sustainability

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A Study of Consumers' Perceptions of Take-Out Food before and after the COVID-19 Outbreak: Applying Big Data Analysis

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Abstract: This study explored changes in consumers' perceptions of take-out food before and after the onset of the COVID-19 pandemic using big data collected from social media. Using "take-out food" as a keyword, 18,544 search results were found in 2019, before the COVID-19 outbreak, compared to 20,718 search results in 2021. These keywords were analyzed using text mining, semantic network analysis, CONCOR analysis, and sentiment analysis, respectively, to understand consumers' perception of take-out food. Using text mining, in 2019, "dining-out" was the most frequent search term associated with take-out food, followed by packing, famous restaurant, family, delicious, menu, and available. In 2021, "dining-out" was again the most popular keyword, followed by packing, famous restaurant, delivery, family, delicious, available, and Corona. A semantic network analysis showed that, in 2019, four categories emerged: delicious, meat, satisfaction, and lunchbox. The same analysis showed that, in 2021, the categories were delicious, meat, good, and home meal. These findings suggest that, after COVID-19, take-out food began to be recognized as a daily meal that can replace home-cooked meals. According to the sentiment analysis, the number of positive keywords decreased by 4.03% after COVID-19, while the number of negative keywords increased at the same rate; regarding the increase in negative keywords, such as sadness, disgust, and fear, since the emergence of COVID-19, consumers' anxiety about eating out due to the virus was observed. This study can be useful by providing core data and an analysis method necessary for food service companies' business activities and decision making related to take-out amid consumers' rapidly changing needs for the dining-out environment caused by COVID-19.

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

Citation: Jang, J.; Lee, E.; Jung, H. A Study of Consumers' Perceptions of Take-Out Food before and after the COVID-19 Outbreak: Applying Big Data Analysis. *Sustainability* **2022**, *14*, 11889. https://doi.org/10.3390/su141911889

Academic Editor: Jun (Justin) Li

Received: 23 August 2022
Accepted: 17 September 2022
Published: 21 September 2022

1. Introduction

The impact of the COVID-19 pandemic, which emerged at the end of 2019, has brought profound changes to people's diets and all aspects of their daily life. In South Korea, as the number of COVID-19 cases increased, the government implemented regulations around social distancing and limited the number of private gatherings. Many schools and companies expanded online classes and telecommuting, and people refrained from going out due to concerns about contracting the virus [1]. These shifts of daily life also brought major changes to the food service market, and on-premises restaurants have experienced great difficulties in business compared to before COVID-19. Meanwhile, the delivery and take-out food service markets have grown in sales and are expanding in connection with the online market [2–4]. Accordingly, many on-premises restaurants are seeking new measures, such as starting or expanding their take-out services [2,3,5].

With the recent expansion of the restaurant market and the introduction of food technology, various types of dining out are emerging. Although the traditional method of eating out is to dine in the restaurant, the food industry is adopting various types of new services, such as delivering food to a place chosen by the consumer, allowing consumers to visit the restaurant and take food out to eat at another desired place, and providing meal kits that consumers can cook at home [6,7]. These services are made even more convenient through mobile applications or online sites. As consumers prefer non-contact services due to COVID-19, such types of dining out are becoming more popular [8]. According to a 2022 Statista report, the global market for online food delivery service is expected to reach USD 223.7 billion in 2025, up from USD 115.07 billion in 2020 [9,10]. According to the National Restaurant Association [11], approximately 60% of restaurant customers in the United States dine out. Restaurants offer delivery, pick-up, drive-through, and curbside services [11,12]. As such, with the consumers' demand for non-contact off-premises services increasing as a result of COVID-19, studies are being actively conducted on these areas [9,13,14]. However, to date, studies have largely focused on online food delivery [13–15], with take-out services mainly being included in the same category as food delivery [8,16]. In other words, few studies focus exclusively on take-out services. Therefore, it is necessary to examine take-out services, which have increased in popularity among restaurant services due to the expansion of non-contact consumption in the wake of COVID-19. Most importantly, it is necessary to investigate consumers' changing perceptions of services due to COVID-19, which has had a great ripple effect on the overall restaurant industry.

As non-contact services have become the new normal for consumers' dining-out behaviors due to the ongoing COVID-19 pandemic, this study aims to investigate the changes in consumers' perceptions and emotions between pre-COVID-19 (2019) and post-COVID-19 (2021) eras in the context of take-out services using a big data analysis. First, we identified the relevant keywords by collecting big data using the search keywords "take-out food" before and after the onset of COVID-19 and performing text mining. Second, using the derived keywords, we identified the correlation between common words using a semantic network analysis and CONCOR analysis. Finally, we examined the change in emotional keywords by using positive and negative words extracted from data through sentiment analysis. In this way, this study aimed to provide key data and analysis methods that can be useful for food service companies' business activities and decision making in relation to take-out services amid rapidly changing consumer needs for the dining environment due to COVID-19.

2. Related Studies

2.1. COVID-19 and Dining Out

The COVID-19 pandemic caused major changes in not only living conditions, but also the dining environment, and many studies have investigated how consumer behaviors related to dining out have changed due to COVID-19 [17–19]. As non-contact consumption became mainstream during the pandemic, research topics have primarily focused on food delivery services [17,18,20]. Meanwhile, the evolution of digital technologies, including smartphones, has provided technological support for non-contact transactions, thereby accelerating the online food delivery industry, and related research is being actively conducted [13,21]. Shroff, Shah, and Gajjar [13], in their review of online food delivery research, reported that, from 2015—when the first research on online food delivery (OFD) was published—until 2021, 368 papers related to OFD were included in Web of Science's core collection. Looking at some examples of related studies, Mehrolia, Alagarsamy, and Solaikutty [17] empirically measured the characteristics of customers who ordered and did not order online food during the COVID-19 crisis in India. They investigated respondents' characteristics such as age, patronage frequency before the lockdown, affective and instrumental beliefs, product involvement, and perceived threat, to investigate significant differences between the two categories of OFD customers. They reported that high perceived threats, less product involvement, low perceived benefit of OFDs, and less frequent online food orders are less likely to lead individuals to order OFD. Brewer and Sebby [20] explored the effect of two dimensions of stimuli—marketing stimuli (menu visual appeal and menu informativeness) and social stimuli (perception of COVID-19 risk)—on desire for food, perceived convenience of online food ordering, and purchase intentions when ordering food online during the COVID-19 pandemic. They discovered the indirect effects of the menu's visual appeal and informativeness and the perception of COVID-19 risks on consumers' purchase intentions.

A new research trend is studying the changed dining-out trends and consumption patterns at two different time points before and after the onset of COVID-19. Jung, Yoon, and Song [22] identified words closely associated with the phrase "dining out" using big data gleaned from social media to investigate consumers' perceptions of dining out and related issues before and after COVID-19. According to the results, before COVID-19, discussions using words such as delicious, nice, and easy were common, but after COVID-19, negative expressions such as struggling and cautious were the main sentiment. The authors noted that, with the outbreak of the pandemic, new search terms such as delivery, take-out, and social distancing emerged. They also reported a decrease in positive emotions and an increase in negative emotions after the outbreak of COVID-19 compared to before the pandemic. Kim and Kim [5] analyzed trends in dining-out consumption before and after the pandemic emerged using text mining of big data such as online comments and SNS. The analysis indicated that, before COVID-19, the internet search for local restaurants mainly related to tourist destinations, family dining out, and family events; after COVID-19, many keywords related to delivery service and specific menus and restaurant names. Zhu et al. [19] studied how the COVID-19 pandemic affected Chinese consumers' food consumption away from home. They analyzed sales records from a large restaurant chain located in 12 cities in China from 1 January 2019 to 31 December 2020. The results indicated that consumers reported ordering and consuming more calories (as well as carbohydrates, protein, fat, and sodium) after the COVID-19 outbreak than during the pre-COVID-19 period. This finding did not support the hypothesis that COVID-19 led consumers to eat more healthily during the pandemic. Chotigo and Kadono [18] examined and compared the important factors that encourage Thai customers to use food delivery apps before and during the COVID-19 pandemic, including external factors such as trust, convenience, application quality, and satisfaction. Their results showed that satisfaction was affected by social influence, trust, convenience, and application quality both before and during the COVID-19 pandemic. In addition, price value was a significant predictor of satisfaction before the pandemic, but not during the pandemic. On the other hand, habits had a significant influence on satisfaction before the pandemic, but they were found to have a negative influence on satisfaction during the pandemic. The results also showed that satisfied customers who use food delivery apps are more likely to continue using them.

As the COVID-19 pandemic led to a "new normal" in dining environments, more multifaceted studies are needed in order to examine the changes in consumers' perceptions and behaviors in terms of dining-related services, products, and issues. Moreover, as constant concerns about infectious diseases, such as the emergence of new strains of viruses, continue and create uncertainty in society at large [23], it is important for academics and industry stakeholders to closely examine and learn about changes in consumers' perceptions due to COVID-19, which will be essential for understanding consumers in a future era of uncertainty.

2.2. Take-Out Food

Delivery and take-out have been explored as the same category in several studies [8,16]. Some studies have focused on fast food among different types of dining out, while certain studies in North America and Europe considered delivery and take-out to be one of the characteristics of fast-food service [24–26]. This is related to the study analyzing the cause-and-effect relationship between both geriatric diseases and obesity problems, which have recently intensified in developed countries, and fast-food consumption [6]. Recent studies have also focused on the food delivery market rather than take-out services, as the development of food technology has led to a growing online food delivery market, which is more convenient for consumers [13–15]. However, Kim and Go [6] found that delivery and take-out consumption differed depending on individual income, occupation, and weight, revealing heterogeneous characteristics. In addition, Kim [8] divided consumers' consumption behavior into rational and emotional motives, finding that rational motives such as economic benefit, ease of use, low price, and convenience had a positive effect on delivery choice, while take-out service use increased when emotional motives such as aspiration, change of mood, desire satisfaction, and rest increased along with rational motives. Recently, in restaurants that provide food delivery, not only general setup restaurants, but also cloud kitchens have risen as the mainstream type of business [27,28]. Cloud kitchens mainly provide delivery services and, as a result, take-out options are mostly offered at restaurants with service facilities [27,28]. In addition, curbside and drive-throughs are popular take-out options that are distinct from delivery [12]. Therefore, delivery and take-out services cannot be considered the same as service providers, and the methods of services provided to consumers are also different, meaning consumers' perceptions and satisfaction toward the related products and services could differ as well.

Although not many recent studies regard take-out food as fast food or a category within online delivery food, certain exceptions exist. Kim and Go [6] analyzed how individual characteristics of Korean adult consumers are related to the consumption of delivery and take-out food. The younger the age or the higher the education level, the higher the rate of consumption of delivery and take-out food reported. According to the authors, higher education levels increase the opportunity cost of time, which in turn increases the rate of choosing time-saving delivery and take-out food consumption options. Meanwhile, younger consumers are more likely to consume delivery or take-out food because it is easier for them to order delivery or take-out food using the Internet or mobile apps according to recent technological advances. These results demonstrate that delivery and take-out foods are non-homogeneous goods, and their consumption varies according to individual weight, income, and occupation. For instance, in the case of delivery food, both the consumption rate and frequency increased as the consumer's body weight or personal income increased. However, for take-out food, higher body weight meant the subjects were less likely to consume it, but there was also no significant difference in consumption with personal income. Furthermore, in terms of occupation, the frequency of consumption of take-out food was higher among those in service or sales positions. Mura et al. [29] examined whether take-out food consumption mediates the association between socioeconomic status and fruit and vegetable intake and, if so, to what extent. The results showed that the lowest-education group consumed fewer fruits and vegetables than the highest education group, leading to the unhealthy consumption of take-out foods. On the contrary, consumers with higher education levels showed higher consumption of healthy take-out food. Although research on take-out food has been conducted, despite the recent increased demand from consumers due to COVID-19, research in this area is still very limited.

In their review paper analyzing studies of consumers' reviews of food delivery services, Adak et al. [30] reported that consumers' complaints commonly related to delivery time, service, food quality, and cost. The Food Consumption Behavior Survey of the Korea Rural Economic Research Institute [31] found that high price, long waiting time, and unsatisfactory taste were the main reasons for rarely or infrequently using delivery services. The most common reasons for using take-out services were saving delivery costs and cheaper prices through discounts on take-out services, followed by a long waiting time for deliveries. In particular, in South Korea, the advancement of food delivery services via mobile applications led to overheated competition due to the explosive demand for delivery, the oligopoly of a small number of applications, and expensive delivery fees [32]. When consumers are dissatisfied with food delivery services, take-out services can provide an alternative.

2.3. Big Data in the Food Service Industry

As the fourth industrial revolution's technology development supports the demand for non-contact services due to COVID-19, various convenient online dining services have become part of daily life. Big data including various types of information have been created by sharing this information on restaurant service and consumers' experiences online, making big data analysis an important tool for understanding industry trends [23]. Consumers share their experiences, emotions, and opinions related to various food products, services, and organizations through online comments and posts. Accordingly, it is important to extract meaningful information from the enormous amounts of data and utilize it in research [33]. Big data analyses can collect a large amount of data accumulated in daily life quickly and accurately. These data can then be used to analyze consumers' opinions objectively. Therefore, the analysis of big data reflecting consumers' opinions in everyday life is of great help when it comes to discovering new results or valuable implications not revealed in previous studies using interview or survey techniques [34].

Typical methods of big data analysis include text mining, semantic network analysis, convergence of iteration correlation (CONCOR) analysis, topic modeling, and sentiment analysis [34,35]. This study used text mining, semantic network analysis, CONCOR analysis, and sentiment analysis to understand consumers' perceptions of take-out food before and after the onset of COVID-19. Text mining is a method of extracting meaningful keywords from unstructured data collected through natural language-processing technology in order to discover useful information and new knowledge that has not previously been revealed [34,36]. In addition, text mining can extract the main keywords from numerous texts in large-scale text data, and the extracted texts can be utilized for sentiment analysis and network analysis [37]. A semantic network analysis is a method of applying social network analysis to text analysis, extracting meaningful words from texts, and identifying the connection system formed through the extracted words and their relationships [38]. In addition, semantic network analysis, like social network analysis, is an analysis method that identifies a phenomenon through a network constructed by representing a specific action entity as a node and the connection between nodes as a link [37]. To understand the characteristics of the network connection structure, degree centrality—an index derived through semantic network analysis—is used, which represents how frequently it is used with other connected keywords [39]. Semantic network analysis helps grasp the meaning of text precisely in detail by identifying keywords that appear simultaneously and adjacent to each other [34,40]. A CONCOR analysis derives clusters formed by words that share similarities based on a semantic network analysis and enables intuitive understanding of the entire network structure. This method is used to find and classify nodes with similarities in structurally equivalent positions among the connections of nodes using correlation coefficients for the main keywords [34,41]. A sentiment analysis, also called opinion mining, is a method of analyzing people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions about products, services, organizations, individuals, issues, events, and topics [42,43]. In general, it is used to classify emotions expressed in texts or to convert them into objective numerical data. In a narrow sense, it can be seen as classifying positive and negative emotions in the text [44]. In addition, this analysis method includes not only simply classifying positive and negative, but also analyzing the intention or stance of the writer by extracting positive and negative words [45].

Recent studies applying big data have been actively utilized to understand the food service industry. Most studies employ customers' reviews and ratings on Google Maps [46,47] or travel, hotel, and restaurant platforms such as Yelp or TripAdvisor [48–50] to investigate words implying positive or negative evaluations [46] and the effects of the intensity of emotions in reviews, length of reviews, and expertise of reviews [50]. For example, Shin et al. [46] collected 5427 restaurant reviews from Google Maps and performed a sentiment analysis. The importance of the collected words was vectorized, and the positive and negative coefficients of the words in the review were calculated using machine learning. The researchers identified four evaluation categories: food, price, service, and atmosphere.

They also identified words to detect positives and negatives in restaurant evaluations in each aspect. Mathayomchan and Taecharungroj [47] analyzed 935,386 Google Maps reviews of 5010 restaurants in London, Birmingham, and Manchester to examine the effects of restaurant attributes and the underlying factors impacting overall customer experience within a range of different restaurant types. They used the VADER sentiment analysis algorithm to measure sentiment related to four key restaurant attributes: food, service, atmosphere, and value. They also tested the relationship between these attributes and five-star ratings, and the top 30 food items of eight types of restaurants were analyzed to explore factors that elicited positive and negative evaluations. Li, Liu, and Zhang [50] examined the impact of emotional intensity on perceived review usefulness, as well as the moderating effects of review length and reviewer expertise with text mining data from 600,686 reviews of 300 popular restaurants in the US from Yelp. Jia [48] analyzed online reviews of restaurant tourist customers from China and the United States using text-mining methods and compared their motivation and satisfaction. The results suggested that Chinese tourists were less inclined to assign lower ratings to restaurants and were more strongly fascinated by the food offered, whereas American tourists were more likely to be fun seeking and were less uncomfortable with crowdedness. Oh and Kim [49] collected 19,194 online reviews from 262 fine dining restaurants on TripAdvisor, classified into Japanese, Cantonese, French, and Italian cuisine, and analyzed the reviews corresponding to each ethnic cuisine by performing a semantic network analysis and Clauset–Newman–Moore clustering. The semantic network analysis revealed that several distinguishable clusters of specific words about the reviewer's Hong Kong fine dining experience were displayed in each cuisine.

Although recent studies have applied big data in the food service industry field, the sources of the data are limited to a few popular global applications or websites with many user reviews, and research topics are also focused on factors with an impact on consumer reviews. Considering that a big data analysis can quickly and accurately collect a large amount of data accumulated in daily life and objectively analyze consumer opinions, we believe research needs to be expanded to a broader range of dining services and products.

3. Research Methodology

3.1. Data Collection

The aim of this study was to investigate changes in consumer attitudes and sentiments in relation to take-out food in the pre- and post-COVID-19 pandemic period by applying big data analytics to social media content. For this purpose, data were collected from *Naver* and *Daum* blogs, two representative online platforms in Korea, in addition to portal sites. The findings of this study can be expected to help food service companies better understand and identify consumers' needs in the post-COVID-19 pandemic era. These online platforms were selected because of ease of data collection compared to *Facebook* or *Instagram*, where posts are private, and because these two online platforms contain a large amount of data. Data were collected during two periods: pre-COVID-19 (January 2019 to December 2019) and post-COVID-19 (January 2021 to December 2021). The keyword entered in the data search was take-out food. Table 1 shows the search results using "take-out food" as the keywords. In 2019, before COVID-19, in total, 18,544 keywords were searched; in 2021, after COVID-19, in total, 20,718 keywords were searched. In a morphemic analysis, the number of words with a frequency of 10 or more was 3031 in 2019 and 2890 in 2021. Considering that 1000 cases per channel is considered appropriate in TEXTOM-based data collection, the number of keywords included in this study was considered sufficient. Narrative coding for take-out food was clustered according to food, emotion, and demand/purpose (Table 2).

Table 1. Survey of collected data.

Data	Channel	Section	2019	2021
Dining out	*Naver*	Blog	62	440
		Cafe	22	113
	Daum	Blog	11,135	10,669
		Cafe	7325	9496

Table 2. Narrative coding index.

Categories	2019	2021	Total
Food	365	367	732
Sentimental	102	108	210
Demand	169	218	387
Total	636	693	1329

3.2. Methodology and Summary Statistics

A number of governments have utilized data-driven decision making to respond to the unprecedented challenges posed by science and the coronavirus [51]. According to a recent report, big data analytics is predicted to be the most influential technology in the industry over the next 5 years [52]. In this study, online data were collected and refined in an effort to apply the big data of social media before and after COVID-19. TEXTOM was used as a big data analysis solution for the research. Core keywords extracted using TEXTOM were clustered into similar groups, and then the analysis tool Ucinet6 was used to detect relationships between these groups of keywords. NodeXL was utilized as a visualization tool, which is based on network analysis data of centrality value, density, clustering, etc. In this study, several analysis methods—including text mining, semantic network analysis, CONCOR analysis, and sentiment analysis—were employed. Text mining is a technique for extracting information from unstructured text data. Using this method, useful words were extracted based on natural language processing and morpheme analysis technology. Major text mining indicators, such as frequency of occurrence and TF-IDF, were then calculated. Semantic network analysis and CONCOR analysis were performed to identify correlations between co-occurring words based on the text mining analysis data. In this study, the following four indicators were considered: (1) the degree of connection, where the higher the value, the higher the correlation with other variables; (2) betweenness centrality, where the higher the value, the greater the mediating role in the presence of other variables; (3) closeness centrality, where the higher the value, the greater the likelihood of a connection with other variables; (4) page link, where the higher the value, the higher the popularity, which means that the connection lines preferentially flock to nodes with more important pages or information. Finally, sentiment analysis—a natural language processing technology that analyzes subjective data, such as people's attitudes, opinions, and tendencies, from a text—was performed by extracting positive and negative words from the data. The words were classified using the emotional vocabulary dictionary independently created by TEXTOM, and their frequency and emotional intensity were then calculated.

4. Results

4.1. Text Mining Analysis

Table 3 shows the results of the text mining analysis using the keyword of take-out food for 2019. The frequency analysis of keywords in documents extracted using take-out food as the keyword revealed that "dining-out" was the most frequent keyword, followed by packing, famous restaurant, family, delicious, menu, and available. This finding indicates that these words appeared frequently in the keyword search of take-out food. The high frequency of their appearance also indicates that they were being utilized with great importance. Some keywords, such as famous restaurant, family, pigs' feet, foundation, kitchen, pork cutlet, and sushi, showed significantly higher TF-IDF values than others. This means that these words have a very rare value for take-out food and that they are essential words. As TF-IDF, in particular, has meaningful implications for short-term trend analysis, it can be inferred that these keywords acted as major factors in the take-out food trend in 2019.

Table 3. Text mining of take-out food (2019).

Rank	Word	Frequency	TF-IDF	Rank	Work	Frequency	TF-IDF
1	dining out	18,098	3538.181	26	weekend	943	2924.873
2	packing	15,253	5181.478	27	order	934	2860.714
3	famous restaurant	9301	9922.506	28	meat	891	2898.268
4	family	5165	7793.548	29	Deagu	873	2954.031
5	delicious	2560	5382.583	30	visit	845	2699.423
6	menu	2254	5153.136	31	meeting	818	2640.529
7	available	2213	5072.353	32	specialty store	805	2560.072
8	delivery	2110	5060.583	33	lunch	785	2558.962
9	place	2068	5124.562	34	kitchen	749	3216.590
10	dish	1929	4715.505	35	chicken	707	2576.133
11	recommend	1658	4302.789	36	market	698	2360.763
12	dinner	1562	3958.426	37	pork cutlet	684	2646.722
13	restaurant	1528	4138.230	38	mother	681	2343.336
14	pigs' feet	1483	5008.730	39	group	679	2310.659
15	foundation	1372	5024.928	40	side dish	672	2349.581
16	people	1358	3692.184	41	because	654	2197.573
17	pizza	1268	3957.478	42	sale	652	2214.564
18	children	1168	3369.422	43	price	635	2229.318
19	thought	1151	3242.007	44	Busan	622	2296.633
20	God	1127	3824.311	45	sushi	615	2502.435
21	rib	1066	3695.395	46	reservation	584	2057.696
22	cart bar	1060	3127.642	47	parking	572	2054.356
23	mind	1011	3167.806	48	discount	560	2030.205
24	meal	987	2969.861	49	myself	540	1911.623
25	get together	981	3010.342	50	food	539	1958.454

According to the results of the text mining analysis for 2021 (Table 4), "dining out" appeared most frequently, followed by packing, famous restaurant, delivery, family, available, and Corona. The following keywords had high TF-IDF values: famous restaurant, ribs, food, sushi, dining table, criticism, and abalone. This indicates that the scarcity value of these words was significantly high among documents related to take-out food after COVID-19. In 2021, after COVID-19, new keywords that did not exist before COVID-19, such as food and dining table, appeared, which indicates that these new keywords started playing an influential role.

4.2. Semantic Network Analysis

A semantic network analysis of take-out food was conducted by combining the emotions and demands (purposes) of data for 2019 and 2021. Table 5 summarizes the results of the semantic network analysis of take-out food and consumers' emotions for 2019. The results showed that discussion including terms such as delicious, recommended, meat, ribs, highly recommended, satisfaction, lunch box, etc., had been formed based on degree centrality, betweenness centrality, closeness centrality, and page rank. Figure 1 illustrates the results of visualizing the semantic network following the clustering process. The analysis results were separated into four categories: delicious, meat, satisfaction, and lunch box. It was presumed that people looking up take-out food in 2019 performed the search to find places where they could take out delicious food with high satisfaction. According to the results of the semantic network analysis in 2021 after COVID-19 (Table 6), discussion including terms such as delicious, recommend, meat, comfortable, good, home meal, and various had been formed. The visualized results were divided into four categories: delicious, meat, good, and home meal (Figure 2). This finding indicates that after COVID-19, people perceived the emotions related to satisfaction with the safety with a relatively high value in order to eat home-cooked meals.

Table 4. Text mining of take-out food (2021).

Rank	Word	Frequency	TF-IDF	Rank	Work	Frequency	TF-IDF
1	dining out	21,001	4929.1533	26	god	991	3033.8611
2	packing	20,967	4885.3692	27	sushi	984	3740.1671
3	famous restaurant	8898	11,036.7455	28	boy	984	3005.3557
4	delivery	4975	8513.8886	29	early	949	2926.0527
5	family	4827	8517.5821	30	discount	924	3032.5526
6	delicious	2439	5627.4516	31	dining table	915	3405.7250
7	available	2357	5662.3294	32	sound	887	3301.5061
8	Corona	2181	5002.7572	33	arrive	884	2791.3646
9	because	2115	5618.7856	34	visit	881	2885.7835
10	dish	2033	5020.7497	35	pigs' feet	868	3595.8221
11	recommend	1919	4942.2508	36	today	868	2785.3129
12	menu	1916	4888.9033	37	meal	861	2825.7877
13	children	1752	4676.2512	38	pass	837	2686.8380
14	people	1525	4013.0491	39	winter	817	2647.4410
15	cart bar	1495	4080.4076	40	wind	817	2646.4342
16	restaurant	1451	4047.6781	41	fish-shaped bun	782	2563.5014
17	order	1446	4007.8377	42	old woman	777	2551.1004
18	rib	1434	4693.5195	43	price	766	2690.3616
19	place	1380	4181.3381	44	prawn	766	2534.9595
20	Western food	1244	4065.3218	45	grandmother	752	2514.9109
21	postscripts	1132	3435.5777	46	store	749	2534.1314
22	fast	1101	3987.3213	47	criticism	728	3143.7290
23	dinner	1094	3322.4481	48	forward	719	2652.2002
24	nowadays	1064	3170.9982	49	meat	714	2571.7453
25	food	1015	3615.4127	50	abalone	711	3228.3291

Table 7 summarizes the results of the semantic network analysis, which connected take-out food and demands (purposes) for 2019, which was before COVID-19. In terms of the demand for take-out food, the analysis revealed that discourses about packing, dining-out, meat, pigs' feet, chicken, and ribs had been formed. The results based on this finding were divided into three categories: packing, meat, and ribs, which indicated that the search was performed for the purpose of taking out food, such as meat and ribs (Figure 3). In contrast, according to the results of the semantic network analysis for 2021 (Table 8), in terms of the demand for take-out food, discourses about order, store, lunch box, food delivery, home meal, packing, dining out, delivery, and Corona had been formed. Notably, and unlike in 2019, in 2021, new keywords such as lunch box, home meal, and Corona appeared, rather than the menu of usual take-out food such as pigs' feet and chicken, which indicated that food that can be eaten on a daily basis had been changed into food for take-out. The visualized results were divided into four categories: order, lunch box, packing, and fermentation (Figure 4). Based on these results and according to the results of the semantic network analysis of data collected in 2019 and 2021, different sets of keywords appeared before and after COVID-19, with discussions including terms such as delicious, recommend, meat, and ribs in 2019 and discussions including terms such as delicious, recommend, meat, comfortable, and good in 2021. In addition, as for the network for demands in 2019, keywords such as packing, dining out, meat, pigs' feet, and chicken appeared together. In 2021, new keywords such as order, store, lunch box, food delivery, and home meal appeared together. These findings revealed vastly different demands/necessary purposes before and after COVID-19.

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

Rank	Work	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
1	delicious	68	788.1907	0.6667	0.0098	1	sentimental
2	recommend	67	743.9533	0.6600	0.0097	1	sentimental
3	after a long time	62	494.8835	0.6286	0.0090	1	sentimental
4	comfortable	56	383.8057	0.5946	0.0086	1	sentimental
5	cart bar	37	368.3657	0.5176	0.0084	1	food
6	health	54	357.0088	0.5841	0.0086	1	sentimental
7	famous	52	304.7368	0.5739	0.0084	1	sentimental
8	hard	48	294.4629	0.5546	0.0083	1	sentimental
9	side dish	42	281.4612	0.5388	0.0081	1	food
10	tasty	48	269.4969	0.5500	0.0083	1	sentimental
11	burden	44	213.4776	0.5366	0.0080	1	sentimental
12	chicken	41	205.8944	0.5344	0.0079	1	food
13	sausage soup	30	172.9101	0.4944	0.0076	1	food
14	like	35	136.2301	0.4962	0.0077	1	sentimental
15	cafe	30	123.1677	0.4907	0.0075	1	food
16	tripe	31	117.4551	0.4944	0.0075	1	food
17	success	29	113.3292	0.4783	0.0076	1	sentimental
18	pork	32	105.6028	0.4944	0.0074	1	food
19	steamed pork	33	102.2850	0.5019	0.0074	1	food
20	diet	21	95.6255	0.4599	0.0073	1	food
21	meat	55	703.5548	0.6083	0.0090	2	food
22	rib	54	537.1492	0.6027	0.0088	2	food
23	very recommend	41	434.5577	0.5238	0.0089	2	sentimental
24	pizza	47	337.5413	0.5617	0.0083	2	food
25	meat restaurant	44	324.5484	0.5523	0.0083	2	food
26	popularity	47	291.9100	0.5500	0.0084	2	sentimental
27	Korean beef	42	281.0153	0.5432	0.0081	2	food
28	pork cutlet	42	261.9730	0.5432	0.0080	2	food
29	sushi	41	245.8489	0.5344	0.0080	2	food
30	happy	45	232.1283	0.5410	0.0081	2	sentimental
31	steak	39	219.3067	0.5217	0.0079	2	food
32	honest	10	202.8054	0.4151	0.0072	2	sentimental
33	pasta	35	193.2385	0.5097	0.0078	2	food
34	high class	42	191.1592	0.5280	0.0080	2	sentimental
35	beef	37	183.2895	0.5217	0.0077	2	food
36	concern	38	172.8140	0.5116	0.0079	2	sentimental
37	cost-effectiveness	40	163.9146	0.5156	0.0079	2	sentimental
38	pork rib	38	162.5582	0.5217	0.0077	2	food
39	special	38	155.2737	0.5077	0.0079	2	sentimental
40	perfect	33	148.3990	0.4925	0.0077	2	sentimental
41	satisfaction	52	389.5565	0.5739	0.0088	3	sentimental
42	home meal	40	367.2877	0.5344	0.0084	3	food
43	worry	56	361.9943	0.5946	0.0086	3	sentimental
44	good	54	352.2871	0.5841	0.0086	3	sentimental
45	sushi restaurant	41	348.7560	0.5344	0.0084	3	food
46	enjoy	52	306.7098	0.5739	0.0084	3	sentimental
47	love	50	287.3126	0.5641	0.0084	3	sentimental
48	troublesome	47	248.7666	0.5500	0.0082	3	sentimental
49	various	44	217.9952	0.5366	0.0081	3	sentimental
50	jackpot	45	200.6281	0.5366	0.0080	3	sentimental
51	eel	35	154.4260	0.5097	0.0077	3	food
52	pork back-bone stew	37	147.6996	0.5176	0.0076	3	food
53	braised short ribs	30	139.8732	0.4871	0.0076	3	food
54	pork belly	34	130.1672	0.5057	0.0076	3	food
55	coffee	27	111.9264	0.4835	0.0074	3	food

Table 5. *Cont.*

Rank	Work	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
56	braised spicy chicken with vegetable	33	110.5132	0.4981	0.0075	3	food
57	delivery food	32	107.8889	0.4944	0.0075	3	food
58	bulgogi	30	87.5713	0.4907	0.0073	3	food
59	appreciation	25	79.8284	0.4648	0.0074	3	sentimental
60	Korean food	28	74.0359	0.4835	0.0073	3	food
61	lunch box	36	398.7887	0.5136	0.0086	4	food
62	pigs' feet	44	245.3609	0.5477	0.0080	4	food
63	kind	41	202.8907	0.5238	0.0080	4	sentimental
64	tired	24	76.0409	0.4615	0.0074	4	sentimental
65	expectation	24	54.2873	0.4615	0.0072	4	sentimental
66	hangover soup	18	25.1692	0.4475	0.0069	4	food
67	stock soup of bone	8	4.7342	0.4190	0.0066	4	food
68	conflict	1	0.0000	0.3402	0.0064	4	sentimental

Table 6. Sentimental network index of take-out food (2021).

Rank	Work	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
1	delicious	68	1054.5730	0.6753	0.0107	1	sentimental
2	recommend	65	640.0539	0.6550	0.0095	1	sentimental
3	pork cutlet	49	502.0212	0.5746	0.0090	1	food
4	enjoy	55	339.1702	0.5955	0.0086	1	sentimental
5	delivery food	45	309.2132	0.5551	0.0083	1	food
6	side dish	43	294.2748	0.5458	0.0083	1	food
7	happy	49	271.8443	0.5647	0.0083	1	sentimental
8	sushi	44	225.4125	0.5504	0.0080	1	food
9	health	42	225.0239	0.5325	0.0082	1	sentimental
10	lunch box	40	190.6555	0.5325	0.0079	1	food
11	pizza	42	188.1433	0.5413	0.0079	1	food
12	salad	37	176.4689	0.5198	0.0078	1	food
13	steak	39	171.2997	0.5282	0.0078	1	food
14	memory	28	142.4575	0.4712	0.0079	1	sentimental
15	cafe	35	138.8876	0.5117	0.0077	1	food
16	duck	34	136.2514	0.5078	0.0076	1	food
17	life	28	109.5398	0.4781	0.0077	1	sentimental
18	high class	32	107.2504	0.4888	0.0076	1	sentimental
19	perfect	34	104.5948	0.4962	0.0076	1	sentimental
20	tripe	31	93.1294	0.4962	0.0075	1	food
21	meat	56	479.8434	0.6122	0.0088	2	food
22	comfortable	57	426.6941	0.6065	0.0089	2	sentimental
23	rib	51	393.5990	0.5848	0.0086	2	food
24	concern	55	334.4623	0.5955	0.0085	2	sentimental
25	satisfaction	51	299.9082	0.5746	0.0084	2	sentimental

Table 6. *Cont.*

Rank	Work	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
26	famous	51	276.5201	0.5696	0.0084	2	sentimental
27	bulgogi	35	220.8852	0.5117	0.0080	2	food
28	pork rib	42	217.3356	0.5413	0.0080	2	food
29	popularity	43	178.0752	0.5369	0.0079	2	sentimental
30	troublesome	42	166.3062	0.5325	0.0079	2	sentimental
31	careful	41	158.5457	0.5282	0.0079	2	sentimental
32	pork	37	150.7627	0.5198	0.0077	2	food
33	short rib soup	36	147.3848	0.5157	0.0077	2	food
34	pasta	37	143.2780	0.5198	0.0077	2	food
35	seasoning	36	125.6680	0.5157	0.0076	2	food
36	noodle soup	32	117.6112	0.5000	0.0076	2	food
37	jackpot	35	110.2295	0.5000	0.0076	2	sentimental
38	gimbab	22	108.9490	0.4645	0.0076	2	food
39	eel	35	108.4759	0.5117	0.0075	2	food
40	kind	33	107.2522	0.4925	0.0076	2	sentimental
41	good	51	310.8201	0.5746	0.0085	3	sentimental
42	ttoekbokki	39	262.1668	0.5282	0.0082	3	food
43	hard	49	261.9161	0.5647	0.0083	3	sentimental
44	eating alone	30	234.4542	0.4925	0.0080	3	food
45	burden	46	224.4007	0.5504	0.0082	3	sentimental
46	Salmon	30	211.2410	0.4925	0.0079	3	food
47	meat restaurant	42	203.9739	0.5413	0.0079	3	food
48	very recommend	42	179.6926	0.5325	0.0080	3	sentimental
49	cost-effectiveness	44	177.8357	0.5413	0.0080	3	sentimental
50	tasty	42	162.6680	0.5325	0.0079	3	sentimental
51	sushi restaurant	38	157.3504	0.5240	0.0078	3	food
52	spice stir-fried chicken	32	130.1392	0.5000	0.0076	3	food
53	Korean beef	30	106.4700	0.4925	0.0075	3	food
54	boiled pork	31	103.7329	0.4962	0.0075	3	food
55	truly	30	101.8243	0.4852	0.0076	3	sentimental
56	roast	32	90.3753	0.5000	0.0074	3	food
57	like	29	78.1699	0.4816	0.0074	3	sentimental
58	tuna	30	72.4485	0.4925	0.0073	3	food
59	beauty	27	60.8545	0.4746	0.0073	3	sentimental
60	cart bar	25	55.1858	0.4746	0.0072	3	food
61	home meal	46	560.9142	0.5598	0.0092	4	food
62	various	55	482.4952	0.5955	0.0092	4	sentimental
63	after a long time	61	467.8246	0.6298	0.0090	4	sentimental
64	pigs' feet	50	424.8488	0.5796	0.0086	4	food

Table 6. *Cont.*

Rank	Work	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
65	worry	52	298.8000	0.5796	0.0084	4	sentimental
66	love	41	211.8994	0.5282	0.0082	4	sentimental
67	chicken	39	175.6434	0.5282	0.0079	4	food
68	anxiety	35	163.5855	0.5000	0.0080	4	sentimental
69	very delicious	35	115.5267	0.5038	0.0077	4	sentimental
70	sausage soup	33	100.9814	0.5038	0.0075	4	food
71	beef	33	99.8112	0.5038	0.0075	4	food
72	shabu-shabu	30	82.4998	0.4925	0.0074	4	food
73	chicken soup with ginseng	23	57.3943	0.4679	0.0072	4	food
74	regrettable	24	48.8926	0.4645	0.0072	4	sentimental
75	seafood	22	41.3834	0.4645	0.0071	4	food
76	charm	16	34.2754	0.4338	0.0071	4	sentimental
77	fun	17	25.1403	0.4396	0.0070	4	sentimental
78	regret	15	19.5320	0.4338	0.0069	4	sentimental
79	abalone	13	10.5323	0.4367	0.0068	4	food
80	chives	6	4.1351	0.4172	0.0066	4	food

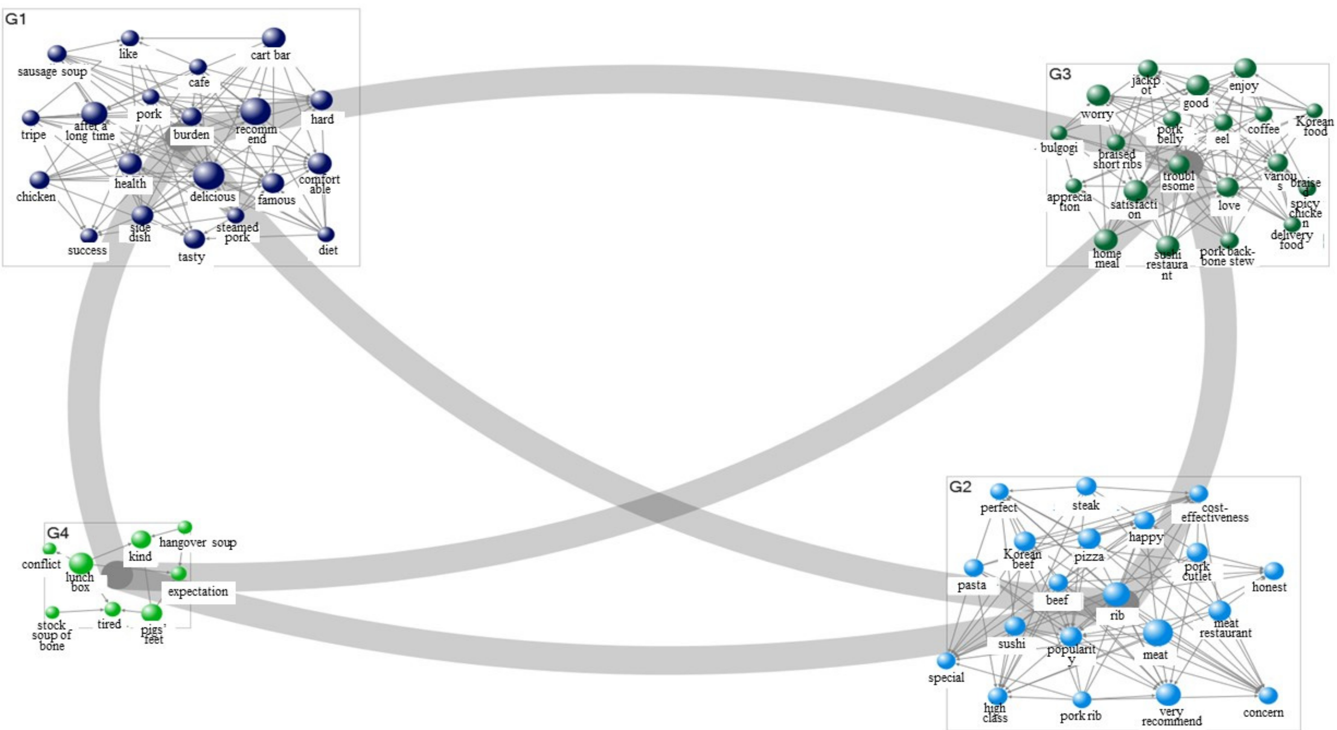

Figure 1. Sentimental network visualization of take-out food (2019).

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

Rank	Work	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
1	**packing**	**70**	**813.5619**	**0.6683**	**0.0096**	**1**	**demand**
2	**dining-out**	**70**	**813.5619**	**0.6683**	**0.0096**	**1**	**demand**
3	menu	68	540.5619	0.6557	0.0087	1	demand
4	restaurant	65	475.9821	0.6376	0.0085	1	demand
5	order	65	471.9518	0.6376	0.0085	1	demand
6	delivery	65	470.8478	0.6376	0.0085	1	demand
7	meeting	63	431.5263	0.6261	0.0084	1	demand
8	price	63	430.2436	0.6261	0.0084	1	demand
9	visit	63	425.1696	0.6261	0.0084	1	demand
10	store	60	398.0021	0.6096	0.0083	1	demand
11	get together	60	386.7828	0.6096	0.0082	1	demand
12	customer	56	319.9172	0.5890	0.0080	1	demand
13	delivery food	40	260.6980	0.5187	0.0076	1	food
14	service	47	229.4840	0.5472	0.0077	1	demand
15	Korean food	34	213.3592	0.4964	0.0076	1	food
16	pork belly	39	209.3090	0.5148	0.0075	1	food
17	beverage	32	171.3319	0.4894	0.0073	1	food
18	tteokbokki	30	164.6579	0.4826	0.0072	1	food
19	buffet	31	127.2651	0.4860	0.0072	1	food
20	kimchi	32	126.3543	0.4894	0.0072	1	food
21	**meat**	**54**	**677.2287**	**0.5792**	**0.0089**	**2**	**food**
22	**pigs' feet**	**50**	**538.7098**	**0.5605**	**0.0085**	**2**	**food**
23	**chicken**	**50**	**526.3024**	**0.5605**	**0.0084**	**2**	**food**
24	pizza	51	415.2706	0.5650	0.0081	2	food
25	meat restaurant	41	262.5618	0.5226	0.0077	2	food
26	short rib soup	39	249.7594	0.5148	0.0076	2	food
27	pork	39	243.6182	0.5148	0.0075	2	food
28	home meal	42	242.7011	0.5265	0.0076	2	food
29	Korean beef	40	228.0527	0.5187	0.0076	2	food
30	picture	49	226.1828	0.5560	0.0077	2	demand
31	side dish	41	209.5325	0.5226	0.0075	2	food
32	seasoning	33	203.4756	0.4929	0.0075	2	food
33	bulgogi	39	202.8138	0.5148	0.0075	2	food
34	container	42	186.1547	0.5226	0.0076	2	demand
35	diet therapy	41	170.2285	0.5187	0.0074	2	demand
36	shop	40	150.6388	0.5187	0.0074	2	demand
37	purchase	38	148.6604	0.5110	0.0073	2	demand
38	birthday	36	139.2651	0.5036	0.0073	2	demand
39	pork cutlet	39	136.6751	0.5148	0.0072	2	food
40	parcel service	36	129.3903	0.5036	0.0073	2	demand

Table 7. *Cont.*

Rank	Work	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
41	**rib**	**49**	**673.7963**	**0.5560**	**0.0090**	**3**	**food**
42	postscripts	61	400.2980	0.6150	0.0083	3	demand
43	cart bar	41	360.1656	0.5226	0.0079	3	food
44	lunch box	41	332.4717	0.5226	0.0079	3	food
45	discount	56	311.4959	0.5890	0.0080	3	demand
46	solution	54	305.3801	0.5792	0.0080	3	demand
47	steak	41	283.3663	0.5226	0.0077	3	food
48	cafe	41	237.9054	0.5226	0.0075	3	food
49	pasta	38	235.0276	0.5110	0.0076	3	food
50	beef	40	220.9038	0.5187	0.0075	3	food
51	gift	44	191.6076	0.5346	0.0075	3	demand
52	coffee	38	180.0816	0.5110	0.0074	3	food
53	need	42	170.6590	0.5265	0.0075	3	demand
54	family party	42	168.0360	0.5265	0.0075	3	demand
55	take-out	41	164.1384	0.5187	0.0075	3	demand
56	event	38	141.5370	0.5110	0.0073	3	demand
57	sushi	36	134.8459	0.5036	0.0072	3	food
58	pork back-bone stew	32	129.8425	0.4894	0.0071	3	food
59	sushi restaurant	36	126.4263	0.5036	0.0072	3	food
60	beer	31	109.6756	0.4860	0.0071	3	food

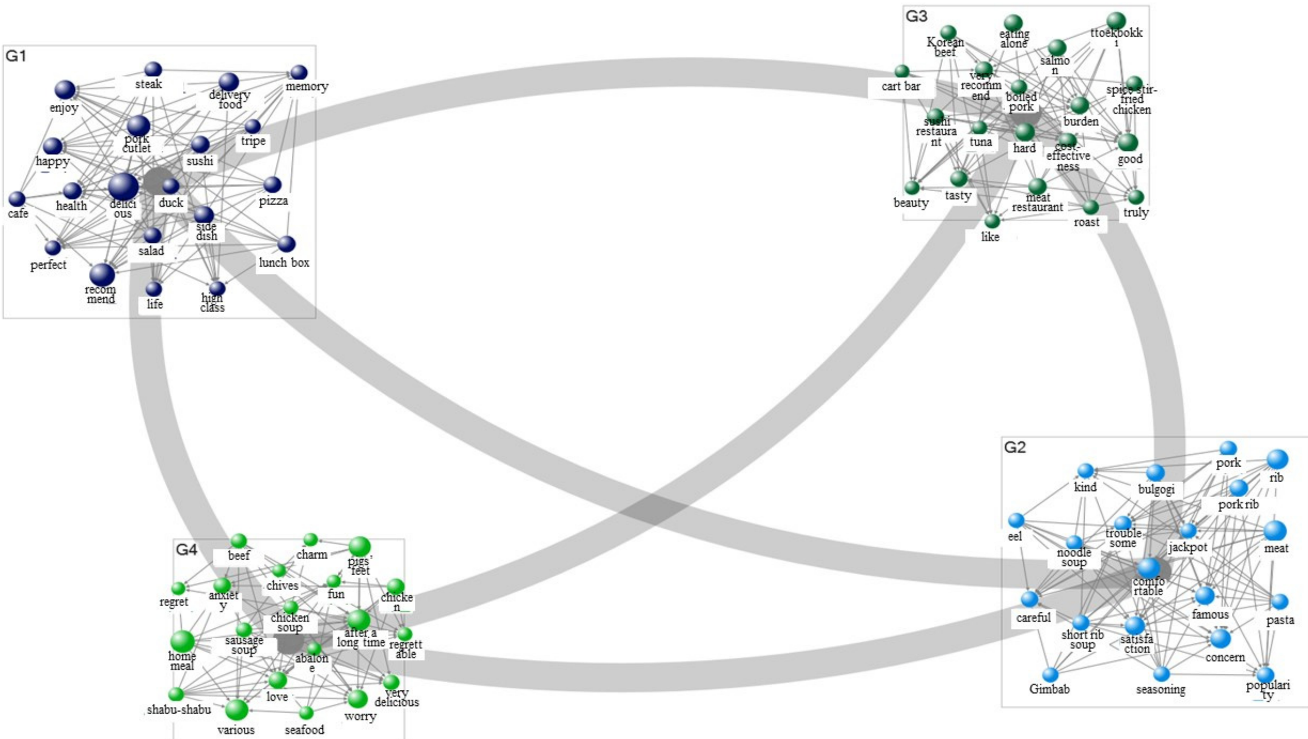

Figure 2. Sentimental network visualization of take-out food (2021).

Table 8. Demand network index of take-out food (2021).

Rank	Work	Degree Centrality	Betweenness Centrality	Closeness Centrality	Page Rank	Group	Categorize
1	order	63	390.1016	0.6273	0.0082	1	demand
2	store	60	339.7156	0.6106	0.0080	1	demand
3	pigs' feet	51	326.6660	0.5679	0.0079	1	food
4	visit	60	316.7037	0.6106	0.0080	1	demand
5	price	56	294.9664	0.5897	0.0080	1	demand
6	review	54	282.6453	0.5798	0.0079	1	demand
7	get together	54	265.3528	0.5798	0.0079	1	demand
8	picture	53	220.9888	0.5750	0.0077	1	demand
9	rib	47	220.0574	0.5498	0.0076	1	food
10	Baemin App.	49	198.8007	0.5565	0.0076	1	demand
11	meeting	48	196.0992	0.5520	0.0076	1	demand
12	shop	49	194.9730	0.5565	0.0076	1	demand
13	Corona pandemic	49	182.4696	0.5520	0.0076	1	demand
14	pasta	42	180.9100	0.5287	0.0075	1	food
15	pork rib	45	169.5753	0.5412	0.0074	1	food
16	discount	48	163.1488	0.5433	0.0075	1	demand
17	beef	43	161.8775	0.5328	0.0074	1	food
18	kimchi	38	159.7534	0.5130	0.0073	1	food
19	steak	39	155.6404	0.5169	0.0073	1	food
20	tuna	40	147.9225	0.5208	0.0073	1	food
21	lunch box	52	605.4228	0.5726	0.0086	2	food
22	delivery food	52	511.3272	0.5726	0.0085	2	food
23	home meal	55	483.0764	0.5872	0.0083	2	food
24	eating alone	33	411.2211	0.4946	0.0081	2	food
25	café	50	378.7693	0.5633	0.0081	2	food
26	chicken	50	296.9758	0.5633	0.0078	2	food
27	pork cutler	48	247.9203	0.5542	0.0077	2	food
28	salad	48	234.7054	0.5542	0.0077	2	food
29	pizza	47	227.8284	0.5498	0.0076	2	food
30	meat	49	207.4582	0.5587	0.0076	2	food
31	tteokbokki	41	195.3839	0.5247	0.0075	2	food
32	bowl of rice with toppings	30	184.1919	0.4842	0.0073	2	food
33	drinking alone	18	183.7255	0.4466	0.0076	2	food
34	sushi	45	173.9405	0.5412	0.0074	2	food
35	need	42	172.5277	0.5267	0.0075	2	demand
36	convenience food	32	148.0147	0.4911	0.0074	2	food
37	take-out	43	142.3060	0.5308	0.0074	2	demand
38	safety	41	136.0192	0.5227	0.0073	2	demand
39	posting	44	131.0854	0.5267	0.0074	2	demand
40	control	41	126.8788	0.5188	0.0073	2	demand
41	packing	70	740.0155	0.6699	0.0092	3	demand
42	dining-out	69	682.1336	0.6635	0.0091	3	demand
43	delivery	68	575.4731	0.6571	0.0088	3	demand
44	Corona	66	503.0773	0.6449	0.0086	3	demand
45	restaurant	64	479.5971	0.6330	0.0085	3	demand
46	menu	64	403.8005	0.6330	0.0083	3	demand
47	postscripts	63	362.9828	0.6273	0.0082	3	demand
48	purchase	52	268.1399	0.5656	0.0079	3	demand
49	side dish	45	182.7376	0.5412	0.0074	3	food
50	Korean beef	42	166.8884	0.5287	0.0074	3	food
51	seafood	28	136.5973	0.4775	0.0072	3	food
52	cart bar	36	132.6444	0.5055	0.0072	3	food
53	eel	39	120.4317	0.5169	0.0072	3	food
54	steamed pork	39	115.2899	0.5169	0.0072	3	food
55	gift	35	94.3039	0.4929	0.0072	3	demand
56	vegetable	35	93.9691	0.5018	0.0071	3	food
57	diet	29	86.7759	0.4808	0.0070	3	food
58	squid	30	75.7941	0.4842	0.0070	3	food
59	spice stir-fried chicken	34	70.2564	0.4982	0.0070	3	food
60	eating show	28	67.7660	0.4694	0.0071	3	demand
61	fermentation	8	13.7353	0.4195	0.0065	4	food
62	distribution	7	5.9996	0.3966	0.0064	4	demand

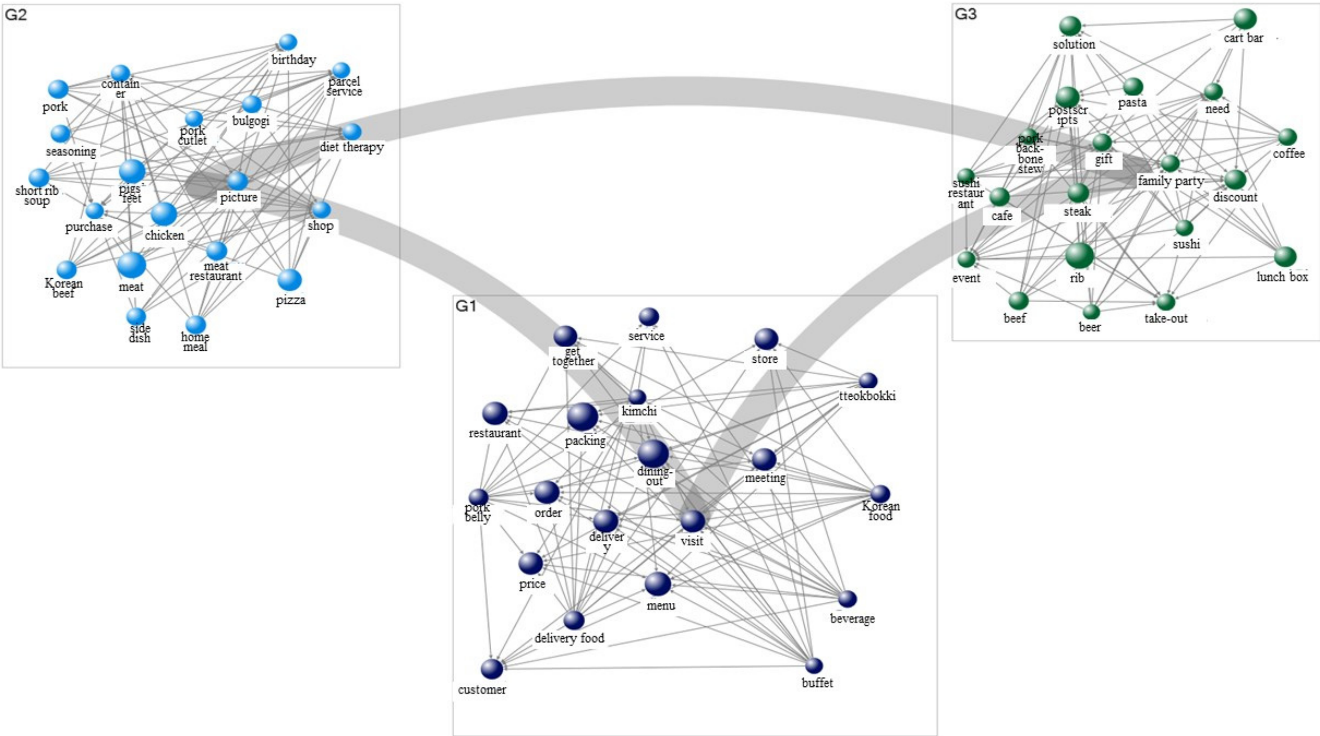

Figure 3. Demand network visualization of take-out food (2019).

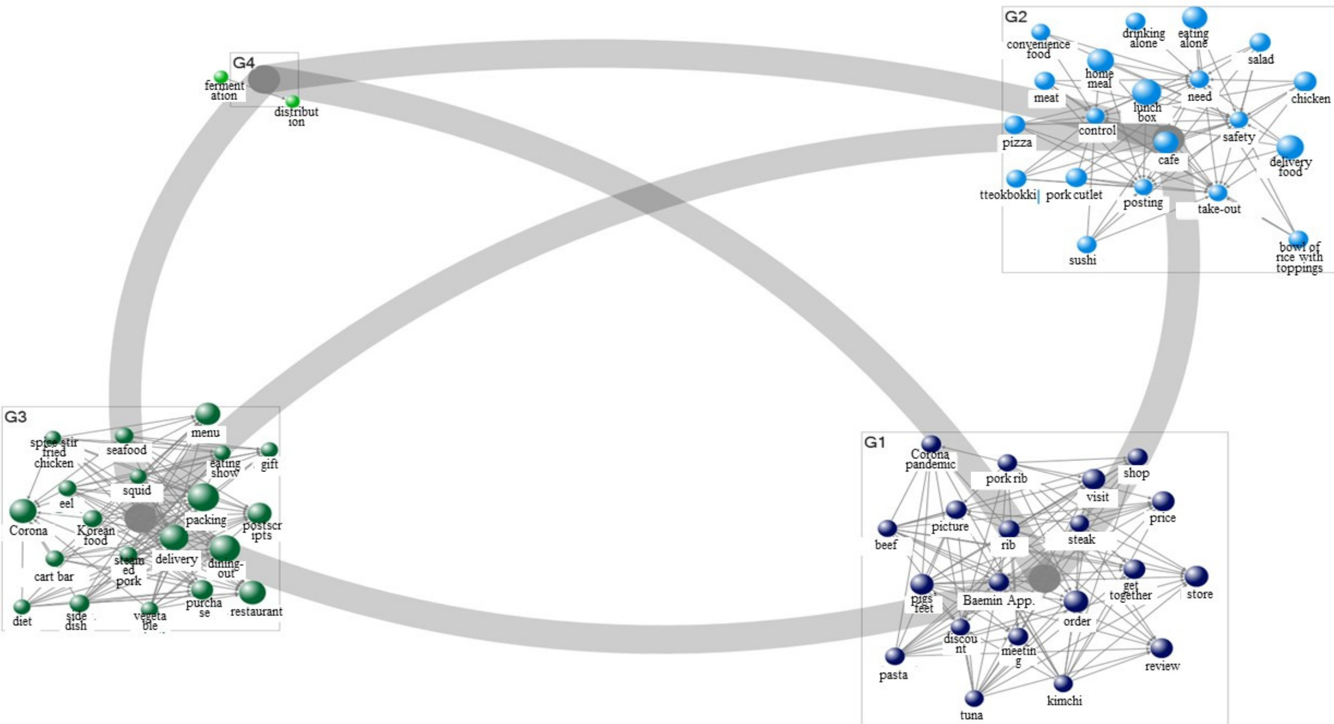

Figure 4. Demand network visualization of take-out food (2021).

4.3. Sentiment Analysis

Sentiment analysis was performed by extracting positive and negative words from the data (Table 9). When the data obtained in 2019 and 2021 in relation to take-out food were compared, the number of positive keywords among sentiment words decreased by 4.03% in 2021, whereas the number of negative keywords increased in 2021 by 4.03%

(Tables 10 and 11). Specifically, sub-emotions of positive categories (e.g., joy, interest) decreased in 2021 compared to 2019, and sub-emotions of negative categories (e.g., sadness, disgust, and fear) increased in 2021 compared to 2019.

Table 9. Sentiment word frequency of take-out food.

	2019	2021	Increase or Decrease
Positive word	78.75	74.72	−4.03%
Negative word	21.25	25.28	+4.03%

Table 10. Sentiment analysis of take-out food (2019).

	Frequency	Sentiment Intensity (%)	Frequency Percentage
Good feeling	14381	68.79	67.91
Joy	1491	6.67	7.04
Interest	805	3.65	3.80
Positive total	16,677	79.11	78.75
Sadness	1982	9.84	9.36
Disgust	886	4.27	4.18
Fear	759	2.85	3.58
Pain	576	2.47	2.72
Anger	169	0.72	0.80
Fright	128	0.73	0.60
Negative total	4500	20.88	21.25
Total	21,177	21,177	100.00

Table 11. Sentiment analysis of take-out food (2021).

	Frequency	Sentiment Intensity (%)	Frequency Percentage
Good feeling	15,989	69.31	67.05
Joy	1129	4.36	4.73
Interest	701	2.74	2.94
Positive total	17,819	76.41	74.72
Sadness	3445	12.93	14.45
Disgust	1611	7.02	6.76
Fear	639	2.41	2.68
Pain	201	0.71	0.84
Anger	70	0.28	0.29
Fright	63	0.23	0.26
Negative total	6029	23.58	25.28
Total	23,848	23,848	100.00

5. Discussion and Implications

5.1. Discussion

This study explored changes in consumers' perceptions and emotions with regard to take-out food before and after the onset of COVID-19 by applying big data from social media. A semantic network analysis of take-out services and consumer sentiment classified the 2019 data into four categories: delicious, meat, satisfaction, and lunch box. The 2021 data were categorized as delicious, meat, good, and home meal. Based on these findings, after the COVID-19 outbreak, it seems that take-out food became recognized as a daily meal that can replace home-cooked meals. According to Kim and Kim [5], who studied the changes in dining-out consumption before and after the COVID-19 outbreak by using big data, before COVID-19, search keywords related to "dining out" were mainly centered around tourist destinations, dining-out information for families gathering for special occasions, and information searches for restaurant foundation; however, after COVID-19, keywords related to food delivery services ranked at the top, and searches for specific menus and restaurant information increased in comparison to general restaurant information. These findings can be interpreted in a similar context as the results of the current study in that, before COVID-19, search terms related to dining out mainly concerned restaurants during travel or for special events whereas, after COVID-19, searched words related to delivery or accessible specific menus and restaurant information to replace meals on a daily basis. In particular, these results can be interpreted more specifically based on the semantic network connecting take-out services and demands (purposes). In 2019, words searched for the purpose of taking out food, such as packing, meat, and ribs, were predominant. In 2021, keywords such as lunch box, home meal, and Corona appeared, confirming the changed demands/necessary purpose of take-out food that can be eaten on a daily basis, such as home-cooked meals, due to COVID-19. The increased use of such keywords confirmed the changed needs and purposes for packaging food that can be eaten similar to home meals due to COVID-19. Indeed, Lee and Ryu's [53] study dealt with changes in mothers' meal preparation stress and food consumption patterns at home after COVID-19 through a qualitative study, as children have spent more time at home due to the expansion of online education in light of COVID-19. The authors reported that stress related to meal preparation went up regardless of the mother's employment status. Accordingly, although the frequency of dining in significantly decreased, the frequency of home delivery of food and online grocery shopping substantially increased. Similar trends have been observed in the United States [54,55], the Netherlands [56], Indonesia [57], Denmark, and Germany [58], among others.

Meanwhile, the result of this study's sentiment analysis, which extracted positive and negative words from the search word data related to take-out food, showed that the number of positive keywords decreased by 4.03% after the outbreak of COVID-19, while the number of negative keywords increased at the same rate. Factors affecting consumers' emotions related to take-out services are believed to be attributes related to menus and services or external environmental influences. However, considering the main focus of this study on changes in consumers' perceptions due to COVID-19 and changes in consumers' emotions identified in the results of the sentiment analysis, here, we highlight the changes in consumers' sentiment toward take-out services caused by COVID-19. Several studies have been conducted to understand the changes in consumers' emotional, psychological, or other perceptions caused by COVID-19; the results tend to vary. Some studies reported that negative emotions or perceptions caused by COVID-19 toward take-out services or online delivery services, such as anxiety, perceived severity, and perceived vulnerability, did not affect consumers using these services [2,8]. However, Smith et al. [59] found that stress associated with COVID-19 increases food motivation in all food categories. In particular, consumers in the group with the highest stress expressed a greater willingness to pay than the other groups for all types of delivery or take-out food presented in the study. In general, all groups in the study were willing to wait longer or pay more for delivery or take-out food, such as sweets and fast food, than for relatively healthy food, such as savory snacks or vegetables. Kim [8] reported that not only rational motives, such as economic benefit, convenience, and labor saving, but also emotional motives, such as changes in mood, fulfillment of desire, comfort, and rest, had a positive effect on consumers' choice of take-out food. In many studies, in general, severe acute stress can inhibit food intake; however, when eating serves as an adaptive means for stress relief, stress has been reported to stimulate food intake [59–62]. Given the increase in take-out consumption in South Korea after COVID-19 [31,63], some of the negative sentiment words (e.g., sadness, fear) that appeared after COVID-19, as found in this study, may have led to the consumption of take-out food. Certainly, some of the negative emotions (e.g., disgust, anger, fright) could have been caused by dissatisfaction with products or services, as more consumers purchased take-out meals more frequently than before. Byrd et al. [64] investigated the risk perception of restaurant food and packages among American consumers during the pandemic, and restaurant food packages were ranked the highest after cooked and uncooked food served in dine-in restaurants. However, carry-out/curbside pick-up/drive-through foods ranked relatively low in terms of risk perception. These findings suggest that concerns about infection through the packaging of take-out food, which were not previously raised, also contributed to negative emotions during the pandemic. Factors related to negative emotion keywords that have increased since COVID-19 need to be identified in greater detail through follow-up studies.

5.2. Implications

As uncertainty related to politics, the economy, and society in general grows due to climate change and pandemic, the change cycle of the food service industry and consumer trends are also getting shorter. The biggest issue of these recent uncertainties is COVID-19, and it is essential for the food service industry as a whole to understand consumers' perceptions and changing trends. As many dine-in restaurants started providing take-out services to recover from poor sales due to COVID-19 and to respond to consumer needs, the perceptions of consumers examined in this study are expected to provide practical information necessary for the marketing plans of food service business. Specifically, this study found that, after COVID-19, consumers recognized take-out food as a home meal; this idea can be developed and applied to menu development and/or promotions. In other words, it is possible to apply the characteristics of home meals that are not special, but comfortable, and can be eaten on a daily basis, to the development of restaurant menus, and promote them in this way. As for individual menu keywords with high frequency or TF-IDF values, pigs' feet, pork cutlet, and sushi were popular in 2019, but ribs, sushi, dining table, pigs' feet, and abalone were more popular in 2021. This finding can be used for menu development that satisfies current consumer trends. As for menu-related keywords that appeared both before and after the onset of COVID-19, dinner showed a high TF-IDF in text mining, and meat was mentioned as a common topic of discourse in sentiment analysis. These findings suggest that consumers mainly use take-out food for dinner, and that there is a continuing interest in the meat on the menu, which provides important insights when developing a main menu for take-out services. In addition, regarding the increase in negative keywords, such as sadness, disgust, and fear, since the emergence of COVID-19, consumers have great anxiety about dining out due to the virus and, therefore, more measures and publicity about hygiene and safety are required to reassure consumers about take-out products, services, and packages. In addition, as previously stated, consumer behaviors surrounding take-out consumption are affected not only by rational motives, but also by emotional motives. Therefore, it is important to apply emotional marketing that can comfort and relieve consumers' negative emotions related to take-out food.

Academically, this study is meaningful in that it limited the research area to take-out food and examined the changing consumer trends and perceptions of dining out before and after the outbreak of COVID-19 in more detail. In particular, recent research on non-contact dining services has tended to concentrate on online delivery services, with few studies focusing exclusively on take-out services. Therefore, this study, focusing on take-out food, which is still popular as an alternative given consumer complaints about delivery services, is of great value due to its rarity. In addition, from the perspective of research methods, this study is meaningful in that it expanded the scope of big data research by approaching data sources and research topics in a popular and pragmatic way. It is also expected to provide good fundamental data for the practical application of big data research in the food service industry in the future.

5.3. Limitations and Future Study

This study has limitations in several areas. First, there are some limitations in the interpretation of the results, as previous studies on take-out food are scarce. Second, the big data in this study used a Korean-based portal website as the data source; thus, the main consumer group is Korean-speaking consumers, and the interpretation of the study results can be mainly related to the Korean food service market. Therefore, it is difficult to directly apply the results of this study to the cases of other countries, considering that the time and extent of each country's lockdown and/or quarantine measures due to COVID-19 differ, and the conditions of the food service industry are also different. Therefore, based on these limitations, similar research should be conducted as follow-up research by applying relevant data from other countries. In particular, in the case of some countries with stronger and more stringent quarantine policies than South Korea, such as countries with long lockdown periods or enforced compulsory closures of dine-in restaurants during the pandemic (e.g., the United States [64]), significant differences are expected in consumers' demands and emotions regarding take-out services since the outbreak of COVID-19. In addition, multifaceted studies on consumers' behaviors are needed, given the insufficient research on the topic of take-out food. Finally, more qualitative and quantitative research is needed to identify factors that caused the increase in negative sentiment keywords since COVID-19, such as dissatisfaction with products and services or general negativity due to the pandemic, in order to understand their effects on the perceived risk of infection via take-out packaging or food.

This study explored how consumers' perceptions toward take-out food, which has recently become more popular as a non-contact dining-out service, changed before and after the outbreak of COVID-19. It achieved this by applying big data. Although uncertainty is growing throughout society due to the pandemic, the findings of this study comparing the pre- and post-COVID-19 outbreak in relation to take-out options as a popular dining-out service are expected to have great implications for academia and industry when it comes to understanding consumers in the future.

Author Contributions: Conceptualization, H.J. and J.J.; methodology, H.J. and E.L.; software, H.J. and E.L.; validation, H.J. and E.L.; formal analysis, H.J. and J.J.; investigation and data curation, H.J. and J.J.; writing—original draft preparation, H.J. and J.J.; writing—review and editing, J.J. and E.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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