Changes in Social Media Big Data on Healing Forests : A Time-series Analysis on the Use Behavior of Healing Forests Before and After the COVID-19 Pandemic in South Korea

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Posted Date: 26 January 2024

doi: 10.20944/preprints202401.1927.v1

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Article

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Abstract : This study aimed to identify changes in visitor behavior and visitor interest in healing forests before and after the COVID-19 pandemic. The study used text mining analysis techniques to identify changes in visitation behavior over time, divided into three periods: pre-COVID-19 (January 1 to December 31, 2019), during the COVID-19 pandemic (November 1, 2020 to October 31, 2022), and post-COVID-19 (November 1, 2022 to October 31, 2023). After the COVID-19 outbreak, healing forest use behavior did not regress to pre-COVID-19 levels. Activity-based keywords such as "hiking," "trekking," and "walking" stood out as the main drivers of this change in behavior. Therefore, related authorities must examine the scalability of the functions, services, and programs of healing forests from a general healing space to a space for leisure and tourism. These findings will contribute to the development of future marketing strategies and programs for healing forests.

Keywords: healing forest; COVID-19; text mining; network analysis; quadratic assignment; procedure correlation analysis

1. Introduction

The COVID-19 pandemic and the resulting sanctions of quarantining, working from home, and social distancing have changed people's lives, particularly rendering a significant impact on areas related to people's health and well-being. According to a survey by the Korea Chamber of Commerce and Industry (2021), nearly 8 in 10 people (78.1%) said that since the COVID-19 pandemic, they are more likely to "care about my health and the health of my family" compared with before the pandemic. Based on credit card spending, Koreans are spending 57% of xx on jogging and climbing, followed by home training and fitness at 36% and 24%, respectively. The data demonstrate that with the prolonged duration of the COVID-19 pandemic, Koreans have become increasingly concerned about their health and well-being, which is impacting their spending and credit card usage behaviors (Samsung card, 2023).

As predicted in various fields, the emergence of viruses, such as COVID-19, is expected to occur in cycles (Kim, 2021). Indeed, since 2000, global infectious diseases, such as SARS in 2003, swine flu in 2009, MERS in 2015, and COVID-19 in 2020, have occurred on a five–six-year cycle. Infectious diseases are becoming a new factor in forest utilization as government restrictions are implemented in relation to these infectious diseases (National Institute of Forest Science, 2021). According to an analysis of changes in national tourism behavior conducted by the Korea Tourism Organization (2020), "safety" has become a top priority in overall tourism activities since the outbreak of COVID-19, with a clear preference for "safe, low-density outdoor activities" for families in nature-friendly spaces near their homes. Notably, while the overall number of hikers has decreased since the start of the COVID-19 pandemic due to reduced outdoor activities, the number of visitors to three urban national parks—Bukhansan, Gyeryongsan, and Chiaksan—has increased by about 21% (National

 doi:10.20944/preprints202401.1927.v1

Park Service, 2020). This shows that people are increasingly visiting mountains for their accessibility and lower risk of infection when indoor activities are limited (Chang et al., 2021).

This trend is also happening internationally. In Germany, the number of visitors to forests has more than doubled since the start of lockdown in March 2020, and the country has seen a shift toward new types of visitors, such as non-local youth and families with children (Derks et al., 2020). In the Czech Republic, the physical and mental stress caused by lockdown restrictions during the COVID-19 pandemic have been mitigated by the recreational services provided by urban forests (Bamwesigye et al., 2023).

In Korea, healing forests are particularly receiving ever larger numbers of visitors. Healing forests are forests that have been created for "forest healing," an activity that utilizes various elements of nature, such as scent and landscape, to enhance the human body's immunity and promote health (Lee et al., 2016). According to the Korea Forest Service, the number of visitors to healing forests exceeded 1.9 million as of 2021. Seogwipo Healing Forest has seen a 260% increase in visitors before and after COVID-19 (as of 2022), with 22,153 visitors compared with the same period last year (6,147). Visits to and demand for healing forests have been on the rise since the COVID-19 pandemic of 2021.

Behavior is not independent of time; thus, behavior over time must be analyzed as changes over time (Woo, 2020). In the aftermath of the COVID-19 pandemic, the authorities must develop strategies to attract and activate increased forest visitation in the medium to long term. Our study aimed to explore changes in healing forest visitation, identify visitor interests, and provide a basis for contributing to the development of future marketing strategies and service programs. Therefore, we identified the usage behavior and interest regarding healing forests in three periods: the pre-COVID-19, during the COVID-19 pandemic, and post-COVID-19 pandemic (Table 2). We aimed to explore mid- and long-term response measures.

2. Materials and Methods

We analyzed the usage behavior of healing forests using time series data. We used Keyword Term Frequency (TF) and Term Frequency-Inverse Document Frequency (TF-IDF) analysis, Convergence of iterated CORrelation (CONCOR) analysis, and Quadratic Assignment Procedure (QAP) correlation analysis with the matrix generated by text mining analysis technique using Textom to identify changes in usage behavior by period. The procedure of the study is shown in Figure 1.

 doi:10.20944/preprints202401.1927.v1

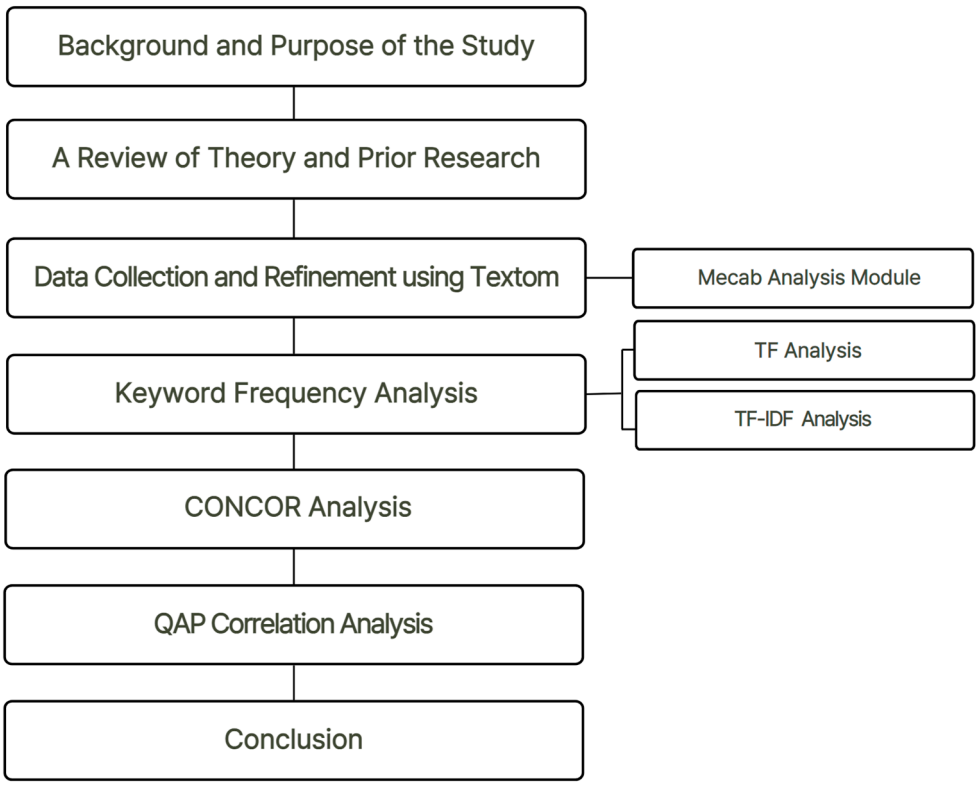

Figure 1. Flowchart of Research Methodology.

2.1. Study Area: Healing Forests

Healing forests are recognized as "forest welfare facilities" under Article 2 of the Act on the Promotion of Forest Welfare. In contrast to other forest welfare facilities, which are centered on "education" and "experience," healing forests focus on "healing" (Table 1).

Table 1. Forest Welfare Facilities under Article 2 of the Act on the Promotion of Forest Welfare.

Facility Name	Definition
Natural Recreation Forest (NRF)	Forests created for people's emotional development, health recreation, and forest education
Forest bathing	Forests created to improve people's health by allowing them to breathe and interact with clean air, walk, and exercise in the forest
Healing Forest	Forests planted for healing
Forest Path	For activities such as mountaineering, trekking, leisure sports, exploration, or recreation and therapy Paths built in forests in accordance with Article 23 of the Forest Culture and Recreation Act
Infant Forest Experience Center	A facility that guides and educates young children to develop their emotions and holistic growth by experiencing the various functions of the forest
Forest Education Center	Facilities designated and created for the purpose of cultivating the creativity and emotions of the people, and promoting values of forests

The project to create healing forests, which began in 2007 at the initiative of the Korea Forest Service, has helped lay the foundation for forest healing. Starting with the opening of Sanyeum Healing Forest, the first healing forest in Korea, 38 are currently in operation nationwide. Each healing forest is characterized by the provision of forest healing programs using the various healing factors of forests, such as landscape, phytoncides, anions, oxygen, sound, and sunlight. International

 doi:10.20944/preprints202401.1927.v1

examples of similar healing forests include Forest Therapy Base in Japan, Vitaparcours in Switzerland, and Kurort in Germany.

Korean scholars have studied many dimensions of healing forests. Lee (2012) examined forest management techniques to maximize healing effects using the landscape in healing forests. Kweon and Kwon (2014) analyzed preferences for forest healing facilities in healing forests. Jeong et al. (2015) aimed to provide policy bases for appropriate area standards for healing forests in metropolitan areas. Lee and Kim (2016) investigated the impacts of the wellness value and loyalty of healing programs on participants in the Sanyeong Healing Forest programs. Lee et al. (2018) reported the difference in stress and positive and negative emotions before and after experiencing forest healing programs among workers engaged in emotional labor. Thus, research in the early 2010s had focused on preferences for forests and facilities located in healing forests, and after 2015, on programs conducted in healing forests and their effects.

2.2. Text Mining

Text mining is a technique for extracting keywords from data and then identifying relations between sets of keywords to extract valuable information (Lee et al., 2021). It is a technology that discovers information by identifying patterns, similarities, and associations of information in data, and its main feature is to explore the objective perceptions of users to provide a basis for more active service strategies and future user-customized programs (Kim, 2016).

A review of previous studies shows that text mining in the forestry field has been mainly used to analyze network structure changes and demand over time. Kim (2016) explored the perception of forest healing using social media big data. Schober et al. (2018) conducted text mining on articles listed in Scopus for sustainable forest management (SFM) to examine changes in the research agenda for SFM research over time. Park and Yeon (2020) analyzed network changes regarding forest healing issues from 2005 to 2019 using news big data. Suguru (2021) identified factors that positively influence the provision of cultural ecosystem services through the essays of recreational activity participants in a mountain village in Japan. Other studies have provided analyses of consumer intention and demand for forest products (Byun & Seok, 2019; Seok et al., 2019).

2.3. Data Collection

We used Textom to collect and clean the data and then conduct morphological and text mining analyses. The keyword we used for data collection was "healing forest," and the collection channel was limited to blogs and Cafes(social media forums) of domestic portal sites NAVER and DAUM.

According to Internet Trend™, domestic portal sites NAVER and DAUM are ranked first and third in terms of domestic search engine share, with 57% and 4.28%, respectively, as of 2023. The blog share is 74.4% for Naver and 11.8% for Daum, ranking first and second, respectively. Thus, both are highly influential domestic portals.

Table 2 shows the periods we used for analyzing differences in usage behavior. T covers the year before the first COVID-19 case in South Korea, which occurred in January 2020. We set T1 to include the period from February 18 to April 20, 2022, when the number of domestic infections peaked amid the stronger quarantine. T2 covers the period from the lifting of the domestic outdoor mask mandate on September 26, 2022, to after the declaration of the end of the pandemic on May 11, 2023.

Table 2. Three periods covered in our analysis.

	Name	Dates
	Pre-COVID-19	January 1 to December 31, 2019 (one year)
T1	**During COVID-19**	November 1, 2020 to October 31, 2022 (two years)
T2	**Post-COVID-19**	November 1, 2022 to October 31, 2023 (one year)

To clean the data, we used the MeCab-ko analysis module, which can separate vocabulary based on dictionary information. The MeCab-ko analyzer we used is based on MeCab, a Japanese open-

 doi:10.20944/preprints202401.1927.v1

source morphological analysis engine. It was created through machine learning using the dictionary and corpus of the 21st Century Sejong Plan to suit the Korean context. It has the advantage of outperforming other Korean morphological analyzers in that it corrects spacing errors (Park et al., 2017). In addition, in the frequency analysis stage, we conducted a refinement process to delete, consolidate, and change words to reduce errors in the original text.

2.4. TF Analysis and TF-IDF Analysis

We conducted two types of frequency analysis: TF analysis, for calculating the frequency of keywords appearing in a document and identifying words that occur with high frequency within the entire document; and TF-IDF analysis, for deriving the relative frequency of words in a particular document and identifying the importance of a particular word (Park et al., 2022). If a particular keyword occurs frequently in a document, then the keyword can be determined to play an important role in the document, but if a word with a high frequency is common in all documents, it can be given a low weight (Bank of Korea, 2019). Therefore, we compared the results of both TF and TF-IDF analyses to identify the differences.

2.5. CONCOR Analysis

CONCOR analysis is an iterative analysis technique that evaluates correlations to identify structural equivalence and find similar and related clusters in complex semantic network environments (Tao & Kim, 2022). The relations between lexemes derived from the text can reveal the importance and patterns of specific lexemes within the network. Given that it is computerized, CONCOR analysis has the advantage of compensating for the limitations of traditional content analysis methods, which are labor intensive and cannot eliminate the researcher's subjectivity (Park & Leydesdorff, 2004).

2.6. QAP Correlation Analysis

The basic structure of social media big data collected is a matrix, which is different from the data used in general statistical analysis. At the same time, most of them are not random samples from the population and each individual observation is interdependent. As such, general inferential statistical methods cannot be directly applied to the data in the matrix, thereby requiring a separate test method to test statistical significance for social media big data (Park & Choi, 2016). Therefore, we conducted QAP correlation analysis using UCINET 6 to identify the similarity in the matrix structure of networks by time period.

QAP correlation analysis is generally divided into two steps: QAP correlation analysis and QAP regression analysis. In this study, QAP correlation analysis (Carrington et al., 2005) was performed to determine whether two matrices are correlated by transposing the matrices, comparing the similarity of the matrix lattice values to calculate the correlation coefficient, and performing a nonparametric test. The degree of correlation between the two matrices was obtained by utilizing the Pearson correlation coefficient.

3. Results

3.1. Data collection results

Using Textom with the keyword "healing forest," we collected 2,000 data points in T, 4,165 in T1, and 2,328 in T2. The keywords derived from the collected data were 3,575 in T, 5,940 in T1, and 7,965 in T2.

3.2. TF and TF-IDF results for the keyword "healing forest"

The results of TF and TF-IDF are shown in **Appendix A**. In all three time periods, the results of both analyses were different, indicating that even the most frequent words had differences in terms of importance according to TF-IDF.

 doi:10.20944/preprints202401.1927.v1

In all three time periods, the search keyword “healing forest” was the most frequent, followed by “forest,” “cure,” and “healing,” indicating that visitors viewed the forest as a place for healing and restoration. We also found that as keywords about COVID-19 were collected from T1, the rankings for keywords on individuals or appointments increased. This indicated a shift toward pre-booking and personalized activities owing to the implementation of social distancing policies in response to the COVID-19 pandemic. In T2, the top frequent words were similar to those in the other time periods, but tourism-related words such as "travel" and "destination" and destinations such as "Gimcheon" and "Busan" emerged as new top frequent words, indicating that visits to traditional healing forests were not limited to the concept of healing, but were embraced as part of a trip or planned in conjunction with nearby tourism resources.

According to the TF analysis, the healing forests frequently mentioned by people were Seogwipo Healing Forest, National Jangseong Healing Forest, and Seocheon Healing Forest. Seogwipo Healing Forest is located on Jeju Island, which has a mild climate that is unique in the Korean Peninsula and a variety of vegetation types, including boreal and temperate forests. National Jangseong Healing Forest boasts of the largest cypress forest in Korea. Seocheon Healing Forest is operating a special healing program in connection with a large lake called Janghang-je.

3.3. CONCOR Analysis Results

Words with higher TF-IDF weight values are more likely to determine the topic or meaning of the documents they belong to, and this measure can be used to extract the main keywords (Park & Suh, 2015). Therefore, we focused on the top 100 occurrences of words by TF-IDF weight by time period. To focus on the usage behavior of healing forests, we excluded the search words “healing forests” and “healing forest destination” from the TF-IDF top 100 occurrences. However, we included the case of Seogwipo Healing Forest, which ranked at the top of the TF and TF-IDF analyses, because it had a unique tourism potential that could not be found elsewhere owing to the unique geographical environment of Jeju Island and the unique folk culture of the former Tamra Kingdom (Shin & Moon, 2010).

The results of the CONCOR analysis are shown in Table 6. The network visualization results are shown in Figures 2, 3, and 4. For the results of the CONCOR analysis at time T, we created groups (topics) containing nodes (keywords) and sorted by size.

Table 3. “Healing Forests” clustering results by period.

Period	Group name	Topics	Included keywords
T	G1	**Healing Forest and NRF**	Seogwipo, NRF, recreation, cure, healing, mind, body, wellness, road, forest path, walk, trail, trekking, place, forest, in the forest, wind, nature, sound, valley, air, person, child, tourist attractiveness, cafe, near, variety, management, guidance, thought, review, operation, location, utilization (34)
	G2	**Programs and Facilities**	health, program, meditation, experience, progress, infant, therapy, facility, deck, hike, possible, city, rest area, parking lot, introduction, Dulle-gil-trail, mountain, footbath, free, enjoy, weekend, family, birch, phytoncides, me, mountain forests, park, education, space, pine, sky, welfare, center (33)
	G3	**Visitation and usage behavior**	reservation, photo, take a picture, memories, course, autumn, entrance fee, description, day, walking, weather, trip, time, car, barrier-free, rest, rain, see, visit, parking, commentary, need, eat, water, travel destination, recommendation (26)
	G4	**Camping**	campground, camp, camping, price, tree, cypress, site (7)

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T1	**G1**	**Healing Forest and NRF**	tourist attractiveness, weekend, Seogwipo, person, summer, accommodation, air, car, body, parking, course, commentary, mind, wellness, possible, home, weather, visit, walking, review, near, trail, trip, entrance, forest, forest path, waterfall, eat, see, itinerary, rain, Dulle-gil-trail, barrier-free, summit, rest, wind, morning, me, cafe, reservation, recommendation, parking lot, photo, distance, location, find, hike, path, NRF, thought, walk (51)
	G2	**Visitation and usage behavior**	trekking, nature, meditation, free, introduction, space, water, sky, hiking, in the forest, deck, valley, arboretum, rest area, phytoncides, park, child, sound, scent, cypress forest, infant, mountain, autumn (23)
	G3	**Programs**	program, COVID-19, family, target, mountain forests, welfare, recreation, culture, participation, facility, utilization, guidance, center, operation, health, cure, variety, activity, experience, progress (20)
	G4	**Camping**	camping, campground, healing, name, site, tree (6)
T2	**G1**	**Healing Forest and NRF**	NRF, mountain, activity, facility, welfare, therapy, space, in the forest, operation, mountain forests, free, family, city, application, mind, introduction, review, utilization, meditation, forest, variety, cure, center, program, coast, participation, health, me, branch, body, rest area, park, nature, scent, progress, healing, experience, child (38)
	G2	**Tourism**	trip, travel destination, near, arboretum, Seogwipo, cafe, accommodation, walk, path, parking, entrance fee, find, place, visit, walking, reservation, home, live, guidance, eat, time, recommendation, trail, location, photo, weather, possible, thought, course, car, rain, barrier-free, see, forest path, rest, distance (36)
	G3	**Visitation and usage behavior**	birch, cypress forest, Dulle-gil-trail, deck, observatory, rental cottage, sound, sky, water, wind, flower, autumn, person, valley, phytoncides (15)
	G4	**Hiking**	hiking, trekking, hike, summit, climb, tree, air, town, waterfall, parking lot, campground (11)

The CONCOR analysis results of T2 contained groups that were not observed in the other periods. The “Tourism” group contained nodes related to tourist resources near the healing forests, and the “Hiking” group contained nodes related to outdoor adventures.

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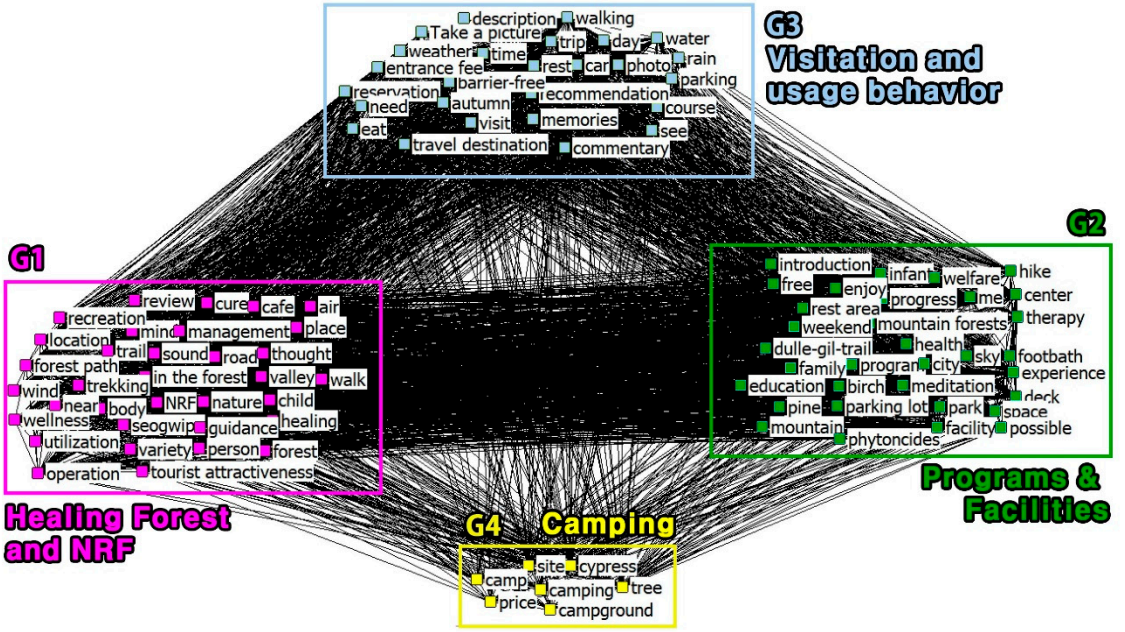

Figure 2. Results of CONCOR analysis of healing forest networks in the pre-COVID-19 period (T, January 1 to December 31, 2019).

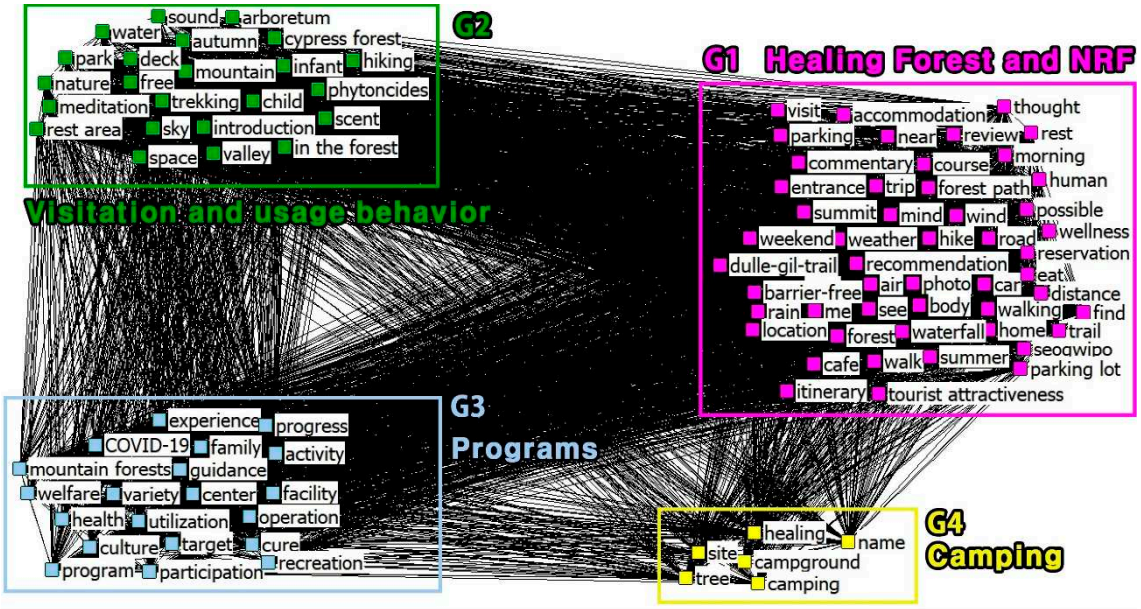

Figure 3. Results of CONCOR analysis of healing forest networks during the COVID-19 pandemic period (T1, November 1, 2020 to October 31, 2022).

 doi:10.20944/preprints202401.1927.v1

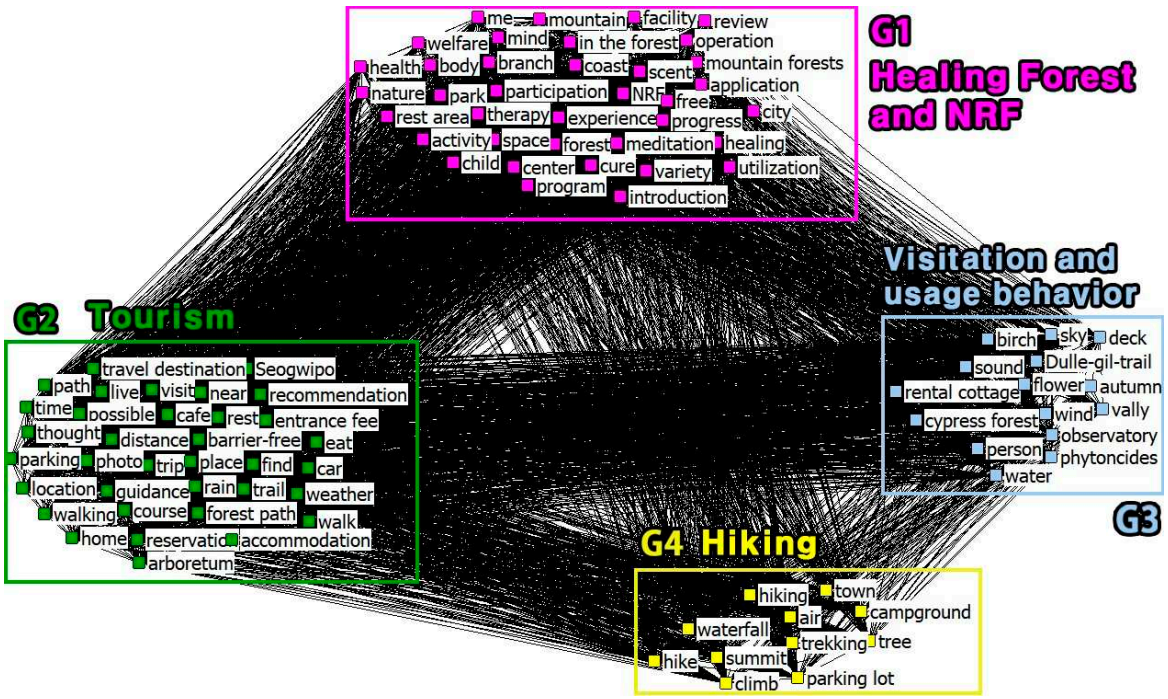

Figure 4. Results of CONCOR analysis of healing forest networks during the post-COVID-19 period (T2, **November** 1, 2022 to **October** 31, 2023).

3.4. QAP Correlation Analysis results

To analyze the network similarity between T, T1, and T2 using the healing forest network, we performed QAP correlation analysis using UCINET 6. QAP correlation analysis requires two systems or matrices, namely, the Observed Matrix and the Model or Expected Matrix. QAP correlation analysis can verify how similar the matrix structure of the dependent matrix is to the independent matrix (Yang & Hwang, 2005). In performing QAP correlation analysis, the nodes and matrix sizes that comprise these independent and dependent matrices must match each other (Seon et al., 2021). Therefore, we derived 100 keywords for each time period and then reconstructed the matrix with 71 keywords that co-occurred in all years. The results are shown in Table 4. The correlation values for each time period were statistically significant and can be statistically interpreted as significantly influencing or correlating with each other.

Table 4. QAP correlation analysis results.

Matrix: QAP Correlations	Section	Collection volume (cases)		
		T	T1	T2
	T	-.	0.909 (0.000)	0.866 (0.000)
	T1	0.909 (0.000)	-.	0.849 (0.000)
	T2	0.866 (0.000)	0.849 (0.000)	-.

$p < 0.05$, indicated in parentheses.

4. Discussion

We aimed to provide findings that could help promote visits to healing forests. First, the use of healing forests shifted toward individual and small group visits in response to the COVID-19 outbreak. Across T, T1, and T2, we found no significant difference in the top trending words. However, we did observe an increase in rankings for personal and appointment keywords related to COVID-19 collected from T1, during COVID-19 pandemic. This suggests that safety and hygiene are prioritized in the wake of the COVID-19 outbreak, and the type of tourism that can ensure recreation and healing-based health has changed. This is consistent with the results of previous studies that

 doi:10.20944/preprints202401.1927.v1

cleanliness, low congestion, and virus-free natural environments are expected to receive significant attention after the COVID-19 outbreak, and ecotourism centered on small groups and healing trips is expected to rise (Jeonbuk Green Environment Center, 2020). Therefore, visits to healing forests have been affected by the COVID-19 pandemic, shifting into individual- and small group-centered visits. This implied the necessity of preparing measures for expanding individual- and small group-centered healing programs rather than large group-centered programs.

Second, “tourism” and “hiking” became new factors in the visitation and use of healing forests. In T2, the words with the highest frequency were similar to those of other periods. However, tourism-related words such as "travel" and "destination" as well as destinations such as "Gimcheon" and "Busan" have emerged as new top frequent words. Thus, for post-COVID-19 visitors, the use of and visit to healing forests are not limited to the concept of healing but are being embraced as part of a trip or planned in conjunction with nearby tourism resources. When comparing the results of the CONCOR analysis by time period, we noted a difference in the keywords included between T and T1. However, we found no significant difference in usage behavior, with themes such as “healing forests and NRF,” “programs and facilities,” “visitation and usage behavior,” and “camping.” In T2, similar themes as in T and T1 emerged, along with distinct ones: “tourism” and “hiking.” This could show that healing forests are perceived more broadly as spaces for tourism and hiking, and not merely as spaces for healing, after the COVID-19 pandemic in Korea. This suggests that healing forests need to expand their functions as tourist destinations and organize programs that do not focus on healing.

Third, the use of healing forests after the COVID-19 pandemic is not likely to change back to that before the COVID-19 pandemic. The QAP correlation analysis showed that the correlation between T and T1 was very high, whereas the correlation between T1 and T2 was significantly lower. This is thought to be similar to the shift in usage behavior, from healing-focused activities during T, to more individual-oriented activities during T1 owing to social distancing measures, to more outdoor activities during T2 after the relaxed social distancing measures. However, although T and T2 were the same, T and T1 were also highly correlated. These results indicated a shift in the use behavior of healing forests during T2, which may not revert to the patterns of T. Therefore, the authorities must expand the function of healing forests, organize service programs, and explore ways to connect with surrounding cultural and tourism resources, focusing on the newly identified keywords of “tourism” and “hiking” as described above.

5. Conclusions

We aimed to explore the changes in the usage behavior of the healing forests before, during, and after the COVID-19 outbreak based on historical data using text mining techniques, and to identify the interests of visitors at different times. We collected big data and categorized the same into before, during, and after pandemic periods, and then created a network to analyze the association between each period.

We conclude that after the COVID-19 pandemic, usage behavior is unlikely to revert to pre-COVID-19 patterns. The main factors of change in usage behavior are “tourism” and “hiking.” Therefore, the authorities must recognize healing forests for their potential to function and develop as tourist destinations. As healing forests are located in forests, the demand and behavior of visitors change depending on the season. Forest managers should provide programs that take into account seasonality and expand activities outside the forest by linking with cultural and tourist resources near the forest.

We utilized text mining techniques to explore changes in the usage behavior of healing forests based on historical data and to identify the interests of visitors by season. Our study provides basic data that can contribute to the provision of healing forest programs and establishment of marketing strategies. Furthermore, we recognized the significance of revealing the possibility of utilizing healing forests as tourist destinations.

Nonetheless, our study had data limitations. We collected data using the keyword “healing forest.” However, given the nature of blogs and Cafes as data collection channels, we used post data

 doi:10.20944/preprints202401.1927.v1

that did not meet the purpose of the study, such as advertisements and recent posts. Therefore, future research should apply a collection method that can control for advertisements and posts that are not related to healing forests and thus achieve sophisticated data collection.

Appendix A

"Healing Forest" keyword data collection over time

Net Above	T			T1			T2			Net Above	T			T1			T2		
	Word	TF	TF IDF	Word	TF	TF IDF	Word	TF	TF IDF		Word	TF	TF IDF	Word	TF	TF IDF	Word	TF	TF IDF
1	Healing Forest	2125	4.33	Healing Forest	4060	57.27	Healing Forest	4985	2.14	51	Sky	40	140.89	Possible	63	226.36	Meditation	135	41205
2	Seogwipo	712	880.81	Seogwipo	1162	1665.01	Seogwipo	1515	2309.24	52	Palyeongsan	38	149.91	Facility	63	225.22	Possible	134	397.34
3	Forest	660	531.36	Forest	1131	1158.06	Forest	1384	1415.74	53	Photo	38	124.58	Yesan	62	262.45	Yesan	131	497.99
4	Cure	606	485.13	Cure	932	981.97	Cure	1207	1315.18	54	Location	37	122.32	Gokseong	61	269.76	Progress	131	392.80
5	Healing	313	451.61	Cypress	535	1079.04	Road	670	1072.02	55	Phytoncides	36	125.58	Welfare	61	231.41	Palyeongsan	130	465.18
6	Mountain Forests	260	438.25	Healing	522	851.74	Program	612	1058.34	56	Body	36	122.15	Utilization	59	214.17	Space	129	391.42
7	Cypress	259	513.93	Mountain Forests	440	854	Healing	609	987.51	57	Facility	36	122.15	Barrier-Free	59	222.53	Chukryongsan	129	474.10
8	Program	239	414.97	Forest Path	429	834.15	Forest Path	593	1071.75	58	Commentary	35	120.94	Infant	57	224.39	Find	124	369.77
9	Forest Path	235	435.37	National	381	833.91	Mountain Forests	583	1070.71	59	Start	35	120.94	Phytoncides	57	204.8	Hiking	123	422.53
10	Trip	204	354.2	Program	364	730.07	Walking	570	987.09	60	Name	35	118.75	Parking	56	208.83	Valley	119	385.78
11	Walking	175	338.4	Walking	308	659.37	Cypress Forest	560	1200.24	61	Site	33	123.88	Covid-19	56	208.83	Family	115	372.81
12	National	163	385.95	Trip	304	639.38	Go	533	906.46	62	Valley	32	117.46	Thought	56	200.2	Parking	115	370.31

doi:10.20944/preprints202401.1927.v1

13	Experience	154	332.97	Reservation	275	638.62	National	502	1087.08	**63**	Hike	31	113.79	Wind	55	199.65	Free	113	363.87
14	Road	153	319.09	Center	253	579.91	Time	502	913.90	**64**	Birch	31	115.05	Cafe	55	216.52	Location	111	414.62
15	Center	153	320.35	Tree	250	576.77	Trip	493	916.17	**65**	Pocheon	30	129.73	Meditation	54	207.31	Guidance	110	350.72
16	Reservation	149	330.29	Experience	242	593.6	Experience	474	921.75	**66**	Parking	30	113.95	Weather	53	199.9	Utilization	110	350.72
17	Time	125	285.55	Time	228	541.42	Reservation	394	850.27	**67**	Wellness	30	112.62	Arboretum	52	213.4	Goheung	110	402.42
18	Tree	118	278.12	Walk	188	471.25	Walk	374	794.80	**68**	Progress	29	106.45	Introduction	50	186.46	Trekking	110	385.46
19	Walk	113	259.27	Jangseong	188	546.9	Tree	363	792.94	**69**	Gokseong	29	127.73	Weekend	50	186.46	Get	110	342.91
20	Jangseong	110	303.87	NRF	169	460.55	Course	361	794.12	**70**	Rest Area	29	105.31	Rest	50	196.84	Entrance	107	343.41
21	Course	82	226.52	Course	168	450.31	Center	341	783.42	**71**	Air	29	105.31	Sound	50	193.13	Body	107	345.71
22	Daegwallyeong	77	256.73	Seocheon	162	536.21	NRF	321	802.65	**72**	Jecheon	29	123.26	Distance	49	185.89	Review	106	345.99
23	Gimcheon	74	248.87	Daegwallyeong	145	496.77	Gimcheon	251	787.54	**73**	Free	29	105.31	Hike	49	186.99	Sky	106	357.29
24	Creation	74	218.87	Activity	145	454.5	Weather	233	574.22	**74**	Therapy	27	105.13	Deck	48	186.56	Person	104	339.46
25	Nrf	71	210	Mind	135	375.31	Mountain	228	576.16	**75**	Baekunsan	27	118.92	In Advance	47	177.27	Eat	103	340.94
26	Seocheon	66	228.06	See	131	367.4	Operation	213	562.48	**76**	Review	26	97.6	Water	46	178.79	Deck	100	329.84
27	Car	64	179.97	Park	131	409.12	Autumn	204	582.40	**77**	Day	26	97.6	Rain	46	178.79	Phytoncides	100	329.84

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28	Mind	62	176.48	Car	129	369.48	Nature	203	525.35	**78**	Open	26	101.24	Forest Healing Instructor	44	180.57	Home	97	314.46
29	Recommendation	61	181.63	Nature	122	349.43	See	200	511.96	**79**	Samcheok Hwalki	26	99.97	Samcheok Hwalki	44	183.32	Barrier-Free	95	328.91
30	See	60	174.03	Recommendation	122	358.3	Mind	195	527.06	**80**	Near	25	94.96	Hiking	44	187.8	Participation	95	316.72
31	Child	57	172.04	Operation	116	348.61	come	194	506.55	**81**	Introduction	25	91.76	Eat	43	167.13	Water	94	313.38
32	Operation	57	170.87	Child	110	339.84	Car	193	510.83	**82**	Guidance	25	91.76	Commentary	43	175.18	Cafe	93	317.03
33	Health	54	160.78	Photo	98	320.42	Parking Lot	183	522.45	**83**	Weather	25	91.76	Camping	43	179.15	Live	91	307.88
34	Mountain	53	159.97	Parking Lot	97	312.18	Park	178	533.39	**84**	Utilization	25	96.12	Home	42	166.43	Hike	91	316.32
35	Yesan	48	182.33	Campground	97	346.77	Me	177	490.14	**85**	Infant	25	98.62	Scent	42	172.36	Scent	91	327.04
36	Nature	47	144.89	Entrance	85	279.04	Seocheon	169	576.11	**86**	Entrance Fee	23	88.43	Travel Destination	41	167.03	city	89	345.45
37	Campground	47	170.68	Family	84	281.56	Jangseong	168	562.13	**87**	Business	23	97.76	Dulle-Gil-Trail	41	165.84	Waterfall	89	333.34
38	Park	47	158.07	Person	84	272.47	Creation	168	477.13	**88**	Trail	23	87.36	Application	41	165.84	Therapy	88	320.48
39	Yangpyeong	47	174.44	Location	82	267.04	Busan	163	555.56	**89**	Rain	22	83.56	Pine	39	160.05	Variety	88	295.53
40	Meditation	47	150.43	Valley	80	276.58	Health	162	456.56	**90**	Footbath	22	86.79	Air	38	152.64	Town	88	329.59
41	Me	46	148.39	Health	78	260.34	in the forest	160	448.64	**91**	Roadway	22	89.24	Waterfall	38	160.85	Start	86	292.06
42	Parking Lot	45	141.83	Space	76	262.75	Daegwallyeong	159	564.14	**92**	Climb	22	84.59	Tourist Attractiveness	38	154.81	Rain	86	295.43

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43	Visit	45	144.03	Sky	73	259.68	Recommendation	158	457.08	**93**	Education	21	89.26	Accommodation	38	158.32	Manisan	85	369.88
44	Chukryongsan	44	158.12	Trail	70	251.51	Child	150	449.87	**94**	Pine	21	83.98	Management	38	159.56	Welfare	84	305.91
45	Barrier-Free	41	139.11	Birch	70	267.13	Jecheon	143	528.00	**95**	Wind	21	83.98	Morning	38	152.64	Air	83	295.73
46	Deck	41	141.67	Visit	69	237.46	Photo	142	415.27	**96**	Management	20	82.34	Sea	37	150.73	Application	82	287.35
47	Family	40	132.24	Body	67	231.63	Place	141	414.62	**97**	Person	20	78.9	Explore	37	152.98	Introduction	81	279.34
48	Space	40	130.08	Rest Area	66	238.35	Visit	140	416.30	**98**	Weekend	20	78.9	Scenery	37	154.15	Distance	81	283.84
49	Changwon	40	155.75	Autumn	66	235.95	Daejeon	140	503.14	**99**	Rest	20	78.9	Trekking	37	162.11	Sound	80	285.04
50	Entrance	40	131.14	Guidance	66	233.63	Facility	138	413.88	**100**	Welfare	20	82.34	Summer	37	150.73	Arboretum	79	300.32

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