between attributes of commercially popular music and cultural artefacts.

Hofstede's dimensions of uncertainty avoidance (UAI) and power distance (PDI) both have strong positive correlations with the audio musical attribute tempo. Amongst the nations studied, the tempo of commercially successful songs tends to be higher in nations scoring higher in UAI and PDI. It can be suggested, therefore, that amongst the cultures in the study, cultures that tend to value societal equality and have less regard for societal norms (in other words, cultures scoring low on both UAI and PDI), slower, more low-tempo music may be more commercially successful.

We have insights in the audio musical attribute key that may be relevant to the analysis. Almost every nation studied had an average key of 6.5 on the CKS; this indicates that on average, commercially successfully tend to be in B-flat major or D minor. However, an average key exactly in the middle may indicate high variability between countries and should be evaluated with additional studies, larger samples, and diverse countries. However, it is interesting to note that there is a strong negative correlation between key and IND. Perhaps nations scoring low on IND (meaning they tend toward hedonistic pleasures) prefer songs on the upper end of the CKS? Perhaps although the lack of variation within the dataset suggests a cautious approach. Average pitch (measured in Hz) showed a strong positive relationship to MAS. Perhaps songs which include higher notes on the musical keyboard tend to be more commercially successful in cultures that emphasize assertiveness and strength.

Finally, song width shows a strong negative correlation with IDV. Amongst the countries in this study, more collectivist societies (those with low IDV scores) also tend to enjoy longer songs, while more individualistic countries prefer shorter songs.

Implications for Listener Recommendation Systems

We provide several preliminary observations from our exploratory study. LRSs at their core, have always been about individual listeners. We offer an alternative method of recommending music through knowledge of the home country and its cultural profile, as well as through consideration of song attributes.

Much of the scholarly discussion on LRCs has centered on creating a highly individualized recommendation system for listeners. Our results suggest that designers of LRCs may have an additional tool to use. Perhaps it is possible to recommend what a country (as a whole) might find appealing (in terms of song attribute). By understanding the home country, it may even be possible to develop incrementally stronger LRSs. However, in is instructive for developers to know that Hofstede's values are meant to be taken from a national perspective and not an individual perspective – although there are numerous instances where culture has been used for individual analyses. Our results do, however, indicate that LRSs may have increased predictive capability when the user's home culture is known. For instance, knowing that individuals in a high MAS-country prefer higher average pitch adds predictive power to the LRS. Combining understanding of the cultural attributes of a home country with knowledge about song attributes and the user (through data analytic profile), enhances the predictive power of LRS.

We have used logistic regression to use quantifiable audio music attributes, along with the country, to predict whether a song will be commercially successful. We caution, however, that we have a small dataset and evaluated only the top eight countries in terms of sales, and only the most successful songs. Our attempt here is to demonstrate that we have another tool which may be of benefit to the musicology community.

Implications for International Music Marketing

Aside from LRSs, the results of our study could have value for record labels, agents and musicians, other holders of IP rights, marketing managers, and technology their music. Technology professionals may better understand musicology and design better systems. Much work remains to be done in this area, and our current research shows one way to explore further.

Future Research Opportunities

We have analyzed eight of the top music-consuming nations of the world. Clearly, it stands to reason that a more comprehensive study should be undertaken which includes many more nations. Further, we only used four audio attributes in our analysis; more attributes may lead to better predictive capabilities for LRSs. In addition, we used a small amount of data, and LRSs typically have millions of data points suggesting deeper insights. Moreover, due to the difficulty in acquiring data on Chinese music, we were unable to analyze how our models might perform in the most populous country in the world.

Building upon the previous suggestion, future research should include more than just the top commercial music of the studied nations and cultures. Also, most charting music in our study was written as "pop" or popular music. Other genres may find different results. Moreover, most of the music was 4/4 (common) time. A more diverse sample may yield different results.

CONCLUSIONS

Although humans have been studying musicology for many years as a method of understanding how music and psychology related, LRSs present a practical business reason for studying musicology. In order to keep listeners engaged with their preferred streaming platform, such platforms need to find a way to gain a deeper understanding of how people from different cultures think and behave. Content-based LRSs, with an added element of cultural awareness, seem to present a potential improvement for solving the difficult problem of knowing what kind of music to market and recommend internationally. This study provides an important contribution to the field, upon which future studies may be built.

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