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A Study on Dining-Out Trends Using Big Data: Focusing on Changes since COVID-19

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Abstract: This study examined consumers' emotions and needs related to dining-out experiences before and during the COVID-19 crisis. This study identifies words closely associated with the keyword "dining-out" based on big data gleaned from social media and investigates consumers' perceptions of dining-out and related issues before and after COVID-19. The research findings can be summarized as follows: In 2019, frequently appearing dining-related words were dining-out, family, famous restaurant, recommend, and dinner. In 2020, they were dining-out, family, famous restaurant, and Corona. The analysis results for the dining-out sentimental network based on 2019 data revealed discourses revolving around delicious, nice, and easily. For the 2020 data, discourses revolved around struggling, and, cautious. The analysis of consumers' dining-out demand network for 2019 data showed discourses centered around reservation, famous restaurant, meal, order, and coffee. However, for 2020 data, discourses were formed around delivery, price, order, take-out, and social distance. In short, with the outbreak of the pandemic, delivery, takeout, and social distance emerged as new search words. In addition, compared with before the COVID-19 pandemic, a weakening trend in positive emotions and an increasing trend in negative emotions were detected after the outbreak of the COVID-19 pandemic; specifically, fear was found to be the fear emotion.

Keywords: dining-out; trend; social media; big data; COVID-19 pandemic

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1. Introduction

With technological advancement, network development, and the popularization of telecommunications, the volume of data has grown exponentially [1]. Big data can be defined from the viewpoint of technology, size, and methodology. Technologically, big data indicates next-generation technology and architecture devised to collect, find, and analyze massive amounts of various data quickly [2]. Big data analysis looks at massive amounts of Internet-based data and is useful for identifying the meaning of information and their relationships [3]. Social big data can be used to analyze current trends and foresee the future directions of these trends [4]. With the advancement of the Internet and the popularization of related devices, people can communicate with each other at low costs on social network services (SNS), where they share experiences and thoughts, freely access social media, and connect with others [5].

According to a recent report, big data analysis is expected to be the most influential tool in the next 5 years [6,7]. Thanks to the advancement of science technology, it is now possible to collect and store big data, including atypical data that were hard to collect before. In particular, analysis can be done for social media data and in connection with the matrix processing of primary data. Moreover, the spread of COVID-19 has enhanced the understanding of big data management. Pandemic data can be used to help workers, scholars, and policy makers obtain a deeper understanding of big data. Governments around the world are relying on data-based decision making to effectively address unprecedented problems caused by the pandemic [8]. Since the outbreak of

COVID-19, consumers' spending patterns have changed dramatically across all industries, including the foodservice industry. The foodservice industry is among the areas hardest hit by the pandemic, and COVID-19 poses both threats and opportunities to the sustainability of the foodservice industry [9]. As activities were limited by the COVID-19 pandemic, people increasingly turn to social media to keep in touch with their family and friends, which added a new dimension to the effects of the COVID-19 pandemic in terms of sharing new information and communicating by an alternative method [10,11].

Since the pandemic broke out, consumers have placed more value on spaces that do not threaten their health and that offer non-contact dining services rather than on food taste or atmosphere [12]. Kim and Lee [13] demonstrated that the coronavirus strengthened people's preference for food delivery and dining-out in private spaces based on a survey of virtual environments. Post-coronavirus changes in people's perceptions of dining-out can be examined and interpreted based on big data search words to produce insights for sustainable business. Most studies on post-coronavirus dining-out patterns have been undertaken based on a survey. Furthermore, there is still a lack of research comparing changes in consumers' perceptions of dining-out before and after the COVID-19 pandemic. The present study examines consumers' emotions and needs related to dining-out experiences before and after COVID-19 based on big data collected from social media. The study findings are expected to help foodservice businesses better understand and identify consumers' demands in the post-pandemic era.

2. Related Studies

2.1. Changes in Dining-Out Patterns after the COVID-19 Pandemic

A previous study found that consumers' dining–out habits had changed during the COVID-19 pandemic and that there was a new trend toward consuming local food in response to the restrictions on consumption. As a result, the number of restaurants that purchased local food based on a perspective of sustainability had increased [14]. Another study by Ferrante et al. [15] also found changes in the lifestyles of most people as well as in their behaviors regarding acquiring or eating food since the outbreak of the COVID-19 pandemic. The findings showed an increase in not only home cooking and online grocery shopping but also in takeout and delivery. In a study conducted by Bogevska et al. [16], the respondents reported that they bought more vegetables and fruits during the COVID-19 pandemic, which, the authors argued, indicated that they had adopted a healthier diet. A study on consumers in the UK by Filimonau et al. [17] also showed that the frequency and variety of home cooking increased during the coronavirus lockdown period, and the preference for consuming more sustainable food at home had also increased since the outbreak of the COVID-19 pandemic. Ronto et al. [18] investigated that because of the COVID-19 pandemic, confidence in cooking skills as well as the understanding of food, including meal planning and purchasing, had improved, and there was an increasing trend toward dining with family. Bender et al. [19] also supported that the amount of food prepared at home had increased significantly due to the COVID-19 pandemic. Byrd et al. [20] demonstrated that because of the coronavirus, people trusted the safety of homemade food more than restaurant food because they were aware of the risks of the food and services provided at restaurants. Kim and Lee [21] said that perceived threats due to the corona virus had resulted in an increased preference for dining out at private restaurants with private tables. Zhong et al. [22] noted that although more than a year had passed since the onset of the COVID-19 pandemic, people were still aware of the great psychological risk and still took considerable precautions and measures to avoid infection by the virus when they dined away from home. The authors argued that these negative emotions could have a lasting effect on consumers' consumption patterns. Combined, the findings of these previous studies suggest that perceptions of dining-out and trends in dining-out have changed since the outbreak of the COVID-19 pandemic.

2.2. Big Data Analysis in the Foodservice Industry

With the advancement of IT, smartphones have become ubiquitous, and the use of social media has increased, generating massive amounts of data [23]. In particular, social media have made it possible for today's consumers to create content [24]. Notable characteristics of big data include volume, velocity, and variety [25]. The term "big data" is used in diverse ways, and yet it always indicates a wide variety of massive data [26]. Lin and Tsai [27] indicated that big data consists of a huge and complex structure and a wide variety of data. Research on the hospitality industry, including dining-out, focuses more on human issues and behaviors compared to other industries [28]; as such, findings from big data research can be more useful for identifying consumer needs and foreseeing future trends to develop a new business model [29]. Hence, it is now possible to analyze various factors that can enhance customer satisfaction and utilize them to identify customer complaints [30]. Big data-based research fits characteristics of the foodservice industry, for which identifying the desires of the masses is crucial [31]. Big data has received heightened attention because now it is possible to analyze massive amounts of data that could not be analyzed before. This makes it possible to create new value. The following is a list of research conducted to date based on big data with "dining-out" as a keyword. Mayasari et al. [32] analyzed *Google* trends to show that pandemic-triggered restrictions on people's movement led them to seek nutrients and herbal medicine that strengthened the immune system and that, as outdoor activities are replaced by indoor activities, people's dietary preferences and lifestyles have shifted to use food delivery or takeout services more. Yang et al. [9] conducted a two-way data analysis on the impact of stay-at-home orders in the US on demand for restaurant services and showed that a 1% increase in newly confirmed COVID-19 cases led to a 0.0556% drop in demand for restaurant services. Jia [33] compiled user content posted by restaurants in 2019–2020 and analyzed customers' dining behaviors before and after the pandemic. The study indicated that customers visited restaurants less frequently after the outbreak of the pandemic but spent more on each visit. Chen et al. [34] used text mining to identify factors that affected customer satisfaction with fast food service based on SNS text replies and revealed that "food quality" and "service quality" continued to be the most influential factors for restaurant customers, even after the COVID-19 outbreak, and they argued that restaurants should maintain excellent service quality in the face of a severe infectious disease while providing protection with safety measures. Studies have found that greater attention has been given to people's safety after the outbreak and have confirmed that words such as coronavirus and face mask were mentioned more frequently. Yang et al. [35] analyzed customer reviews on O2O food delivery platforms provided by five-star hotel restaurants and found that adhering to the customer-oriented principle was important because customers deemed elements that evoked the excellence of top-tier hotels (e.g., exclusive and elaborate packaging and visible logo brands) as important. Jeong et al. [36] analyzed post-coronavirus big data on food delivery services in daily life and consumers' spending patterns and found that the demand for food delivery increased by 60% or more on the day after media coverage of the pandemic, resulting in an increase in spending on dining-out. Zhang et al. [37] conducted a big data analysis, finding that before the COVID-19 pandemic, consumers were concerned about the taste of food, but after the COVID-19 pandemic, they became more sensitive to changes in the dining environment and increasingly preferred packaged and takeout food.

Big data-based research on dining out before and after COVID-19 has been mostly used as an analytical tool to revitalize the foodservice industry by understanding changes in consumers' perceptions and behaviors. In this study, we make a distinction between "sentimental" aspects and "demand (purpose)" aspects for consumer search words before and after COVID-19, and we identify changes in consumers' dining-out patterns before and after the pandemic.

To this end, the following research question is addressed: How did dining-related search words change before and after the outbreak of COVID-19 on social media? How have emotional keywords regarding dining out changed since the COVID-19 pandemic?

3. Research Methodology

3.1. Data and Summary Statistics

This study extracts dining-related keywords from social media big data and identifies changes in those keywords before and after COVID-19 to provide practical implications. To do so, related texts were collected from websites, online cafes, news outlets, and blogs of social media portal sites. The collection channels were largely divided into portal SNS and news outlets, as data collection on social media is widely used to analyze consumer trends. Collection of Internet data was limited to blogs and cafes on *Naver* and *Daum*, which have the largest data volume, as it is hard to collect data from undisclosed accounts from *Facebook* or *Instagram*. Particularly, *Naver* is a trendy channel and receives news data from numerous media outlets, and blogs and cafes are in active use. Moreover, data on *Naver* cafes are useful for identifying the current issues and perceptions of particular groups of people. Blogs contain all kinds of data, including information, users' feelings and opinions toward specific topics, and review data on various themes, such as products and travel, which can be collected, which is difficult to do on other channels. For these reasons, this study retrieved data from *Naver* and *Daum*, whose combined market share is nearly 80% in Korea and which has the largest number of users in the country. Data were collected for the period between 1 January 2019, and 31 December 2020, with the keyword "dining-out."

3.2. Methodology

To investigate consumers' change of perception on dining-out before and after COVID-19, data were collected from online social media and refined. Regarding search keywords for data extraction, commonly used terms on respective websites were chosen, or domain experts selected keywords in consideration of the purpose of data analysis and the relevance of searched keywords. Research data were collected by a firm specializing in big data. The IMC and its big data analysis solution, TEXTOM, were used for data extraction and analysis. TEXTOM is a data solution that automatically collects data from Internet portal sites, refines them, and generates a matrix. It has been used in several studies before, including Hwang [26], Sung et al. [38], and Park [39]. First, a text refinement process was performed on the collected data to identify atypical data for the analysis. Texts were refined for the analysis because the data contained misspellings, new words, and special characters. Several words with the same meaning were combined into one word, and all postpositions and pronouns not allowed in the analysis were deleted. The selected words were then categorized into matrix data, which were then used in the semantic network analysis. For the word selection process, a group of experts consisting of three professors related to food service was employed. In this way, the matrix data of selected keywords were created. Once TEXTOM extracted important keywords, they were clustered into quasi-groups, and Ucinet6 was used to analyze significant correlations among connecting structures. NodeXL provided visualization tools based on the results of network analysis, including centrality, density, and clustering. Specifically, text mining, frequency, TF-IDF, semantic network analysis, Concor analysis, and sentiment analysis were used.

4. Results

4.1. Content Analysis

Internet searches with the keyword "dining-out" produced 39,144 results for 2019 data and 39,240 results for 2020 data on the abovementioned portal sites' blogs and cafes (See Table 1). Narrative coding was done for text-mining indicators on dining-out and clustered into food, sentimental, demand/purpose, and tourism/region (Table 2). The most important keyword, food, was placed in the center and combined with sentimental, and demand/purpose, which represented the purpose and meaning of the search for network analysis and visualization.

Table 1. Survey of collected data.

Data	Channel	Section	2019	2020
Dining-out	*Naver*	Blog	10,899	11,147
		Cafe	11,789	11,799
	Daum	Blog	9896	10,464
		Cafe	6560	5830

Table 2. Narrative coding index.

Categories	2019	2020	Total
Food	256	245	295
Sentimental	83	89	102
Demand	89	116	127
Tourism/Region	160	165	189
Total	588	615	713

4.2. Text-Mining Analysis

Table 3 shows the results of the text-mining analysis (e.g., frequency and TF-IDF) for dining-related data for 2019. Text mining is a process of deriving information and knowledge from unstructured texts, such as data on the Internet and social media. From unstructured data, meaningful words are extracted through natural language processing and morphological analysis, and key indicators are derived, such as frequency and TF-IDF. Frequency analysis of keywords in documents extracted with "dining-out" as a keyword showed that "dining-out" was the most frequently appearing keyword, followed by family, famous restaurant, recommend, dinner, delicious, weekend, menu, restaurant, and meat. These results revealed how often these words appeared in search results with the keyword "dining-out" and indicate that frequently appearing words are used more importantly. Particularly, high TF-IDF value was observed for industry, sale, restaurant management, pork cutlet, foundation, and Suwon, indicating that these words have high scarcity value in dining-related documents and that they were essential words, even when they did not appear frequently. Since the TF-IDF value considers both text frequency and irregularity across different documents, it is a proper indicator for short-term and mid-term trend analysis. That is, regarding dining-related search trends for 2019, keywords such as sale, management, and foundation were important factors.

Frequency analysis was performed for keywords extracted from dining-related documents in 2020. The most frequently appearing word was "dining-out," as in 2020 (Table 4), followed by family, famous restaurant, recommend, taste, Corona, weekend, dinner, restaurant, and menu. A high TF-IDF value was observed for words such as home meal, delivery, hotel, restaurant management, and cooking, indicating that these words had a high scarcity value in dining-related documents generated in 2020 amid the COVID-19 pandemic. Compared to the pre-pandemic period, keywords such as home meal, delivery, and cooking became very influential for dining-related data in 2020.

Table 3. Text mining of dining-out (2019).

Rank	Word	Freq.	TF-IDF	Rank	Word	Freq.	TF-IDF
1	dining-out	70,288	0.09164	26	industry	1454	0.07708
2	family	23,807	0.07547	27	husband	1381	0.05833
3	famous restaurant	17,242	0.06471	28	baby	1307	0.06571
4	recommend	4820	0.05504	29	sale	1292	0.08035
5	dinner	4784	0.06592	30	visit	1261	0.04357
6	delicious	4286	0.05309	31	restaurant management	1243	0.11043
7	weekend	4283	0.06258	32	price	1231	0.04361
8	menu	3717	0.05702	33	beef	1146	0.05700
9	restaurant	3465	0.05526	34	buffet	1121	0.06578
10	meat	2966	0.05803	35	friend	1119	0.04866
11	children	2943	0.05517	36	bride	1115	0.05595
12	barbecued ribs	2485	0.06895	37	pork cutlet	1068	0.07999
13	after a long interval	2446	0.05645	38	cooking	1065	0.05390
14	lunch	2411	0.05758	39	pork belly	1064	0.06436
15	get-together	2283	0.05036	40	birthday	1061	0.06792
16	BBQ restaurant	2275	0.05831	41	neighborhood	1046	0.04460
17	Pusan	2207	0.06539	42	mood	1033	0.04735
18	food	2191	0.05241	43	foundation	1030	0.09500
19	meal	1970	0.04980	44	Suwon	1022	0.08136
20	people	1866	0.05426	45	ingredient	1010	0.06238
21	taste	1762	0.05221	46	parents	1006	0.05192
22	rice	1679	0.05378	47	Korean beef	999	0.07039
23	time	1628	0.04714	48	son	982	0.05974
24	meeting	1540	0.04591	49	business	980	0.06028
25	mother	1536	0.05363	50	home meal	975	0.05862

Table 4. Text mining of dining-out (2020).

Rank	Word	Freq.	TF-IDF	Rank	Word	Freq.	TF-IDF
1	dining-out	69,850	0.06887	26	rice	1437	0.03745
2	family	20,063	0.05595	27	hotel	1415	0.07046
3	famous restaurant	15,536	0.04978	28	restaurant management	1386	0.08942
4	recommend	4610	0.04021	29	meeting	1349	0.03644
5	taste	4117	0.03626	30	mother	1335	0.03664
6	Corona	3584	0.03927	31	cuisine	1289	0.04262
7	weekend	3486	0.04453	32	cooking	1278	0.07097
8	dinner	3333	0.04344	33	visit	1265	0.03169
9	restaurant	3177	0.04028	34	beef	1233	0.04467
10	menu	2994	0.04267	35	Korean beef	1226	0.05640

Table 4. *Cont.*

Rank	Word	Freq.	TF-IDF	Rank	Word	Freq.	TF-IDF
11	after a long interval	2856	0.04271	36	husband	1154	0.03834
12	Pusan	2490	0.05282	37	business	1129	0.04545
13	meat	2299	0.04113	38	discount	1114	0.05478
14	lunch	2107	0.04031	39	industry	1106	0.06390
15	children	2096	0.03843	40	government	1020	0.05345
16	barbecued ribs	2061	0.04983	41	delicious	1007	0.03579
17	foundation	1990	0.04396	42	support	985	0.04867
18	food	1929	0.03997	43	Jongro	978	0.12561
19	time	1839	0.03623	44	Ulsan	965	0.06643
20	get-together	1780	0.03715	45	mood	957	0.03580
21	people	1775	0.03819	46	birthday	955	0.04450
22	meal	1732	0.03563	47	diet	947	0.05561
23	BBQ restaurant	1697	0.04072	48	neighborhood	943	0.03262
24	home meal	1638	0.04191	49	ingredient	937	0.05085
25	delivery	1560	0.04345	50	foodservice industry	932	0.04521

4.3. Semantic Network Analysis

Concor analysis was conducted to examine the correlation among co-occurring words; keywords were clustered to form word groups, within which the main themes of respective document groups were derived. The key is to identify common characteristics among highly relevant words, which is effective for the contextual interpretation of data. Based on the analysis results of text mining, a distinction was made between indicators for sentimental networks and demand (purpose) network. Based on semantic network indicators, the location and role of individual nodes can be analyzed. A higher degree of centrality means that the variable has a strong correlation with other variables and thus is an element that directly influences consumers' sentimental (or demand). A higher betweenness centrality means that the variable plays a strong intermediary role for other variables and thus is an element that relies heavily on consumers' perception over sentimental (or demand); a higher closeness centrality means that the variable may be easily connected to other variables and creates synergy effects on consumer sentimental (or demand) when combined with other variables; a higher page rank value means that the variable is popular among consumers' sentimental (or demand) and indicates that connecting links gravitate toward nodes that contain relatively more important pages or information. In this study, a semantic network analysis that combines dining-out with sentimental (or demand) for 2019 and 2020 data was implemented.

First, the results of the semantic network analysis on the relationship between dining-out and consumer sentimental for 2019 data are shown in Table 5. Discourses on consumers' sentimental on dining-out were formed revolving around words such as delicious, recommend, nice, famous restaurant, rice, meat, BBQ restaurant, meal, barbecued ribs, café, and easily, and they were based on degree centrality, betweenness centrality, and page rank. Word groups were formed based on clustering, and an inter-group network was visualized (Figure 1). Four categories that stood out included visualized-recommend, famous restaurant, café, and easily. Furthermore, people who searched "dining-out" did so to solicit recommendations for dining-out places with a special and satisfying atmosphere, and they displayed pleasant and healthy sentiments toward famous restaurants that had menus including meat, BBQ, meal (cooked rice), buffet, and *Shabu Shabu*. The results of the semantic network analysis on the relationship between dining-out and consumer sentiment for 2020 data are depicted in Table 6. Discourses on consumers and sentiments on dining-out were formed revolving around words such as enjoy, recommend, new, mood, satisfaction, delicious, meal, famous restaurant, home meal, famous, and feeling. Visualization of semantic network yielded three categories—recommend, famous restaurant, and famous (Figure 2), and it showed that people searched "dining-out" to solicit recommendations for tasty places with a pleasant atmosphere, as with 2019 data. Furthermore, these results revealed that they searched home meal, cooking, and delivery food; however, unlike in 2019, consumers associated words such as worry, caution, concern, scary, and difficult with dining-out in 2020.

Table 5. Sentimental network index of dining-out (2019).

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
delicious	70	322.294229	0.004808	1.577226	1	Sentimental
recommend	70	322.294229	0.004808	1.577226	1	Sentimental
nice	69	311.684104	0.004762	1.556164	1	Sentimental
worry	68	299.836921	0.004717	1.534461	1	Sentimental
mood	68	298.947117	0.004717	1.534301	1	Sentimental
famous	67	287.777914	0.004673	1.512909	1	Sentimental
feeling	67	287.514979	0.004673	1.512666	1	Sentimental
love	66	276.160605	0.00463	1.491242	1	Sentimental
happy	64	258.469303	0.004545	1.449704	1	Sentimental
enjoy	61	237.359899	0.004425	1.390506	1	Sentimental
satisfaction	61	233.549063	0.004425	1.388615	1	Sentimental
burden	59	215.047136	0.004348	1.346004	1	Sentimental
cost-effectiveness	59	212.152358	0.004348	1.344833	1	Sentimental
special	57	209.369735	0.004274	1.309802	1	Sentimental
variety	56	193.102542	0.004237	1.284526	1	Sentimental
side-dish	51	184.269454	0.004065	1.191853	1	Food
specialty store	51	178.795206	0.004065	1.188236	1	Food
success	54	174.592019	0.004167	1.241266	1	Sentimental
high-grade	51	159.37688	0.004065	1.183023	1	Sentimental
pork cutlet	50	147.473698	0.004032	1.155163	1	Food
coffee	47	138.989366	0.003937	1.099501	1	Food
pork	45	124.424039	0.003876	1.057743	1	Food
appreciation	45	119.79205	0.003876	1.058784	1	Sentimental
big win	45	116.48295	0.003876	1.057254	1	Sentimental
Korean cuisine	43	107.56309	0.003817	1.013455	1	Food
steak	45	107.00543	0.003876	1.047406	1	Food
pork back-bone stew	39	106.163375	0.003704	0.944944	1	Food
home-cooked meal restaurant	42	104.875629	0.003788	0.994696	1	Food

Table 5. *Cont.*

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
Chinese restaurant	42	97.191562	0.003788	0.98965	1	Food
franchise	37	89.082361	0.00365	0.899498	1	Food
famous restaurant	70	453.728098	0.004808	1.622257	2	Food
rice	67	391.863766	0.004673	1.549125	2	Food
meat	67	363.09434	0.004673	1.537617	2	Food
BBQ restaurant	64	354.105045	0.004545	1.484834	2	Food
meal	66	340.119854	0.00463	1.511436	2	Food
barbecued ribs	64	301.245644	0.004545	1.462569	2	Food
cuisine	60	268.723507	0.004386	1.382303	2	Food
home meal	59	250.955652	0.004348	1.35819	2	Food
beef	59	250.38176	0.004348	1.357289	2	Food
shabu-shabu	55	215.167636	0.004202	1.273755	2	Food
health	57	197.198505	0.004274	1.303429	2	Sentimental
buffet	54	195.108557	0.004167	1.24745	2	Food
Korean beef	51	183.897275	0.004065	1.191413	2	Food
very recommendable	54	177.229625	0.004167	1.24283	2	Sentimental
restaurant	52	171.959886	0.004098	1.201941	2	Food
celebrate	51	158.560252	0.004065	1.182022	2	Sentimental
expectation	48	144.735317	0.003968	1.123962	2	Sentimental
pizza	48	132.592664	0.003968	1.113391	2	Food
Bulgogi	45	123.041638	0.003876	1.057008	2	Food
Korean table d'hote	45	117.786204	0.003876	1.053752	2	Food
duck	43	115.664111	0.003817	1.019094	2	Food
excuse	44	114.850094	0.003846	1.038363	2	Sentimental
composure	41	98.315522	0.003759	0.976806	2	Sentimental
expensive	41	98.290686	0.003759	0.976734	2	Sentimental
celebration	41	96.451363	0.003759	0.975602	2	Sentimental
enjoy	41	96.393733	0.003759	0.975888	2	Sentimental
Kimchi	40	92.126833	0.003731	0.952724	2	Food
hardship	40	91.449893	0.003731	0.955335	2	Sentimental
unlimited serving	40	82.310442	0.003731	0.946301	2	Food
memory	37	76.409433	0.00365	0.893819	2	Sentimental
easily	66	283.975878	0.00463	1.494265	3	Sentimental
popularity	58	215.191137	0.00431	1.329886	3	Sentimental
pork belly	54	207.084581	0.004167	1.252918	3	Food
tired	55	182.286979	0.004202	1.262206	3	Sentimental

Table 5. *Cont.*

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
troublesome	53	161.501796	0.004132	1.217797	3	Sentimental
BBQ	51	153.432128	0.004065	1.175257	3	Food
pasta	44	114.069034	0.003846	1.034075	3	Food
fried-chicken	43	108.751885	0.003817	1.014057	3	Food
tripe	38	80.656331	0.003676	0.911228	3	Food
tonic	37	77.570752	0.00365	0.891711	3	Food
sweet taste	34	69.004339	0.003571	0.837939	3	Sentimental
stress	28	43.469819	0.003425	0.712831	3	Sentimental
octopus	24	28.7657	0.003333	0.627516	3	Food
cafe	59	284.026186	0.004348	1.373213	4	Food
tasty	63	250.735072	0.004505	1.429842	4	Sentimental
kind	52	165.324757	0.004098	1.203034	4	Sentimental
concern	50	152.409821	0.004032	1.162438	4	Sentimental
cold noodles	34	95.005162	0.003571	0.854982	4	Food
lifetime	33	66.153523	0.003546	0.818428	4	Sentimental
charm	34	64.719298	0.003571	0.834013	4	Sentimental
pigs' feet	33	60.387609	0.003546	0.810589	4	Food
charcoal fire	32	54.701426	0.003521	0.788868	4	Food
grilled	31	50.421126	0.003497	0.768134	4	Food
fortunate	24	31.97706	0.003333	0.633348	4	Sentimental
miss	15	11.454291	0.003145	0.451106	4	Sentimental
trust	6	1.4844	0.002976	0.270825	4	Sentimental

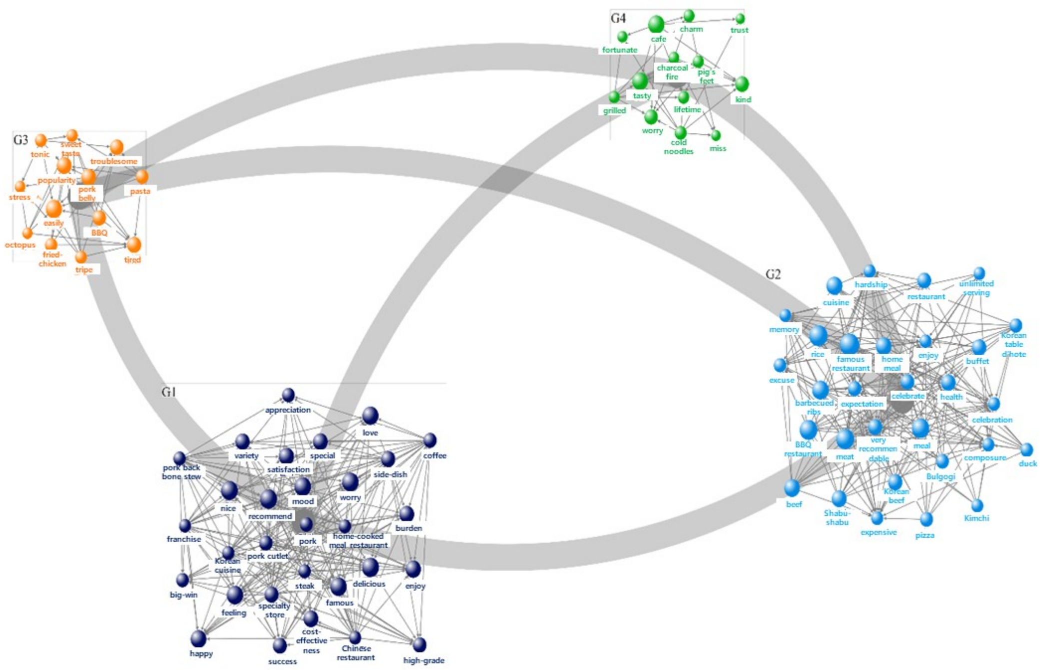

Figure 1. Sentimental network visualization of dining-out (2019).

Table 6. Sentimental network index of dining-out (2020).

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
enjoy	68	440.899372	0.004717	1.559007	1	Sentimental
recommend	69	408.194809	0.004762	1.55905	1	Sentimental
new	52	340.918363	0.004098	1.277353	1	Sentimental
mood	67	275.721365	0.004673	1.476108	1	Sentimental
satisfaction	66	262.917894	0.00463	1.454095	1	Sentimental
delicious	65	258.643622	0.004587	1.436707	1	Sentimental
cost-effectiveness	61	231.132277	0.004425	1.358892	1	Sentimental
love	62	224.527813	0.004464	1.371853	1	Sentimental
tired	62	222.432191	0.004464	1.371116	1	Sentimental
variety	61	221.630996	0.004425	1.354707	1	Sentimental
tasty	61	215.560356	0.004425	1.350838	1	Sentimental
health	60	214.609013	0.004386	1.33497	1	Sentimental
merry	61	210.170468	0.004425	1.348807	1	Sentimental
happy	58	192.750317	0.00431	1.291029	1	Sentimental
Sashimi	53	188.306519	0.004132	1.204808	1	Food
popularity	47	186.102392	0.003937	1.108562	1	Sentimental
specialty store	53	173.51095	0.004132	1.197633	1	Food
burden	55	167.541026	0.004202	1.228985	1	Sentimental
pizza	52	165.629174	0.004098	1.177149	1	Food
fried-chicken	47	147.380719	0.003937	1.085467	1	Food
home-cooked meal restaurant	50	137.5473	0.004032	1.129937	1	Food
high-grade	50	135.741742	0.004032	1.129093	1	Sentimental
very recommendable	49	135.209445	0.004	1.11295	1	Sentimental
kind	49	134.760867	0.004	1.112486	1	Sentimental
salad	48	132.020688	0.003968	1.093723	1	Food
duck	47	129.868121	0.003937	1.075394	1	Food
franchise	44	126.092065	0.003846	1.024459	1	Food
BBQ	47	117.818291	0.003937	1.06877	1	Food
unlimited serving	45	112.340337	0.003876	1.032249	1	Food
pork	45	107.835939	0.003876	1.028672	1	Food
meal	70	348.439369	0.004808	1.552481	2	Food
famous restaurant	70	348.439369	0.004808	1.552481	2	Food
home meal	68	315.729419	0.004717	1.507602	2	Food
meat	66	273.996738	0.00463	1.458074	2	Food
cuisine	64	268.244295	0.004545	1.422209	2	Food
barbecued ribs	65	255.493466	0.004587	1.433877	2	Food
rice	63	254.980259	0.004505	1.40065	2	Food
cafe	62	250.541379	0.004464	1.382279	2	Food

Table 6. *Cont.*

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
BBQ restaurant	62	244.225864	0.004464	1.378948	2	Food
beef	62	243.881168	0.004464	1.379042	2	Food
coffee	57	210.86832	0.004274	1.282546	2	Food
worry	57	190.436448	0.004274	1.273748	2	Sentimental
pasta	55	174.499946	0.004202	1.231711	2	Food
Sushi	55	172.395991	0.004202	1.23078	2	Food
pork belly	56	172.202498	0.004237	1.247301	2	Food
shabu-shabu	53	169.109242	0.004132	1.196152	2	Food
celebrate	53	164.794163	0.004132	1.194158	2	Sentimental
success	54	163.97476	0.004167	1.210411	2	Sentimental
restaurant	52	158.886622	0.004098	1.173677	2	Food
side-dish	52	153.366772	0.004098	1.171326	2	Food
buffet	50	149.883366	0.004032	1.136371	2	Food
special	52	149.003294	0.004098	1.169634	2	Sentimental
caution	51	142.850348	0.004065	1.150003	2	Sentimental
spicy stir-fried chicken	47	133.344585	0.003937	1.078022	2	Food
difficult	50	124.635092	0.004032	1.122582	2	Sentimental
delivery food	45	116.485076	0.003876	1.034367	2	Food
troublesome	44	95.330837	0.003846	1.005397	2	Sentimental
scary	42	90.405209	0.003788	0.969127	2	Sentimental
appreciation	40	86.897962	0.003731	0.933243	2	Sentimental
Outback steak house	39	86.864768	0.003704	0.916839	2	Food
nice	66	267.084691	0.00463	1.456131	3	Sentimental
concern	63	237.829579	0.004505	1.393748	3	Sentimental
famous	61	216.099775	0.004425	1.351752	3	Sentimental
pork cutlet	56	197.967183	0.004237	1.259735	3	Food
feeling	59	192.541133	0.004348	1.307373	3	Sentimental
Korean beef	54	175.408641	0.004167	1.215263	3	Food
steak	52	146.183606	0.004098	1.167631	3	Food
Korean table d'hote	50	131.808401	0.004032	1.126672	3	Food
box lunch	45	115.83974	0.003876	1.034597	3	Food
busy	46	107.317171	0.003906	1.045794	3	Sentimental
the past	43	93.08553	0.003817	0.987292	3	Sentimental
chopped noodle	41	87.202013	0.003759	0.950296	3	Food
premium	39	83.241308	0.003704	0.914457	3	Sentimental
Chinese-style noodles	40	82.100424	0.003731	0.929421	3	Food
frankness	39	81.397102	0.003704	0.91291	3	Sentimental

Table 6. *Cont.*

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
cheese	36	68.767121	0.003623	0.853211	3	Food
sincerity	35	61.67607	0.003597	0.832038	3	Sentimental
healing	27	34.288564	0.003401	0.673715	3	Sentimental
Shabu-shabu buffet	21	21.667991	0.003268	0.559834	3	Food
stress	22	20.71771	0.003289	0.574884	3	Sentimental
thistle	18	12.553157	0.003205	0.496886	3	Food

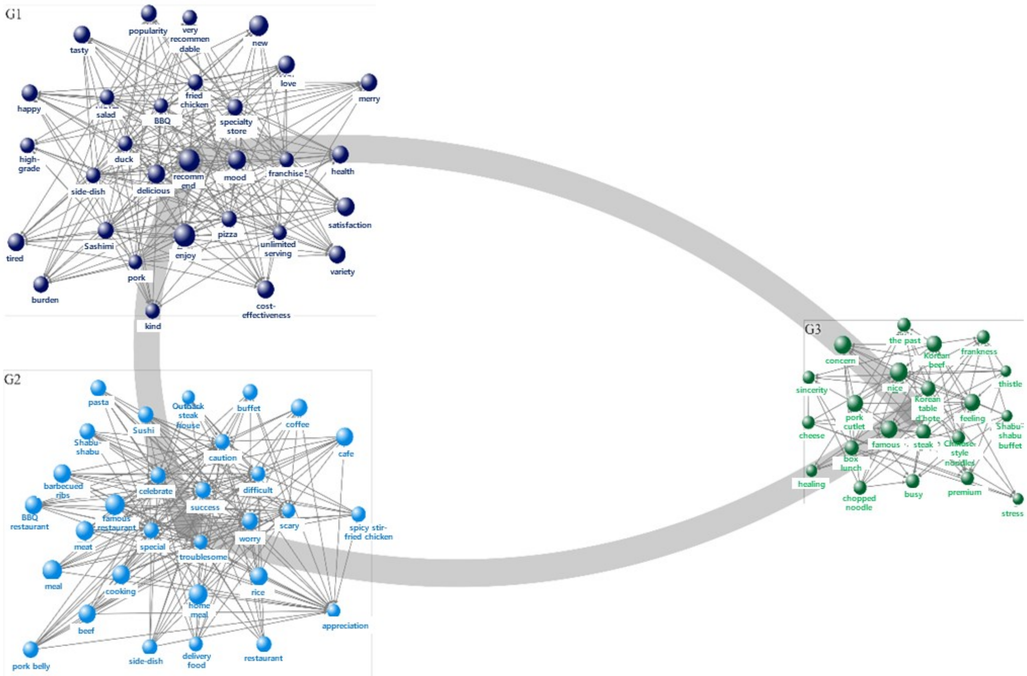

Figure 2. Sentimental network visualization of dining-out (2020).

Second, the results for semantic network analysis regarding the relationship between dining-out and consumer demand (purpose) for the 2019 data are depicted in Table 7. Regarding consumer demand for dining-out experience, discourses were formed revolving around words such as reservation, famous restaurant, meal, order, coffee, price, and sales. Particular attention needs to be paid to "reservation" and "famous restaurant," which produced a high value in all dining-related demand analyses, suggesting that the foremost purpose of searching with the keyword "dining-out" was to acquire information on reservations and famous restaurants. Consumer demand for information on meal, order, and price were especially pronounced, clearly showing consumers' purpose of searching "dining-out" on portal sites. The visualization of the demand network yielded three categories—famous restaurant, order, and price—confirming that consumers have keen demand for famous restaurants where they can make reservations and eat, and they search to order a variety of foods and also have price-related demand (Figure 3).

Table 7. Demand network index of dining-out (2019).

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
reservation	64	797.470922	0.004545	2.17584	1	Demand
famous restaurant	66	785.902987	0.00463	2.210304	1	Food
meal	61	632.06387	0.004425	2.038584	1	Food
cafe	55	528.291905	0.004202	1.858234	1	Food
rice	54	489.566346	0.004167	1.818386	1	Food
franchise	50	484.077206	0.004032	1.742427	1	Food
meat	54	461.573986	0.004167	1.805738	1	Food
restaurant	50	455.714825	0.004032	1.709666	1	Food
need	50	398.908795	0.004032	1.685233	1	Demand
barbecued ribs	49	367.200539	0.004	1.645367	1	Food
Korean cuisine	45	330.189035	0.003876	1.538223	1	Food
information	45	303.760925	0.003876	1.52143	1	Demand
plan	41	257.665268	0.003759	1.402606	1	Demand
Sushi	37	243.515131	0.00365	1.299266	1	Food
pork	40	242.208857	0.003731	1.370158	1	Food
buffet	38	198.672189	0.003676	1.295512	1	Food
specialty store	35	173.703943	0.003597	1.20724	1	Food
business	36	173.470822	0.003623	1.229887	1	Demand
facilities	31	172.946922	0.003497	1.116657	1	Demand
1 person	33	163.407887	0.003546	1.150719	1	Demand
pork cutlet	29	137.095746	0.003448	1.036453	1	Food
company	31	129.651836	0.003497	1.080755	1	Demand
dining voucher	28	126.105361	0.003425	1.006501	1	Demand
education	29	108.270836	0.003448	1.016802	1	Demand
help	28	107.423992	0.003425	0.99164	1	Demand
Japanese food	25	101.359003	0.003356	0.918269	1	Food
talk	25	95.216971	0.003356	0.912971	1	Demand
develop	22	84.653806	0.003289	0.828394	1	Demand
steamed pork	23	84.09314	0.003311	0.857146	1	Food
economic	26	80.825921	0.003378	0.921261	1	Demand
order	65	755.090093	0.004587	2.185213	2	Demand
coffee	54	510.186796	0.004167	1.829752	2	Food
solution	54	479.523213	0.004167	1.819816	2	Demand
take-out	53	460.135528	0.004132	1.788445	2	Demand
Delivery	51	443.284429	0.004065	1.728307	2	Demand
cuisine	51	435.727635	0.004065	1.72589	2	Food
food show	50	418.449551	0.004032	1.69896	2	Demand
fried-chicken	44	330.586755	0.003846	1.505421	2	Food

Table 7. *Cont.*

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
home meal	43	279.618268	0.003817	1.4619	2	Food
pizza	40	237.250726	0.003731	1.367106	2	Food
delivery food	35	200.993955	0.003597	1.231174	2	Food
expenses of dining-out	34	198.587997	0.003571	1.199892	2	Demand
foundation	36	198.414759	0.003623	1.244003	2	Demand
side-dish	36	189.832788	0.003623	1.243523	2	Food
effort	32	153.213665	0.003521	1.123898	2	Demand
price	31	149.938024	0.003497	1.098571	2	Demand
administration	30	147.066656	0.003472	1.069709	2	Demand
pasta	32	139.283028	0.003521	1.112205	2	Food
Kimchi	31	137.737133	0.003497	1.089665	2	Food
discount	30	137.095817	0.003472	1.064892	2	Demand
beef	32	127.219503	0.003521	1.103435	2	Food
shabu-shabu	29	117.158385	0.003448	1.024257	2	Food
industry	30	103.815577	0.003472	1.037495	2	Demand
food expenses	26	100.322078	0.003378	0.941752	2	Demand
steak	29	98.712928	0.003448	1.009557	2	Food
salad	24	84.41505	0.003333	0.877673	2	Food
coupon	26	79.76715	0.003378	0.920865	2	Demand
accident	23	73.564528	0.003311	0.842634	2	Demand
consumption	23	62.055311	0.003311	0.832573	2	Demand
poor	21	58.966211	0.003268	0.782713	2	Demand
cost	69	909.735046	0.004762	2.322271	3	Demand
sale	50	410.123353	0.004032	1.691861	3	Demand
operate	49	368.839937	0.004	1.645838	3	Demand
sell	37	225.504147	0.00365	1.292445	3	Demand
Chinses food	33	191.933074	0.003546	1.172243	3	Food
charge	37	180.051015	0.00365	1.259376	3	Demand
pork belly	36	174.300492	0.003623	1.230647	3	Food
BBQ restaurant	35	162.372335	0.003597	1.199899	3	Food
chance	33	159.888637	0.003546	1.149984	3	Demand
support	31	152.679513	0.003497	1.101476	3	Demand
purchase	30	137.777301	0.003472	1.06422	3	Demand
BBQ	27	93.720121	0.003401	0.956429	3	Food
resident	23	88.402854	0.003311	0.866486	3	Demand
pigs' feet	25	85.78213	0.003356	0.904768	3	Food
test	25	85.617066	0.003356	0.903689	3	Demand
Korean beef	25	82.215865	0.003356	0.898171	3	Food

Table 7. *Cont.*

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
consulting	25	81.01189	0.003356	0.897511	3	Demand
Bulgogi	24	72.777947	0.003333	0.865727	3	Food
Sushi restaurant	23	65.296239	0.003311	0.834241	3	Food
cold noodles	20	62.789884	0.003247	0.758093	3	Food
black soybean noodle	22	61.753778	0.003289	0.806894	3	Food
Korean table d'hote	20	49.884784	0.003247	0.747209	3	Food
Growth	19	49.299321	0.003226	0.72107	3	Demand
Chinese-style noodles	19	44.64515	0.003226	0.715376	3	Food
consumer	18	37.982898	0.003205	0.683535	3	Demand
soup	17	35.649719	0.003185	0.65714	3	Food
pork back-bone stew	16	32.083259	0.003165	0.626322	3	Food
grilled	16	30.176911	0.003165	0.624164	3	Food
Outback steak house	16	29.323732	0.003165	0.624976	3	Food
Shabu	12	25.322948	0.003086	0.520164	3	Food

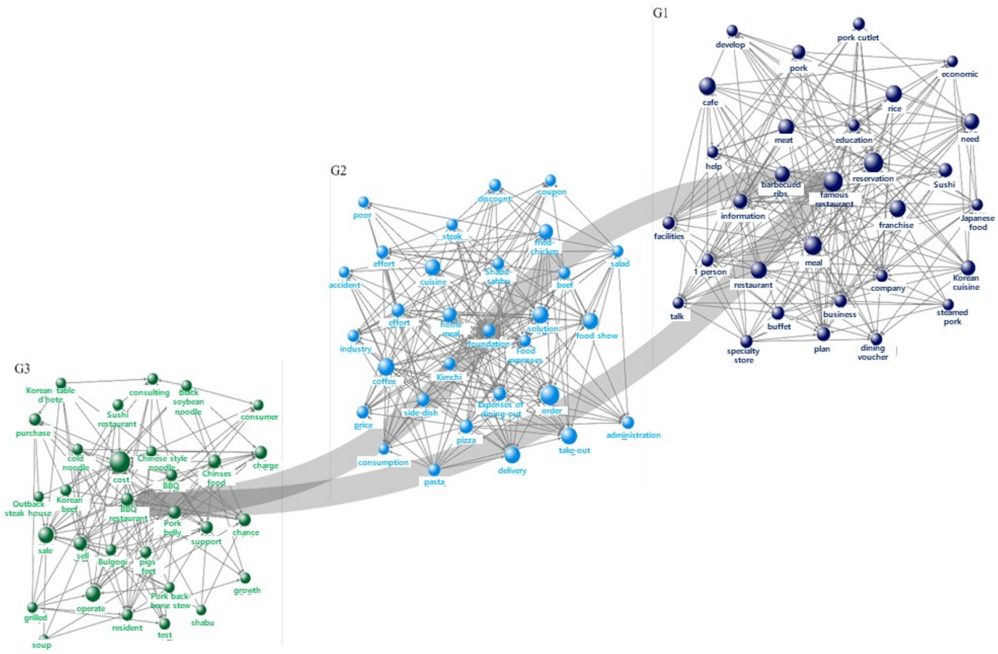

Figure 3. Demand network visualization of dining-out (2019).

The results of the semantic network analysis on the relationship between dining-out and consumer demand (purpose) for 2020 data are depicted in Table 8. Discourses were formed revolving around keywords such as price, delivery, order, take-out, famous restaurant, café, meal, rice, meat, barbecued ribs, pizza, and social distance. Unlike in 2019, the foremost purpose of the search for dining-out was to obtain information on food delivery, order, and take-out, indicating that consumers' dining-out demand shifted toward this amid the COVID-19 pandemic. The same result was observed in the demand network visualization, as three categories were identified: delivery, famous restaurants, and social distance (Figure 4). That is, consumers searched "dining-out" on portal sites for information on food take-out, order, and delivery to meet their demand for dining-out experience in compliance with social distance, thereby generating strikingly different results from the 2019 data.

Table 8. Demand network index of dining-out (2020).

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
price	65	753.577869	0.004587	2.156064	1	Demand
delivery	66	743.580499	0.00463	2.175311	1	Demand
order	64	713.973257	0.004545	2.110157	1	Demand
take-out	63	610.409801	0.004505	2.055841	1	Demand
reservation	58	513.525267	0.00431	1.904466	1	Demand
solution	58	511.006219	0.00431	1.898237	1	Demand
need	56	472.396154	0.004237	1.838031	1	Demand
operate	53	430.713433	0.004132	1.745185	1	Demand
sale	50	392.584543	0.004032	1.664849	1	Demand
information	49	317.853367	0.004	1.599476	1	Demand
expenses of dining-out	43	236.584794	0.003817	1.417147	1	Demand
BBQ restaurant	42	216.878305	0.003788	1.38134	1	Food
Korean beef	40	210.940305	0.003731	1.328835	1	Food
purchase	38	204.997075	0.003676	1.279821	1	Demand
buffet	35	173.381866	0.003597	1.189104	1	Food
pork belly	36	158.019368	0.003623	1.203344	1	Food
steak	36	157.888266	0.003623	1.202163	1	Food
food show	36	151.892945	0.003623	1.201917	1	Demand
safety	35	147.926619	0.003597	1.173527	1	Demand
food expenses	35	147.665422	0.003597	1.17435	1	Demand
distancing	32	147.051057	0.003521	1.103845	1	Demand
plan	32	139.882656	0.003521	1.102034	1	Demand
spread	31	137.001023	0.003497	1.072903	1	Demand
stimulus check	32	128.440692	0.003521	1.092867	1	Demand
pork cutlet	30	117.946322	0.003472	1.032443	1	Food
spicy stir-fried chicken	29	115.941438	0.003448	1.008674	1	Food
beef	31	111.294116	0.003497	1.051863	1	Food
side-dish	30	102.67317	0.003472	1.01995	1	Food
cheese	28	95.439848	0.003425	0.968055	1	Food
revenue	24	91.653767	0.003333	0.869018	1	Demand
famous restaurant	68	836.825037	0.004717	2.25661	2	Food
cafe	66	802.226792	0.00463	2.204632	2	Food
meal	61	625.758876	0.004425	2.019672	2	Food
Sashimi	57	583.940076	0.004274	1.922639	2	Food
franchise	58	539.574148	0.00431	1.911204	2	Food

Table 8. *Cont.*

Word	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
delivery food	54	532.664604	0.004167	1.83269	2	Food
cuisine	54	438.756065	0.004167	1.774375	2	Food
fried-chicken	49	386.663831	0.004	1.63942	2	Food
home meal	49	364.400855	0.004	1.625339	2	Food
coffee	50	358.617647	0.004032	1.645642	2	Food
discount	41	302.000188	0.003759	1.385031	2	Demand
administration	37	281.176252	0.00365	1.29098	2	Demand
restaurant	43	258.231127	0.003817	1.429782	2	Food
specialty store	41	247.060278	0.003759	1.379772	2	Food
support	40	238.284133	0.003731	1.349089	2	Demand
business	33	208.870111	0.003546	1.152666	2	Demand
Korean cuisine	36	187.477842	0.003623	1.226806	2	Food
foundation	39	181.326074	0.003704	1.289612	2	Demand
box lunch	36	157.110387	0.003623	1.202653	2	Food
company	34	135.898005	0.003571	1.142304	2	Demand
prevention	27	119.277605	0.003401	0.961696	2	Demand
government	31	113.685187	0.003497	1.053777	2	Demand
Chinses food	28	107.884402	0.003425	0.978714	2	Food
rice cake	27	105.380137	0.003401	0.955441	2	Food
industry	28	87.888155	0.003425	0.961717	2	Demand
damage	27	84.295056	0.003401	0.934965	2	Demand
steamed pork	26	81.54425	0.003378	0.908448	2	Food
help	26	74.889147	0.003378	0.904532	2	Demand
recruitment	16	74.269798	0.003165	0.675009	2	Demand
pigs' feet	26	70.822506	0.003378	0.899606	2	Food
rice	49	320.909707	0.004	1.599567	3	Food
meat	44	259.40111	0.003846	1.450645	3	Food
barbecued ribs	40	231.633728	0.003731	1.344203	3	Food
pizza	40	210.245023	0.003731	1.330354	3	Food
social distance	40	182.211182	0.003731	1.312169	3	Demand
situation	32	154.636898	0.003521	1.103237	3	Demand
effort	35	152.636383	0.003597	1.175636	3	Demand
prohibit	32	117.355774	0.003521	1.080988	3	Demand
salad	25	78.445464	0.003356	0.882549	3	Food
coupon	25	63.403519	0.003356	0.869361	3	Demand
Sushi	22	55.469974	0.003289	0.788607	3	Food
application	19	49.648969	0.003226	0.71365	3	Demand
test	17	25.586032	0.003185	0.635372	3	Demand

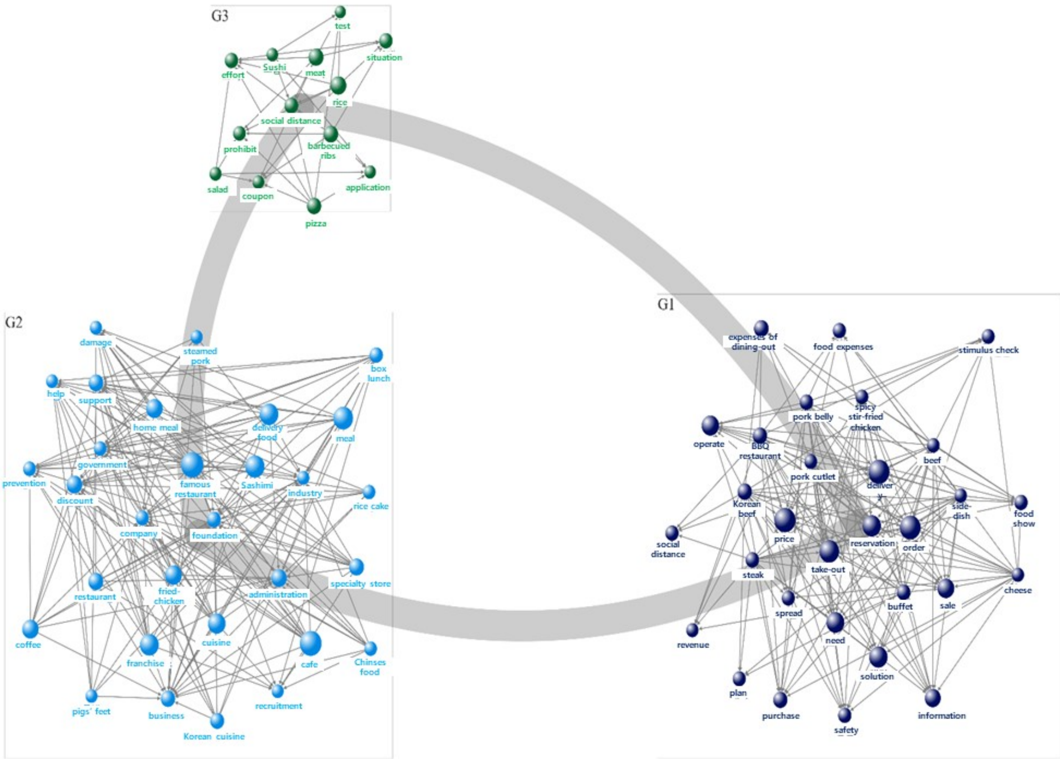

Figure 4. Demand network visualization of dining-out (2020).

Based on the analysis results, we found that the network on consumers' dining-out sentimental consisted of discourses on delicious, recommend, nice, famous restaurant, rice, meat, BBQ restaurant, meal, barbecued ribs, café, easily for 2019 data, and discourses on enjoy, recommend, new, mood, satisfaction, delicious, meal, famous restaurant, home meal, famous, and feeling for 2020 data. The demand network for 2019 data contained words such as reservation, famous restaurant, meal, order, coffee, price, sale, whereas for 2020 data, it contained words such as delivery, price, order, take-out, famous restaurant, café, meal, rice, meat, barbecued ribs, pizza, and social distance, indicating widely different consumer demand or needs.

4.4. Sentiment Analysis

A sentiment analysis was performed using a text mining technology that automatically extracted emotion-related information from the collected keywords. A natural language processing technology that analyzes subjective data in texts, such as people's attitudes, opinions, and tendencies, sentiment analysis was used in this study to detect positive and negative words extracted from the data and analyze them. After the words were categorized using the emotional vocabulary dictionary, which was created independently by TEXTOM, their frequency and emotional intensity were calculated. Among emotional words, the following keywords showed significant increases in usage from 2019 to 2020 in the frequency of their appearance: stifling (by 196 times); scary (by 179 times); difficult (by 146 times); and anxiety (by 134 times) (See Table 9). Moreover, compared with 2019, the number of negative keywords increased by 4.36% in 2020, whereas the number of positive keywords decreased by 4.365%. Specifically, sub-emotions in the positive category (i.e., good feeling and joy) decreased in 2020 compared with 2019, whereas sub-emotions in the negative category (i.e., fear, pain, and anger) increased in 2020 compared with 2019. The sub-emotion of fear was found to have increased the most (Tables 10 and 11).

Table 9. Sentiment word frequency of dining-out.

	2019	2020	Increase or Decrease
Positive word	82.31%	77.95%	−4.36%
Negative word	17.69%	20.05%	+4.36%

Table 10. Sentiment analysis of dining-out (2019).

	Frequency	Sentiment Intensity (%)	Frequency (%)
Positive	36,495	82.68	82.31
Good feeling	30,324	69.21	68.39
Joy	3949	8.74	8.91
Interest	2222	4.73	5.01
Negative	7844	17.32	17.69
Sadness	2456	5.64	5.54
Disgust	3579	8.23	8.07
Fear	796	1.21	1.80
Pain	265	0.65	0.60
Anger	620	1.24	1.40
Fright	125	0.34	0.29
Total	44,339	100.00	100.00

Table 11. Sentiment analysis of dining-out (2020).

	Frequency	Sentiment Intensity (%)	Frequency (%)
Positive	31,680	78.93	77.95
Good feeling	26,547	66.86	65.32
Joy	3292	7.86	8.10
Interest	1841	4.21	4.53
Negative	8962	21.07	22.05
Sadness	2629	6.53	6.47
Disgust	893	1.73	2.20
Fear	3545	8.67	8.72
Pain	1367	2.98	3.36
Anger	396	0.78	0.97
Fright	132	0.38	0.32
Total	40,642	100.00	100.00

5. Discussion and Implications

This study identifies words closely associated with the keyword "dining-out" based on big data gleaned from social media and investigates consumers' perceptions of dining-out and related issues before and after COVID-19. The study findings can be summarized as follows. In 2019, a total of 39,144 dining-related keywords appeared on social media, and 39,240 in 2020. In 2019, frequently appearing dining-related words were dining-out, family, famous restaurant, recommend, dinner, delicious menu, and restaurants. In 2020, they were dining-out, family, famous restaurant, recommend, dinner, taste, Corona, and weekend. Compared to 2019, home meal, delivery, and cooking produced high TF-IDF values in 2020, indicating consumers' changing perceptions over dining-out amid the COVID-19 outbreak. These findings were partially consistent with Jia's [33] study, which demonstrated that the number of visits to restaurants decreased significantly after the outbreak of the COVID-19 pandemic. Yang et al. [35] reported that the number of meals through delivery platforms increased compared to sitting at restaurants due to the COVID-19. A similar pattern was reported by Jeong et al. [36], who found that the number of food deliveries increased drastically after the corona virus-related articles were published. Additionally, Dsouza and Sharma [40] showed a similar result to the fact that the use of delivery food increased significantly after Corona. The analysis results for the dining-out sentimental network based on 2019 data revealed discourses revolving around delicious, recommend, nice, and easily. For the 2020 data, discourses revolved around struggling, burdensome, concerned, cautious, and fearful. The analysis of consumers' dining-out demand network for 2019 data showed discourses centered around reservation, famous restaurant, meal, order, coffee, price, and sale. However, for 2020 data, discourses were formed around delivery, price, order, take-out, famous restaurant, café, meal, rice, meat, pizza, and social distance. In short, with the outbreak of the pandemic, delivery, takeout, and social distance emerged as new search words. This finding was in line with Mayasari et al. [32] and Kowalczuk et al.'s [41] results, which showed that after the outbreak of the COVID-19 pandemic, new eating habits centered on food delivery or digital consumer had emerged, as there were more indoor activities than outdoor activities after the outbreak of the COVID-19 pandemic. In addition, the results of the sentiment analysis revealed that the frequency and intensity of negative emotions increased in 2020 after the outbreak of the COVID-19 pandemic compared with those in 2019 before the pandemic. This increasing trend in negative emotions regarding dining-out could have been due to negative emotions that emerged in daily life as a result of restrictions on dining-out during the COVID-19 pandemic. Furthermore, the increasing trend in negative emotions is expected to continue for the time being.

Academic implications can be derived from these research findings. Most big data-based research on the hospitality industry, including dining-out, has been conducted with "travel" as a keyword; none has been undertaken with "dining-out" as a keyword, which severely bore the brunt of the pandemic. This study derived dining-related words on portal sites for periods before and after COVID-19 and also examined pandemic-triggered changes in them from the perspective of consumer sentimental and demand. Moreover, longitudinal interpretations were conducted, and these are not possible for surveys that have a limited sample size. As this study collected and analyzed big data gleaned from *Naver* and *Daum* portal sites for the 2019–2020 period, it is deemed the first research to investigate changes in consumers' sentimental perceptions and trends relating to dining-out before and after COVID-19. Moreover, the sentiment analysis confirmed that changes in consumers' emotional keywords related to dining-out became increasingly negative after the outbreak of COVID-19 compared with before the outbreak. From an academic perspective, findings on changes in dining-related keywords can provide preliminary data for foodservice businesses to strengthen their competitive edge.

Regarding more practical implications, we provide policy proposals to further develop the foodservice industry. First, compared to 2019, keywords such as home meal, delivery, and cooking became strongly influential and valuable in 2020, and these may be applied to post-COVID-19 dining-out trend analyses. After the outbreak of COVID-19, consumer interest in home meals and cooking increased, and their preference for delivery food grew sharply. Related data may be used to launch new brands or products. Big data on dining-related keywords on social media vividly displayed consumers' thoughts and feelings before and after the pandemic. In 2019, consumers sought an enjoyable, satisfying atmosphere and delicious food, whereas in 2020, they associated dining-out with concerned, cautious, fearful, and hard feelings. Accordingly, restaurants must provide safe and reliable food to consumers who are worried about being infected by the corona virus. In addition, based on the findings that positive emotions related to dining-out decreased and negative emotions increased after the outbreak of COVID-19, it is necessary to develop a dining-out marketing strategy that could assuage such negative emotions. Therefore, it is also necessary to provide objective and factual information to alleviate the negative emotions perceived by consumers regarding dining out, such as fear. The findings of this research are expected to help businesses adapt to pandemic situations in the future and stimulate sustainable business management.

This study has several limitations. First, due to the scarcity of academic research and big data analysis of dining-related social media data, a comparative analysis with previous research could not be done properly. This is expected to improve as follow-up studies continue. Second, this study investigated consumers' perceptions of dining-out before and after COVID-19 based on big data, and in doing so, it posed a question instead of establishing a hypothesis. Third, due to constraints of time and budget, data were collected from only two portal sites—*Naver* and *Daum*. Going forward, more diverse channels, such as Instagram, Facebook, and Twitter, may be tapped for data collection. Fourth, because consumers' perceptions of and concerns about dining out may have varied at different stages of the pandemic and may have differed in other regions of the world, in future research, a keyword analysis should be conducted when the pandemic is over to compare results before and after the COVID-19 pandemic. It would be advisable to undertake follow-up studies to address these limitations and produce more objective results.

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