The Study of Comparing Korean Consumers' Attitudes Toward Spotify and MelOn: Using Semantic Network Analysis

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Abstract

This study examines Korean users' attitudes and emotions toward Melon and Spotify, which lead the music streaming market. We used Text Mining, Semantic Network Analysis, TF-IDF, Centrality, CONCOR, and Word2Vec analysis. As a result of the study, MelOn was used in a user's daily life. Based on Melon's advantages of providing various contents, the advantage is judged to have considerable competitiveness beyond the limits of the streaming app. However, the MelOn users had negative emotions such as anger, repulsion, and pressure. On the contrary, in the case of Spotify, users were highly interested in the music content. In particular, interest in foreign music was high, and users were also interested in stock investment. In addition, positive emotions such as interest and pleasure were higher than MelOn users, which could be interpreted as providing attractive services to Korean users. While previous studies have mainly focused on technical or personal factors, this study focuses on consumer reactions (online reviews) according to corporate strategies, and this point is the differentiation from others.

Keywords : Semantic Network Analysis, Spotify, MelOn, Streaming Music, Consumer Attitude

1. Introduction

Advances in Information Technology (IT) have brought to rapid changes in various industries, and the changes are still underway. The music industry is also going through a turbulent period with the incorporation of IT technology [Avdeeff, 2012]. Technological advances have transformed the concept of music from listening with physical constraints such as place and time to relishing with a new concept that anyone can enjoy anytime, anywhere [Krause et al., 2015; Heye and Lamont, 2010]. On account of research on the digitalization of the music industry has been discussed for a long time [Snadler, 2007], researchers nowadays enable research and analysis of various musical elements. However, there has been research and controversy in the past about digital music (called online music) consumption. Sharing P2P files provided by Napster, it initially approached mainly from an illegal and unscrupulous perspective [Fisher, 2004; Levin et al., 2007]. However, over time, music consumption has expanded from analog to digital and has been chosen by consumers, and it has changed from an illegal and unscrupulous perspective to a legitimate and moral perspective [Sinclair and Green, 2016].

Some studies have shown that online music consumption accounts for 50% of the global music market [IFPI, 2016]. Therefore, it is evidence that online music is leading the growth of the music market and being possible a new source of revenue. In particular, many users use online services using smart devices, and the rate of using smartphones (85.8%) is overwhelmingly higher than other devices such as computers (38.5%) and TVs (31.5%) [The Korea Creative Content Agency, 2020].

In other words, this could be interpreted that consumers who consume online music prefer streaming services on smartphones based on accessibility and convenience [Heye and Lamont, 2010]. In a report on the music industry published by the Korea Creative Content Agency [2020], the Korean music market ranked sixth globally, indicating that 63.6% of users who use music streaming and download services have experienced digitalization. In the study, 52.4% of total users only used streaming services. It means that online music service is expanding in the Korean music market. The development of IT technology has brought about a significant change in the music industry. The technology changed the concept of music consumption and brought about the music market's growth. As a result, the environment of consuming music is also changed from offline to online.

This study aims to understand the attitudes of Korean consumers toward online music services by comparing and analyzing Spotify, a global leader company, and MelOn, a Korean leader company. Furthermore, we would extract important keywords from users' reviews of each company and analyze differences in the service evaluation of users. Previous studies focused on changes due to demographic differences such as income or sex and effects due to technical factors, but this study has a differentiation in that it focuses on consumer reactions (using reviews) by corporate strategies. The purpose of this study is as follows. First, by analyzing the reviews of streaming music users, we would strive to derive user emotion and interest keywords. The user's attitude and preference for streaming music services would be identified based on the result. Second, by comparing and analyzing users' reviews of Spotify and MelOn, we would

identify how Korean users experience the two companies. Finally, we would provide guidelines that reflected user emotions to online music service companies.

2. Theoretical Background

2.1 Previous Studies on Online Music

The online music market began with the first evaluation of illegality and pirates [Cesareo and Pasteore, 2014[. At the time, studies were conducted to prevent such illegal activities [Levin et al., 2007], and psychological and demographic characteristics of illegal activities were conducted [Gray, 2012]. In other words, the online music market was recognized as having a negative effect on the existing music market. However, as a new way of making profits was generated in the music market, the perception of online music changed rapidly. Moreover, the online music market has grown steadily. For example, in IFPI's report [2019], which was the comparative analysis of album sales and online (including streaming) services from 2001 to 2018, album sales, which generated more than \$23billion in revenue in 2001, were reduced to \$4.7billion in 2018, but streaming services achieved rapid growth over \$8.9billion in 2018 after achieving \$1billion in 2012 [IFPI, 2019; Korea Creative Content Agency, 2019].

In general, consumers can take pleasure with music by paying a certain amount of money to listen to online music, downloading and using streaming services, or watching advertisements provided in the middle of the music and listening to music for free. In addition, if consumers pay more than a certain fee, consumers could use both services. The new way of providing music also changed the supply chain of music companies [Graham et al., 2004], and in particular, online music services resulted in a direct connection between consumers and artists, reducing the influence of the companies [Hughes et al., 2003]. In addition, however, consumers could listen to their preferred music more easily and quickly.

Research on online music services has been conducted actively. The research has been conducted on various perspectives, including the negative role of sales as a substitute in the music market [Hiller, 2016; Aguiar and Waldfogel, 2018], the role of supplementary materials [Aguiar, 2017; Kretschmer and Peukert, 2015], and the economic analysis and legal issues of streaming music service platforms [Aguiar and Waldfogel, 2018]. Besides, Tepper and Hargittai [2009] and Smith [2012] conducted research based on demographic criteria. According to the studies, the younger prefer to use the higher use of YouTube and online music, and the older prefer using analog music such as CDs. In addition, research on consumer technology adaptation and music piracy in the online music market was conducted, and specific patterns according to income and gender were also found [North and Hargreaves, 2008]. It could be explained that this research has a difference from previous studies in that users' emotions after experiencing the service depending on the company's strategy would be directly analyzed and make a conclusion from the results.

2.2 Spotify and MelOn

Spotify was a small company that started in Sweden in 2006. Spotify introduced a streaming method based on advertisements [Sletten, 2021]. Two types of free and paid services were provided, and free users had to

listen to advertisements every 30 minutes to continue listening to the following music. Such a system was revolutionary because the existing way to listen to music had to pay a specific cost to buy CDs or LPs or illegally reproduce music on the Internet. However, Spotify's new system reduced the user's debt for illegal copying or downloading music and even provided satisfaction that they paid legitimate costs through watching advertisements [Carver, 2016]. Although Spotify suffered management difficulties due to copyrights, the company had 345 million subscribers as of March 2021, and nearly half are paid users. Spotify launched its service, providing various content and music in South Korea in 2021.

MelOn, which SK Telecom established in 2004, went through Loen Entertainment in 2008 and was merged by Kakao in 2016. It has been divided from Kakao as a subsidiary, and the total sales increased by more than half a billion dollars in 2020. MelOn accounted for about 40% of the market share in Korea, and more than 50% of users listened to music by streaming or downloading services [Korea Creative Content Agency, 2020]. In particular, in the survey, the primary age group using MelOn was 25 to 29 years old, and the number of users subscribed to the service for more than three years. Spotify and MelOn are leaders in the online music market worldwide and Korea. However, with launching Spotify's service in Korea, which could be a changer for the market, direct competition with MelOn has become inevitable. This circumstance could be explained as the background and reason of this study focusing on Spotify and MelOn.

2.3 The Differences between Spotify and MelOn

The streaming service model strategy provided by Spotify and MelOn to users is different. MelOn uses a strategy to listen to music after purchasing a subscription fee. If the license is not subscribed, the user could only listen to up to 60 seconds per song, and more than it could not be played. On the other hand, Spotify provides a seven-day free experience without a procedure for log-in or registration. In addition, from June 2021, if a user registers credit card information, the user could use the service for free for three months and use various other functions. Furthermore, MelOn provides a variety of music-related content, including music videos, radio, comment writing, and most of the lyrics for the songs provided. On the other hand, Spotify provides songs and radio services focusing on listening to music and does not provide functions such as writing comments or videos. In addition, the lyrics of songs are provided fewer than MelOn, and only paid users could check the lyrics. The characteristic differences between Spotify and MelOn could be summarized (〈Table 1〉).

〈Table 1〉 The Difference between Spotify and MelOn Service Models

		Spotify			MelOn		
			Member	Nonmember		Member	Nonmember
Basic Service	Listening Music	Free Service For 7days	○	○	Unable to Listen for free	○	×
	Download Songs		○	○		○	×
Service-related Music	Lyrics	Focusing on Listening	Fewer	×	Providing various contents	○	×
	Music Videos		×	×		○	○

The difference between Spotify and Melon analyzed. Spotify is making efforts to meet customer needs based on an algorithmic customized playlist of individuals. It analyzed the reviews of various users and explained that Spotify also showed advantages in sound quality. However, the cost for service and the number of Korean users who could listen, MelOn is far ahead of Spotify. Spotify and MelOn's service models and strategies are found distinct differences. However, research for comparative analysis from the user's point of view according to the difference in service strategies is not enough. In this study, we intend to proceed with the analysis by judging that such differences in strategies would affect the attitude and emotion of users.

3. Research Methodology

3.1 The Subject and Method of Analysis

For this study, review data was collected. Social Network Service (SNS) was mainly used, and the primary analysis procedure is as follows. After setting the search terms: "Melon App" and "Spotify." The websites for the review data were Naver Blog, Daum Blog, Instagram, Twitter, and Facebook. The programs used for data collection were Textom and Python.

3.2 Text Mining

The text form is generally divided into unstructured and structured data. For example, data classified based on certain conditions and criteria could be defined as standardized data. On the other hand, data composed of various documents or pages on the Internet could be unstructured data. Text mining is a process of finding hidden meanings of text by analyzing various patterns, models, and flows of data from documents [Feldman, 1995; Nahm, 2004]. Text mining has various advantages, such as extracting features from structured or unstructured data, collecting research-related topics or terms from documents, and categorizing in-document data (Choudhary et al., 2009). Because of these advantages, we set up the plan to collect data through text mining.

3.3 Term Frequency - Inverse Document Frequency (TF-IDF)

Term Frequency is a result of calculating the frequency of all words in a single document, and the result could be interpreted that the higher the frequency, the higher the importance of the document [Li and Liu, 2012]. Although, to interpret the importance according to the frequency, it is a possibility that the word is also high in documents on other issues. Therefore, the Inverse Document Frequency value should be obtained, and words with high frequency in other documents should be excluded [Robertson, 2004]. In this study, TF-IDF was used to extract accurate keywords. The method is suitable for extracting words with high frequency from collected reviews and low frequency from other reviews or Internet pages.

3.4 Semantic Network Analysis

Semantic Network Analysis (SNA) is a methodology that could interpret the meaning of the result in detail through using the strength of nodes and links [Feldman and Dagan, 1995]. SNA is different from focusing on a two-way mode for identifying the shape

and pattern of a relationship in the existing network analysis. SNA is a differentiated methodology in that the content of messages flowing in the relationship of results could be interpreted by including the two-way mode analysis.

The advantages and characteristics of SNA are as follows [An, 2017; Jang and Barnett, 1994]. First, collecting data using Social Network Service (SNS) is mainly done, and it enhances efficiency to collect tens of thousands of reviews in a few hours. Second, compared to the survey, SNA could be described that the reviews of participating users are vast and more objective in individual expressions of opinion. Furthermore, users express their opinions in various ways, making it possible to obtain unexpected results. Finally, SNA has the characteristic that research could be conducted by quantitatively analyzing a large amount of qualitative data. For this study, we utilize SNA with these advantages and characteristics.

3.5 Convergence of iteration Corealtion (CONCOR) Analysis

In general, when analyzing keyword-oriented big data, research topics are analyzed through frequency analysis of the main keyword. CONCOR analysis, however, is able to analyze one step more in detail and in-depth than a frequency analysis study. Additionally, CONCOR analysis classifies structural equivalence based on correlations existing between formalized keywords [Wasserman and Faust, 1994]. In addition, CONCOR has the advantage of forming a meaningful cluster and explaining the characteristics centering on the attributes related to between keywords. CONCOR is also the most commonly used analysis method to understand structural equivalence. Therefore, the CONCOR analysis will be used in this study, and the program used is Ucinet 6.0.

3.6 Analyzing Emotional Vocabulary

As the last step of this study, the topics
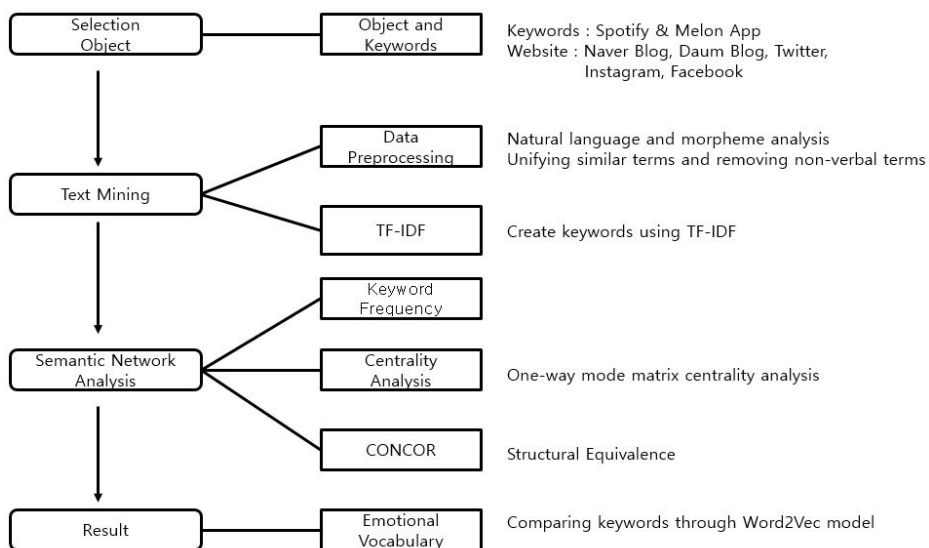
⟨Figure 1⟩ Research Process and Employed Tools

and keywords were summarized again, and the emotional intensity scores of keywords were calculated and compared using Textom's emotional vocabulary dictionary. The model used in this study was Word2Vec, and five words closest to the keyword were selected. Then, the words were specifically compared and analyzed in the consumers' evaluation in detail. The Word2Vec model learns and identifies words belonging to sentences in data as a specific criterion for analyzing word matching. The model expresses meaningfully similar words [Mikolov et al., 2013].

4. Results of Analysis

4.1 Result of Collecting Data

Review data was collected on SNS with keywords 'MelOn App' and 'spotify.' In the case of Spotify, since it started its service on February 2, 2021, in Korea. 5,172 cases of MelOn data and 4,269 cases of Spotify data were collected. Through data preprocessing, 4,630 cases of MelOn and 3,858 cases of Spotify were used for analysis.

4.2 Result of Analyzing MelOn Data

After preprocessing data, elimination of stop-words was conducted, and data were extracted in the form of nouns and adjectives. The processed data identified the frequency of each word, and the top 50 words with a high frequency are as follows (⟨Table 2⟩). For example, Melon showed a high frequency of use, good, song, possible, function, recommendation, YouTube, photo, video, and payment. Additionally, TF-IDF analysis was conducted, and the result is as follows (⟨Table 3⟩).

⟨Table 2⟩ Top 50 Frequency Keywords in MelOn

Rank	Word	Freq.	%
1	Use	6120	0.927
2	Good	5209	0.789
3	Song	4258	0.645
4	Possibility	2616	0.396
5	Function	2008	0.304
6	Recommendation	1755	0.266
7	YouTube	1692	0.256
8	Photo	1673	0.253
9	Video	1563	0.237
10	Payment	1465	0.222
11	Friend	1408	0.213
12	Discount	1400	0.212
13	iPhone	1389	0.21
14	Change	1380	0.209
15	Android	1378	0.209
16	Naver	1349	0.204
17	Free	1329	0.201
18	Information	1309	0.198
19	Search	1275	0.193
20	Various	1265	0.192
21	Subscription	1257	0.19
22	Beginning	1251	0.189
23	Benefit	1251	0.189
24	Choice	1248	0.189
25	Voucher	1234	0.187
26	Provision	1234	0.187
27	Necessity	1197	0.181
28	Screen	1184	0.179
29	Purchase	1134	0.172
30	Life	1129	0.171
31	Domestic	1123	0.17
32	Setting	1087	0.165
33	Price	1072	0.162
34	Card	1055	0.16
35	Mobile	1050	0.159
36	Kakao	1044	0.158
37	Cafe	1012	0.153
38	Product	1004	0.152
39	Rating	1004	0.152
40	Company	982	0.149
41	Taste	973	0.147
42	Content	971	0.147
43	Connection	965	0.146
44	Expression	956	0.145
45	Spotify	955	0.145
46	Smartphone	931	0.141
47	Streaming	917	0.139
48	Support	909	0.138
49	Pretty	904	0.137
50	Addition	903	0.137

⟨Table 3⟩ Analyzing TF-IDF in MelOn

Rank	Word	TF-IDF
1	Use	3907.233
2	Song	3899.831
3	Discount	3095.069
4	Voucher	3063.361
5	Function	3054.852
6	Good	2882.768
7	Android	2882.42
8	Car audio	2839.161
9	Kang Daniel	2740.503
10	iPhone	2737.252
11	Spotify	2721.413
12	Benefit	2625.054
13	Kakao	2546.837
14	Possibility	2546.731
15	Card	2525.489
16	Payment	2517.895
17	Life	2504.377
18	YouTube	2487.951
19	Recommendation	2408.798
20	Vote	2382.5
21	Naver	2327.755
22	Photo	2320.635
23	Rating	2293.15
24	Friend	2277.032
25	Free	2225.076
26	Provision	2220.116
27	Company	2110.792
28	Domestic	2088.841
29	Taste	2071.245
30	Saving	2054.228
31	Video	2008.226
32	Galaxy	2004.835
33	Price	1999.605
34	Subscription	1974.827
35	Car	1972.804
36	Information	1969.638
37	Setting	1950.303
38	Apple	1937.766
39	Screen	1917.211
40	Music source	1914.225
41	Purchase	1908.501
42	Connection	1893.263
43	Supernatural power	1886.434
44	Change	1852.574
45	Termination	1846.299
46	Smartphone	1840.149
47	Search	1830.356
48	Choice	1810.979
49	Various	1771.311
50	Car	1761.974

Connection centrality means that a specific node is directly connected to another node, and Proximity centrality refers to how a node is central in the entire network. Eigenvector centrality means that the degree of authority is based on the importance of connected nodes. Finally, mediation centrality means the degree to which a specific word is located between two other words. For finding the relationship among the words, we analyzed four centralities. The analysis included the top 25 words. However, the case of Proximity- and Mediation- centrality had no obvious difference between the data. Because of the result, we focused on Connection- and Eigenvector- centrality.

The aggregated TF-DIF top 100 keywords were made into a one-way mode matrix, and the correlation between keywords was calculated and divided by group using Ucinet's CONCOR analysis, and the keyword frequency of each group was summed to derive six categories finally. Category 1 set the topic as 'content and function' and accounted for 11%. The topic contained the most keywords and was confirmed by text, and consumers often evaluated their software use experiences with the topic, so the topic was highly related. Category 2, "Car Audio Connection," possessed 10% of the frequency, and keywords such as Android, Bluetooth, CarPlay, Speakers, Audio, Car Audio, Support, Smartphones, Navigation, Vehicles, Apple, and Cars were found to be common attributes. Category 3 accounted for 2% under the topic of 'smart Product Connection.' Many contents mainly were related to song playback. 'Life', set as Category 4, constituted 20%, and the summarized main keywords were a Song, Video, Album, Life, Impression, and Memory. Category 5, 'singer' accounted for 1% of the

⟨Table 4⟩ Results of Centralities in MelOn

Rank	Connection		Eigenvector	
1	Use	0.152	Use	0.383
2	Good	0.097	Car audio	0.27
3	Car audio	0.078	Good	0.247
4	Song	0.069	Car	0.222
5	Possibility	0.068	Possibility	0.2
6	Function	0.061	Audio	0.195
7	Car	0.06	Function	0.187
8	Recommendation	0.058	Song	0.182
9	Audio	0.052	Recommendation	0.179
10	Provision	0.045	Android	0.159
11	Price	0.043	Speaker	0.154
12	Android	0.043	Price	0.142
13	YouTube	0.042	Apple	0.139
14	Apple	0.04	Smartphone	0.129
15	Speaker	0.04	Carplay	0.123
16	Smartphone	0.037	YouTube	0.121
17	Discount	0.037	Support	0.116
18	Payment	0.037	Connection	0.114
19	iPhone	0.036	iPhone	0.113
20	Photo	0.035	Provision	0.111
21	Domestic	0.035	Galaxy	0.104
22	Naver	0.035	Search	0.1
23	Various	0.034	Install	0.099
24	Support	0.034	Photo	0.098
25	Search	0.033	Screen	0.097

⟨Table 5⟩ Keywords Classified by CONCOR Analysis in MelOn

Category	%	Keyword	Main Keyword
Contents and Function	11%	Use, Premium, Content, YouTube, Streaming, Function, Good, Need, Click, Register, Advertisement, Spotify, Information, Possibility, Kakao, Market, Music Source, Purchase, Free, Naver, Price, Game, Relation, Choice, Reference, download, Setting, Domestic, Play, Data, Gini, Apple watch, Addition, Change, Subscription, Individual, Mobile, Various, Delete, Content	Premium, Content, Function, Advertisement, Music source, Free, Download, Play
Car Audio Connection	10%	Android, Bluetooth, Carplay, Speaker, Audio, Caraudio, Support, Smartphone, Navigation, Car, Apple, Vehicle	Speaker, Smartphone, Car
Smart Product Connection	2%	Product, State, Search, Screen, Impossibility, Install, iPhone, Recommendation, Galaxy, Lexus, Price, Connection	iPhone, Galaxy
Life	20%	Taste, Café, Song, Photo, Study, Video, Song, Album, Beginning, Mom, Friend	Song, Video, Album
		Unusal, Word, Life, Supernatual power, Impression	Life, Impression
		Book, Memory, Love, Pretty	Memory
Singer	1%	Kang Daniel, Vote	Kang Daniel, Vote
Voucher	8%	Application, Saving, Payment, Benefit, Discount, Card, Voucher, Event, Provision, Termination, Point, Rating	Benefit, Voucher, Point, Rating

frequency, and Kang Daniel and Voting were derived as keywords. Category 6 was set as 'Price', and the ratio was 8% of the frequency. The main keywords were Benefits, Vouchers, Points, and Ratings. Keywords and main keywords for each category were shown in the following table.

4.3 Result of Analyzing Spotify Data

The results of frequency analysis of the Spotify data used were as follows. The result showed that Spotify had a high frequency of songs, uses, likes, company, and BTS (〈Table 6〉). 〈Table 7〉 shows the analysis result of TF-IDF.

The results of each centrality analysis of Spotify are as follows. As with Melon's centrality analysis results, Spotify was found to have no significant difference in Proximity- and Mediation- centrality. The results of Spotify's CONCOR analysis were as follows. Spotify was classified into five categories. Category 1 was 'Content and Function', Category 2 was 'Music Conflict', Category 3 was 'Hobby Life', Category 4 was 'singer', and Category 5 was 'stock Investment', and the details of each category were as follows.

〈Table 6〉 Top 50 Frequency Keywords in Spotify

Rank	Word	Frequency	%	Rank	Word	Frequency	%
1	Song	3902	0.719	26	New	1005	0.185
2	Use	3598	0.663	27	Global	974	0.179
3	Good	3224	0.594	28	Product	903	0.166
4	Company	2870	0.529	29	Dollar	897	0.165
5	BTS	2218	0.409	30	Video	896	0.165
6	World	1777	0.327	31	Love	891	0.164
7	Music source	1643	0.303	32	High	861	0.159
8	Streaming	1642	0.303	33	Need	860	0.158
9	Market	1570	0.289	34	Presentation	854	0.157
10	Song	1521	0.28	35	Change	839	0.155
11	Possibility	1490	0.275	36	Speaker	836	0.154
12	Content	1301	0.24	37	Support	819	0.151
13	Album	1294	0.238	38	Free	799	0.147
14	Beginning	1285	0.237	39	Disclosure	778	0.143
15	Apple	1240	0.228	40	Breakthrough	774	0.143
16	Domestic	1230	0.227	41	Content	772	0.142
17	Function	1216	0.224	42	Skill	765	0.141
18	Provision	1179	0.217	43	Friend	758	0.14
19	Recommendation	1159	0.214	44	Maximum	748	0.138
20	Chart	1113	0.205	45	Price	744	0.137
21	Photo	1111	0.205	46	Solo	735	0.135
22	Audio	1081	0.199	47	Digital	730	0.135
23	Record	1044	0.192	48	Launching	718	0.132
24	Various	1032	0.19	49	Melon	713	0.131
25	Investment	1016	0.187	50	Individual	706	0.13

〈Table 7〉 Analyzing TF-IDF in Spotify

Rank	Word	TF-IDF	Rank	Word	TF-IDF
1	Company	4236.148	26	Recommendation	1815.733
2	BTS	4104.132	27	Solo	1804.893
3	Use	3633.437	28	Rose	1803.932
4	Song	3474.464	29	Record	1781.481
5	Content	2997.812	30	Skill	1737.861
6	Good	2797.075	31	Game	1734.971
7	Market	2718.796	32	Free	1682.853
8	Audio	2649.358	33	Various	1673.361
9	Speaker	2492.108	34	Global	1670.928
10	Apple	2424.75	35	Digital	1652.534
11	Chart	2347.979	36	Support	1638.132
12	Function	2342.875	37	Beginning	1614.58
13	Music source	2327.223	38	Connection	1611.796
14	Investment	2272.128	39	Video	1566.359
15	Singer	2245.011	40	New	1552.857
16	World	2167.041	41	Love	1547.124
17	Album	2128.25	42	Friend	1541.979
18	Domestic	2118.597	43	Presentation	1538.66
19	Dollar	2085.627	44	Customer	1535.902
20	Possibility	2058.221	45	Price	1525.327
21	Jimin	2021.617	46	Breakthrough	1522.593
22	Product	2012.475	47	Launching	1497.794
23	Provision	1990.601	48	Kakao	1485.604
24	Streaming	1966.121	49	Play	1480.737
25	Photo	1898.338	50	Growth	1477.196

〈Table 8〉 Results of Centralities in Spotify

Rank	Connection		Eigenvector	
1	Company	0.213	Company	0.373
2	Use	0.193	Use	0.321
3	Market	0.125	Market	0.244
4	Good	0.104	Good	0.18
5	Song	0.094	Possibility	0.171
6	World	0.09	Investment	0.17
7	Possibility	0.088	World	0.162
8	Content	0.083	Content	0.158
9	Provision	0.079	Provision	0.157
10	Investment	0.079	Domestic	0.143
11	Domestic	0.075	Song	0.137
12	Function	0.069	Function	0.133
13	Music source	0.068	Skill	0.132
14	Beginning	0.066	Product	0.131

〈Table 8〉 Results of Centralities in Spotify(Continued)

Rank	Connection		Eigenvector	
15	Product	0.065	Beginning	0.128
16	Streaming	0.064	Growth	0.12
17	Skill	0.063	Game	0.12
18	Audio	0.061	High	0.119
19	High	0.059	Audio	0.115
20	Growth	0.058	Music source	0.112
21	Apple	0.058	Apple	0.111
22	Various	0.058	Various	0.111
23	Game	0.056	Streaming	0.108
24	Singer	0.055	Dollar	0.107
25	Dollar	0.055	Support	0.106

〈Table 9〉 Keywords Classified by CONCOR Analysis in Spotify

Category	%	Keyword	Main Keyword
Content and Function	38%	Apple, Digital, Various, Beginning, Individual, Content, Provision, Story, Book, Audio, Model, Subscription, New, Reference, Launching, Data, Information, Movie, Need	Content, Audio, Subscription
		Product, Sound, Speaker, Possibility, Function, Support, Google, Use, design, Setting, Choice, Play, Addition, Free, Price, Connection	Speaker, Function, Design, Play, Free, Price
Music Conflict	12%	Market, Naver, Kakao, Game, Global, Skill, Maximum, Content, World, Domestic, Customer, Base	Kakao, Content
Hobby Life	12%	Friend, Lyrics, Good, Taste, Song, Love, Photo	Lyrics, Song
Singer	10%	Rose, Singer, Streaming, Album, Launching, Release, Record, Pan, Chart	Singer, Album, Launching, Chart
	7%	BTS, Breakthrough, Music source, Solo, Jimin, Solo song	BTS, Music source
Invest-ment	14%	Dollar, Upturn, Forecast, Company, Sales, Investment, China, Performance, Company, Stock, Growth, High, Presentation, Listed, Business, Profit, Stock, Increase	Sales, Investment, Performance, Company, Stock

4.4 Result of Comparing Emotional Vocabulary

Among the results of MelOn and Spotify, the adjective form was extracted, and the overall emotional score was calculated by using Textom's emotional vocabulary analysis. MelOn was summed with 75.71% positive adjective frequency, 74.59 emotional intensity score, 77.15% positive adjective frequency for Spotify, and 76.63 emotional intensity score. Spotify had a slightly higher positive evaluation than MelOn. In terms of

〈Table 10〉 Result of Analyzing Emotional Vocabulary

Category	MelOn		Spotify	
	Frequency (%)	Emotional Intensity (%)	Frequency (%)	Emotional Intensity (%)
Positive	75.71	74.59	77.15	76.63
Negative	24.29	25.41	22.85	23.37

〈Table 11〉 Result of Detailed Emotion Vocabulary

	Detailed Emotion	MelOn			Spotify		
		Frequency (case)	Ratio (%)	Ratio (%)	Frequency (case)	Ratio (%)	Ratio (%)
Positive	Favorable	40078	57.59	74.59	24895	51.96	76.64
	Interest	6537	8.91		5711	11.47	
	Pleasure	6131	8.09		6598	13.21	
Negative	Sad	5671	9.18	25.42	3494	8.44	23.35
	Repulsion	7361	10.47		4743	9.12	
	Pain	721	1.24		1097	2.07	
	Fear	1564	2.15		807	1.63	
	Angry	1053	1.45		378	0.8	
	Surprise	551	0.93		503	1.29	
TOTAL		69667	100%	100%	48226	100%	100%

detailed emotions, MelOn's "likes" and "rejection" were higher than Spotify while Spotify's "interest" and "pleasure" were higher than MelOn's.

4.5 Keywords and Comparative Analysis of Emotional Vocabulary

Based on the results of the CONCOR analysis, the main keywords of MelOn and Spotify were summarized and classified again, and the following categories and keywords were extracted.

Textom's emotional dictionary was used to calculate the adjective form and emotional intensity score, and the emotional vocabulary results of the keywords are as follows.

MelOn was higher in the "device connection" category than Spotify. Spotify scored higher than MelOn in the categories of "content and function," "musical taste," and "price." However, the overall average of MelOn was slightly higher than Spotify. The result was different from the emotional vocabulary analysis.

We analyzed a keyword comparison between them by using the Word2Vec model. We judged to exclude "content and function" and "device connection" because the keywords had high congestion and could not be extracted meaningful keywords. Finally, an analysis focusing on "musical taste" and "price" was conducted based on the result. The analysis results were as follows.

〈Table 12〉 Category and Keyword after Analyzing CONCOR

Category	Keyword
Content and Function	Content, Music source, Lyrics, Video, Advertisement, Function, Search, Download, Play, Design
Device Connection	Car, Smartphone
Musical Taste	Singer, Chart, Song, Album
Price	Price, Voucher, Benefit, Premium, Free

〈Table 13〉 Emotional Vocabulary Analysis Result for Each Keyword

Category	Keyword	MelOn	Average	Spotify	Average
Content and Function	Content	76.6052	74.041422	76.6301	76.0334528
	Music source	74.3408		76.1364	
	Lyrics	71.8996		76.1583	
	Video	71.9483		76.5978	
	Advertisement	72.8482		76.812	
	Function	73.7772		75.4151	
	Search	76.8471		75.745	
	Download	75.4789		76.9798	
	Play	74.2223		74.7601	
	Design	72.4467		75.1	
Device Connection	Speaker	83.5063	83.212447	74.2309	74.5803803
	Car	87.2717		74.3957	
	Smartphone	78.8594		75.1146	
Musical Taste	Singer	75.1801	74.559109	75.8628	76.2032747
	Chart	74.6113		77.1714	
	Song	74.0418		76.1825	
	Album	74.4033		75.5965	
Price	Price	74.7661	74.372396	74.2943	74.7695821
	Voucher	69.3088		71.7289	
	Benefit	78.7041		75.2226	
	Premium	73.4218		76.195	
	Free	74.8494		75.705	
Average		75.1843	76.546343	75.4717	75.3966725

〈Table 14〉 Result of Word2Vec in Musical Taste Category

		MelOn		Spotify	
Musical Taste	Singer	Song	0.827708244	Nah, Youn-Sun	0.791765
		Indie	0.818846166	Mariah	0.784667
		Sound Cloud	0.804601133	Artist	0.764128
		Recommendation	0.783969104	Released Work	0.749536
		New Song	0.779929698	Bieber	0.74465096
	Chart	Released Song	0.816392	Billboard	0.817009
		Guysome	0.803154	Tajikistan	0.794783
		Number of Streaming	0.791645	Duet Song	0.780005
		Idol Fandom	0.769968	Malaysia	0.776193
		Gini Chart	0.764817	Group Name	0.772847
	Song	Playlist	0.846552	Song	0.847697
		P.L(Playlist)	0.841397	R&B	0.795012
		Favorite Song	0.830014	P.L(Playlist)	0.787866
		Singer	0.827708	New Song	0.78532
		Superb	0.825548	Lo-fi	0.782616
	Album	IU	0.804434	Song in the album	0.792576
		Formality	0.803003	Repackage	0.786059
		Release	0.785609	Changes	0.781878
		Formality Album	0.784807	Listed	0.771125
		Demo	0.782242	Scene	0.769926

〈Table 15〉 Result of Word2Vec in Price Category

			MelOn		Spotify	
Price	Price	Expensive	0.717831	Around 10,000won	0.772298
		Waste	0.712178	10,000won	0.758605
		Burdensome	0.71173	Dodge Coin	0.748225
		Spotify Free Download	0.705628	Expensive	0.738616
		Comparison	0.703891	Bait	0.715485
	Voucher	Termination	0.892931	City Card	0.827221
		Angry	0.835788	Frugality	0.816899
		Apply Termination	0.834235	Undercoverage	0.815265
		Voucher Management	0.827182	Listen to Music	0.806559
		Mobile Termination	0.82151	Gini Music	0.803443
	Benefit	Additional Discount	0.845479	Gini Pack	0.809518
		Lotte Card	0.835631	City Card	0.802699
		Discount	0.830535	Affiliate	0.793912
		Delivery App	0.820755	Discount	0.788741
		Card Benefit	0.818758	Deduction	0.788068
	Premium	Premium Register	0.792002	Free	0.860708
		Regular Payment	0.791966	Price System	0.844527
		Experience	0.783825	Price	0.836394
		YouTube Premium	0.780907	Free Trial	0.827061
		Price	0.776977	Use	0.819965
	Free	Experience	0.827774	Use	0.867851
		Trial Period	0.784676	Experience Period	0.86479
		Charge	0.751676	Trial Period	0.864402
		Register	0.749209	Premium	0.860708
		Regular Payment	0.74724	Ncube	0.844476

5. Conclusion

5.1 Research Conclusion

This study analyzed users' attitudes and emotions toward MelOn, a leading Korean company that provides online music services, and Spotify, the world-leading company recently launched services in Korea. The analysis results are as follows. First of all, the main interests of users using MelOn were content and function, car audio connection, and life. In particular, car audio connection and life were found to have 32% of lavish attention, which could be interpreted as meaning that melon was used in everyday life for Korean users. MelOn does not simply exist as an online music service app, but MelOn has competitiveness in the market by establishing itself as an essential app in everyday life. However, MelOn was found that users had a higher negative attitude than Spotify. Despite MelOn having a high market share and long-term service in the Korean market, rejection, fear, and anger of users' negative attitudes were higher than Spotify. In the case of "anger," MelOn was about twice as high as Spotify. In other words, it means that MelOn users had an extremely negative attitude toward the service, which was judged to be actively analyzed and reflected in Melon's customer man-

agement or strategy in the future.

Second, as a result of Spotify, the main interests of users were content and function, music conflict, and stock investment. In the case of MelOn, connection with various IT devices or automobiles was one of the main concerns. However, Spotify users were highly interested in the content itself. Besides, the users recently expressed high interest in the conflict over music sources supplied by Korean music producers. While the music conflict happened, Korean users had considerable limitations to listening to domestic music. Therefore, the music conflict is an acute problem for Korean users. An unusual point for the result of Spotify was that the users showed high interest in stock investment, not related to music. The point is a possibility that the users experience the service with positive emotion. Based on the emotion, they could judge that the value of Spotify would be increased. The users were found to have more positive emotions about the service than MelOn. In particular, interest and joy were higher than MelOn, and rejection was also lower than MelOn. From the perspective of these results, it could be interpreted that Spotify provides sufficiently attractive services to Korean users.

Third, due to emotional intensity analysis through Word2vec analysis, MelOn users were mainly related to domestic music sources such as IU, Indie, and guysome. In the case of Spotify, topics related to overseas music sources such as Mariah Carey, Justin Bieber, and Billboard chart. In the price category, users thought that MelOn and Spotify were both expensive, and there were various experiences such as free experience period and price. Among the detailed categories, in the case of Melon, results directly related to service interruption such as termination, termination application, and mobile termination. The result indicates that MelOn users' satisfaction is lower than they think of the quality of service. It could be interpreted that the customer churn rate would be increased in the future. Therefore, MelOn is needed a detailed analysis to solidify its position in the domestic market, and Spotify is required to secure domestic customers through a strategic approach to the service desired by Korean users.

5.2 Research Implication and Limitation

The implication of this study is as follows. First, previous studies were conducted by analyzing Spotify and MelOn, respectively. However, this study is meant to conduct a comparative analysis to derive the results of the difference between the company's strategy and service provision. Second, this study is significant because it was approached from the user's point of view, not from the technical point. According to the difference in the company's services, the users' emotions were directly analyzed through reviews left by the users. The results of this study are believed to be helpful in practice for companies that provide online music services.

The limitations of this study are as follows. First, when collecting data on MelOn, we set up the keyword as the MelOn App. Melon is a homonym with a melon meant a fruit. Therefore, when we searched the MelOn app, it is a possibility and limitation that information meaning fruit melon could be derived or duplicated. Through several processes, we attempted more detailed classification. However, the process needs to be classified more clearly and accurately in future studies. Second, the user's evaluation of the app is multilateral. However, in this study,

only review data was used for analysis. Therefore, it has a limitation to reflect the multilateral perspective of the user. It seems necessary to collect and analyze multilateral data of users in future studies. In addition, in the case of Spotify, it has not much data on reviews accumulated so far, so it is judged that research should be conducted based on more data in the future.

References

[1] Avdeeff, M., "Technological engagement and musical eclecticism: An examination of contemporary listening practices", Journal of Audience & Reception Studies, Vol.9, No.2, 2012, pp. 265-285.

[2] Aguiar, L., "Let the music play? Free streaming, product discovery and digital music consumption", Information Economics and Policy, Vol.41, 2017, pp. 1-14.

[3] Aguiar, L. and Waldfogel, J., "As streaming reaches flood stage, Does it stimulate or depress music sales?", International Journal of Industrial Organization, Vol.57, 2018, pp. 278-307.

[4] An, H., "A study on the sentiment analysis in fashion design using big data – focused on text mining and semantic network analysis", Doctoral Dissertation, The Graduate School, Ewha Womans University, 2017.

[5] Carver, S. A., "Changing the industry, spotify: How streaming services affect music consumption", Seth Carver Honors Undergraduate Thesis, 2016.

[6] Cesareo, L. and Pastore, A., "Consumers' attitude and behaviour towards online music piracy and subscription-based services", Journal of Consumer Marketing, Vol.31, Vo.6/7, 2014, pp. 515-525.

[7] Choudhary, A. K., Oluikpe, P. I., Harding, J. A., and Carrillo, P. M., "The needs and benefits of text mining applications on post-project reviews", Computers in Industry, Vol.60, 2009, pp. 728-740.

[8] Feldman, R. D., "Knowledge discovery in textual databases (KDT)." Paper presented at the First International Conference on Knowledge Discovery and Data Mining (KDD-95), Montreal, Canada, 1995.

[9] Fisher, W., "Technology, Law, and the Future of Entertainment", Stanford University Press: Stanford, CA, 2004.

[10] Graham, G., Burnes, B., Lewis, G. J., and Langer, J., "The transformation of the music industry supply chain: A major label perspective", International Journal of Operations and Production Management, Vol.24, No.11, 2004, pp. 1087-1103.

[11] Gray, K., "Stealing from the rich to entertain the poor? A survey of literature on the ethics of digital piracy", The Serials Librarian, Vol.63, No.3/4, 2012, pp. 288-295.

[12] Hughes, J. and Lang, K. R., "If I had a song: The culture of digital community networks and its impact on the music industry", International Journal on Media Management, Vol.5, No.3, 2003, pp. 180-189.

[13] Heye, A. and Lamont, A., "Mobile listening situations in everyday life: The use of MP3 players while travelling", Musicae Scientiae, Vol.14, No.1, 2010, pp. 95-120.

[14] Hiller, R. S., "Sales displacement and streaming music: Evidence from youtube." Information Economics and Policy, Vol.34, 2016, pp. 16-26.

[15] International Federation of the Phonographic Industry, Global Music Report, 2016, Report.

[16] International Federation of the Phonographic Industry. Global Music Report, 2019, Report.

[17] Jang, H. Y. and Barnett, G. A., "Cultural differences in organizational communication: A semantic network analysis", Bulletin of Sociological Methodology/Bulletin de Méthodologie Sociologique, Vol.44, No.1, 1994, pp. 31-59.

[18] Korea Creative Content Agency, Music Industry White Paper, 2019.

[19] Korea Creative Content Agency, Music Industry White Paper, 2020.

[20] Krause, A. E., North, A. C., and Hewitt, L. Y., "Music-listening in everyday life: Devices and choice", Psychology of Music, Vol.43, No.2, 2015, pp. 155-170.

[21] Kretschmer, T. and Peukert, C., "Video killed the radio star? Online music Videos and recorded music sales", Information Systems Resaerch, Vol.31, No.3, 2015, pp. 776-800.

[22] Levin A. M., Dato-on, M. C., and Manolis, C., "Deterring illegal downloading: The effects of threat appeals, past behaviour, subjective norms, and attributions of harm", Journal of Consumer Behaviour, Vol.62, No.3, 2007, pp. 111-122.

[23] Li, G. and Liu, F., "Application of a clustering method on sentiment analysis", Journal of Information Science, Vol.38, No.2, 2012, pp. 127-139.

[24] Mikolov, T., Sutskever, I., Chen, K., Corrado, G., and Dean, J., "Distributed Representations of Words and Phrases and their Compositionality", Proceedings of The 27th Annual Conference on Neural Information Processing Systems, 2013, pp. 1-9.

[25] Nahm, U. Y., "Text-mining with information extraction." Doctoral dissertation, The University of Texas at Austin, Austin, 2004.

[26] North, A. C. and Hargreaves, D. J., "The social and applied psychology of music", Oxford, UK: Oxford University Press, 2008.

[27] Robertson, S., "Understanding inverse document frequency: on theoretical arguments for IDF", Journal of Documentation, Vol.60, No.5, 2004, pp. 503-520.

[28] Sandler, M., "Interacting with Digital Music", Journal of New Music Research, Vol.36, No.3, 2007, pp. 227-239,

[29] Sinclair, G. and Green, T., "Download or stream? Steal or buy? Developing a typology of today's music consumer", Journal of Consumer Behaviour, Vol.15, 2016, pp. 3-14.

[30] Sletten, R. T., "Spotify: Strategic Plan and Analysis", Undergraduate Theses, Professional Papers, and Capstone Artifacts, 2021.

[31] Smith, E., "Forget CDs. Teens are tuning in to YouTube. Nielsen survey says more youngsters listen to music via video-sharing site, while some adults still groove to cassettes", The Wall Street Journal, 2012, p. B3.

[32] Tepper, S. J. and Hargittai, E., "Pathways to music exploration in a digital age", Poetics, Vol.37, 2009, pp. 227-249.

[33] Wasserman, S. and Faust, K., "Social network analysis: methods and applications." Cambridge University Press, Cambridge, 1994.

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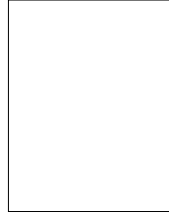
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