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How do People Understand and Express "Smart City?": Analysis of Transition in Smart-city Keywords through Semantic Network Analysis of SNS Big Data between 2011 and 2020

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Abstract The purpose of this study is to grasp the understanding of smart cities and to review whether the common perception of smart cities, as people understand it, is changing over time. This study analyzes keywords related to smart cities used in social network services (SNSs) in 2011, 2016, and 2020 respectively through semantic network analysis. Smart city discussions appearing on SNS in 2011 mainly focused on technology, and the results of 2016 were generally similar to those of 2011. We can also find policy or business-oriented characteristics in emerging countries in 2020. We highlight that all the results of 2011, 2016, and 2020 have some correlation with each other through QAP(Quadratic Assignment Procedure) correlation analysis, and among them, the correlation between 2011 and 2016 is analyzed the most. The results of the frequency analysis, centrality analysis, and CONCOR(CONvergence of interaction CORrelation) analysis support these results. The results of this study help establish policies that reflect the needs and opinions of citizens in planning smart cities by identifying trends and paradigm transitions expressed by people in SNS. Furthermore, it is expected to help emerging countries by enhancing the understanding of the essence and trend of smart cities and to contribute by suggesting the direction of more sustainable technology development in future smart city policies for leading countries.

Keywords: Smart City, Social Media, SNS, Semantic Network Analysis, Keyword Analysis, Text Mining

1. INTRODUCTION

Among The 4th industrial revolution triggered a rapid growth in smart cities around the world. "Smart City" is a high-tech city that strategically solves or alleviates problems that arise from rapid urbanization through the convergence of ICT (Information and Communications Technology), IoT (Internet of Things), and SW (SoftWare), and at the same time seeks to improve people's quality of life (Bencke et al., 2020). It is also one of the most actively pursued policies in India and Singapore, countries commonly referred to as smart city emerging countries that the ranking of the Global Smart City Index has recently risen (IMD, 2021), as well as smart city leading countries that have the highest number and proportion of smart cities such as the UK, Spain, and Italy (European Parliament, 2014; OECD, 2020).

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Smart cities ultimately have a common goal of improving the living environment and quality of life of citizens. Therefore, the technology and service of smart cities should consequentially be made by citizens, and citizens' opinions are crucial in the policy making (Johnson et al., 2020). This is because a focus on computing technology without the participation of citizens, who are the owners of the public space, and reflection of their opinions, policies, and plans, reduces the sustainability and efficiency of the city (Verma et al., 2019; Oh, 2020).

Looking at smart city policies, most countries have declared a bottom-up approach in which citizens participate in a smart city strategy. In reality, however, policies are devised in a top-down manner, led by the government (Nicolas et al., 2021). In addition, although people-centric policies are discussed for a sustainable smart city, technology-oriented policies and business inputs are still predominant. This is one of the most critical problems plaguing the development of smart cities (Kubina et al., 2021).

Against this backdrop, recently, the importance of a bottom-up approach was mentioned, and analysis using social media data is being actively conducted as a way to hear citizens' stories most closely (Bencke et al., 2020; Doran et al., 2016; Pereira, 2017; Alotaibi et al., 2019; Alkhammash et al., 2019; Yigitcanlar et al., 2020). The number of social media users worldwide was 4.48 billion in July 2021, and because many people who account for 57% of the world's population use social media (DataReportal, 2021). Like this social media data, which are big data, can analyze the thoughts and opinions of various people in real time, so it is possible to accurately grasp urban phenomena and social problems from a citizen's point of view. In addition, it has the advantage of being able to overcome time and cost limitations of the survey method, which is often used to listen to citizens' voices (Drahosova and Balco, 2017).

However, as a result of examining previous studies related to social media and smart city, as data from tweets had mainly been used among social media, the analysis has conducted only with short-term cross-sectional data (owing to the nature of data collection) (Bencke et al., 2020; Pereira, 2017; Alkhammash et al., 2019; Yigitcanlar et al., 2020). In addition, these studies have confirmed that citizens' opinions on smart cities have been analyzed only in a few countries and cities such as Australia, the United States, Canada, and Madrid (Doran et al., 2016; Alotaibi et al., 2019; Yigitcanlar et al., 2020).

The existing smart cities have been carried out differently for each country, city, and government in terms of concepts, policy methods, and models. Some have argued that a common understanding is not necessary because the smart city is locally defined (Clement and Crutzen, 2021). However, there have been other arguments that are necessary to identify common characteristics within a broad definition of smart cities to promote smart city policies more successfully and to boost citizen understanding and participation (SO et al., 2019). The ASEAN Smart City Network (ASCN), where the Association of South East Asian Nations (ASEAN) countries jointly built a smart city cooperation platform, also has supported the need for a common understanding of smart cities by establishing a smart city framework encompassing regional diversity to achieve interoperability and integrated synergy among different countries and cities (ASCN, 2021).

In this context, this study raises the following research questions: How do people understand and express smart cities?; What are the common perceptions of people about smart cities on social media, which is a major means of mentioning smart cities? Is this changing over time?; and if so, how is it changing? The purpose of this study to solve the research questions is, first, to identify smart cities-related perceptions appearing in SNS big data by extracting meaningful words from social media and confirming the connectivity and relationship between words through semantic network analysis. Second, this study aims to compare the trends of changes in keyword characteristics of smart cities that have been discussed by people on social media in the most recent, five, and ten years ago. Third, the purpose of this study is to expand the scope of the study compared to previous studies. Instead of setting the analysis target area in advance, this study intends to lay the research framework that encompasses regional diversity by identifying the perceptions of the smart cities that appears to English-speaking users on SNS. In addition, as utilizing Facebook and YouTube data as well as Twitter in SNS data, this study intends to check the changes in main keyword characteristics related to smart cities at each of the three-time points. Finally, this study aims to provide policy implications for smart cities to policymakers in various countries.

This study consists of 5 chapters. Chapter 2 explains smart city, social media, and semantic network analysis and reviews precedent literature. Chapter 3 describes the analysis method and the process of data collection and purification, and Chapter 4 describes the semantic network analysis results and discussion. Finally, Chapter 5 describes the conclusion.

2. LITERATURE REVIEW

2.1. Smart City

Existing cities tend to rely mostly on physical expansion to solve urban problems. For example, in response to traffic congestion, lanes were widened or new roads were built, and new parking lots were installed to alleviate the parking problem. On the other hand, information on congested roads has recently been delivered to drivers in real time to facilitate road detours, or information about nearby parking lots is shared by platform services, enabling convenient parking. Smart cities can be created by sharing the information needed by citizens, efficient use of resources, and active utilization of city data. A "Smart City" is one that strategically solves and alleviates urban problems caused by urbanization through technological convergence such as ICT and IoT and is spotlighted as a new sustainable and competitive city model worldwide (Bencke et al., 2020).

However, the definition of a smart city is still fluctuating, depending on the purpose and model of countries and governments. According to the International Telecommunication Union (ITU, 2021), there were 116 definitions of smart cities in 2014 alone. In the EU, the smart city concept was defined as "the place where traditional networks and services are made more efficient with the use of digital solutions for the benefit of its inhabitants and business" (EU, 2021). The US Obama administration also defined the smart city as "building an infrastructure to continuously improve the collection, aggregation, and use of data to improve the life of their residents" (Obama White House, 2021). The British government described the smart city concept as "a process rather than a static outcome, in which increased citizen engagement, hard infrastructure, social capital and digital technologies make cities more liveable, resilient and better able to respond to challenges" (UK BIS, 2021).

In India, it is defined as "city to promote sustainable and inclusive cities that provide core infrastructure and give a decent quality of life to its citizens, a clean and sustainable environment and application of 'smart' solutions" (India Ministry of Housing and Urban Affairs, 2021), and the Chinese government defined the concept as "providing citizens with improvements in transportation, communication, environmental management and crime prevention as a way to increase the efficiency and effectiveness of its rapidly growing cities" (NDRC, 2021).

In particular, leading countries of the smart city initiative focus on solving urban problems and climate change, and addressing the need for development of new and renewable energy, while emerging and developing countries pursue large-scale development, such as building infrastructure and securing energy sources. As there is a large difference in access strategies depending on the country, the definition of a smart city is different for each country, and the understanding of the concept is different for each region, policy and institution.

The same applies to academia. Despite the ongoing discussion regarding smart cities, the concept is still defined as multifaceted and arbitrary without a consensus of concept (Caragliu et al., 2011; Harrison, C and Donnelly, 2011; Batty et al., 2012; Albino et al., 2015; Silva et al., 2018). This has caused confusion around the smart cities, and recently, the need to identify common understanding encompassing diversity rather than broad smart city definitions has been raised (SO et al., 2019; ASCN, 2021). Therefore, this study intends to identify common understandings and opinions of smart cities based on this necessity.

2.2. Social Media and Semantic Network Analysis

Social media, such as Social Network Services (SNS), is a tool for people to communicate and share information. As social media that connects people from different parts of the world, ages, and nationalities spread, problems such as personal information leakage, invasion of privacy and, hacking and SMiShing occur around the world. However, as it is a key component of city data accumulated in real-time, the significance of social media for academia is unquestionable (Injadat et al., 2016).

As social media provides policy contributions and useful information by revealing the most challenging issues faced by citizens (Pereira, 2017), the use of data to listen to the public's stories in real time, to solve urban problems, continues to grow and needs urban policy research (Ciuccarelli et al., 2014).

Social media is very useful in exploring individual opinions, as it is used not only to network and communicate with others, but also to express and share opinions on various fields such as politics, economy, society, culture, art, entertainment, and sports (Alkhammash et al., 2019; Weiler et al., 2017). For example, by extracting demographics such as age, gender, and residence of SNS users, the characteristics of community groups necessary for market analysis can be identified (Ikeda et al., 2013). Also, by analyzing social media data, we can identify early public discourse and dialogue on contemporary events like the Me-Too movement (Modrek and Chakalov, 2019).

In addition, users' activity patterns can be identified by collecting SNS data and visualizing the density of posts through heat map techniques to understand the influence of citizens on smart tourism policies (Brandt et al., 2017). By collecting and analyzing real-time location information in flooded areas, SNS (including location data) can be used to identify and analyze the impact of disasters and calamities (Kankanamge et al., 2020). As such, social media data have the advantage of being highly utilized in policy and academic terms to reflect citizens' opinions. In addition, it is being used as an effective means of collecting opinions because it can save money and time compared to citizens' survey methods.

In the analysis, because of the nature of social media data, public opinions and discourses are expressed in an atypical text format, so methods such as social networks or semantic networks are mainly used. In particular, semantic network analysis is a method that combines big data and social network analysis. If social network analysis analyzes relationships between people, semantic network analysis analyzes relationships between keywords and analyzes influences, directions, and clusters by characteristics. In this context, semantic network analysis is used to analyze text and keyword data in various fields such as politics, economy, cities, and the environment (Freeman, 2007), and identify the connectivity and overall structure between keywords (Drieger, 2013; Sevin, 2014; Shim and Park, 2015; Kang, 2019; Colladon et al., 2020).

Therefore, this study intends to identify the main keywords characteristics of smart cities through social media data and utilize semantic network analysis techniques to check the connectivity and relationship between smart city-related keywords used on SNSs.

2.3. Previous Studies Related to Smart Cities Using Social Media Data

By examining previous studies related to smart cities using social media data, it was confirmed that tweet data from social media are mainly used for analysis. To compare physical sensor data with Twitter's location information data, the movement and activity patterns of citizens living in smart cities were identified by utilizing people's post updates (Doran et al., 2016). The analysis process also collects usernames, latitudes and longitudes, posting dates and times, hashtags, and other relevant data from location-tagged tweet data to provide meaningful implications for smart cities using location information (Osorio-Arjona and García-Palomares, 2019).

In addition, compared to other social media where data collection is heavily constrained, tweet data provide a public API, which allows people to understand their perceptions of smart cities through keyword data and text analysis. It is beneficial and useful as a policy-making tool based on public opinion (Yigitcanlar et al., 2020; Alizadeh et al., 2019). In addition, Twitter is evaluated as a representative data platform for the scalability of the academic use of social media in that it is used in various languages (Alotaibi et al., 2019; Yigitcanlar et al., 2020; Alizadeh et al., 2019).

However, since the access of tweet API data is restricted on a weekly basis, there is a limitation in that data collection and analysis are very short-term and lateral, given most existing studies collecting data for about a month (Doran et al., 2016; Alotaibi et al., 2019; Yigitcanlar et al., 2020; Osorio-Arjona and García-Palomares, 2019; Alizadeh et al., 2019). Therefore, this study utilized TEXTOM 5.0, a big data collection and analysis program, to supplement the limitations of previous studies related to social media and smart cities and to enhance the diversity of data and the scalability of the collection period. Through TEXTOM, not only Twitter but also various social media channels, such as Facebook and YouTube, were used for analysis. Data for one year were collected at each time point by dividing them into three time points: recent past, five years ago, and ten years ago. Using these data, we tried to understand the change in people's perception over time and to analyze the keyword network structure change for each point of time in the smart city.

Taken together, the differences between previous studies and this study are as follows: First, while previous smart city-related studies mainly analyzed the characteristics of specific cities, countries, and regions (Caragliu et al., 2011; Harrison and Donnelly, 2011; Batty et al., 2012; Albino et al., 2015; Silva et al., 2018; Giffinger et al., 2007; Angelidou, 2017), this study intended to identify the opinion of the smart cities encompassing regional diversity, instead of setting the analysis target area in advance. Second, while most of the previous studies used fragmentary and cross-sectional data for specific one-time points (Doran et al., 2016; Alotaibi et al., 2019; Yigitcanlar et al., 2020; Osorio-Arjona and García-Palomares, 2019; Alizadeh et al., 2019; Giffinger et al., 2007; Angelidou, 2017), this study compares and analyzes the changes in the characteristics of smart cities between three-time points using 2011, 2016, and 2020 data. Third, this study identifies the awareness of smart cities through people-centered SNS data, not policy-centered public data provided by specific governments or agencies (Choi, 2011; Angelidou, 2017), and analyzes them by applying text mining and keyword analysis called semantic network analysis.

3. FRAMEWORK FOR ANALYSIS

3.1. Analysis Method

This study set the data collection period when the most recent point, from January 1 to December 31, 2020, when the five years ago, from January 1 to December 31, 2016, and when the ten years ago, from January 1 to December 31, 2011, to identify the keywords characteristics and transitions by era of keywords related to smart cities used on SNSs.

The analysis method is as follows: First, smart city-related keywords were collected from SNS (Twitter, Facebook, and YouTube) data, and then the collected keywords were extracted and refined. Second, to examine the overall trend of the collected keywords, frequently used words were extracted from SNS, and the frequency of each event was checked. Third, by conducting semantic network analysis, smart city-related keywords were identified in the form of nodes and links in the SNS data. In particular, this study sequentially analyzed centrality and structural equivalence, which are the most important factors in semantic network analysis. Centrality was measured through centrality analysis indicators such as degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality, and structural equivalence clustered characteristics by topic through CONCOR analysis. Finally, three time points were compared and analyzed to confirm the keyword change of smart city circulated in SNS, and the relationship and correlation between the three time points were statistically confirmed through QAP correlation analysis. The analysis system used in this study is shown in Figure 1.

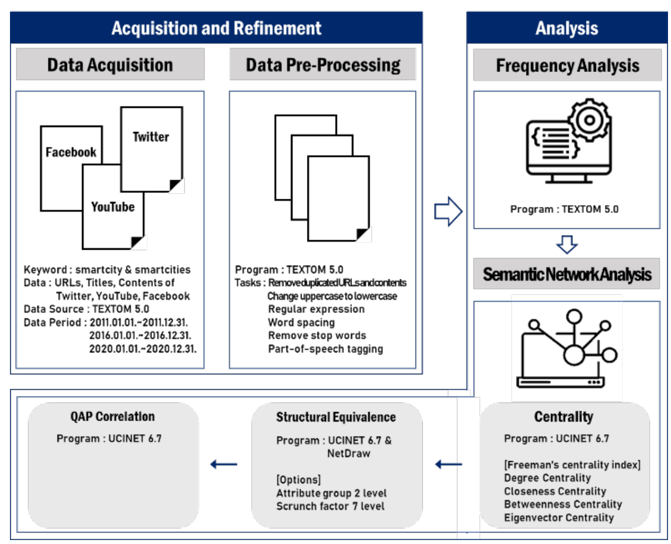

Figure 1. Analysis Framework

As a program for analysis, TEXTOM 5.0 was used for data collection and purification, and UCINET 6.7 and NetDraw were used for semantic network analysis, visualization, and statistical significance tests. TEXTOM is a big data software that collects various channel data on SNSs at high speed and enables efficient Hadoop-based data storage and management, batch keyword purification and stopword processing, and matrix generation for semantic network analysis. Programs for network analysis include KrKwic, NetMiner, UCINET, and NodeXL. Among them, UCINET is the most popular and has the advantage of providing various visualizations and statistical analyses.

3.2. Data Collection and Purification

The data collection period for analysis was set to three points in 2020 (most recent), 2016 (5 years ago), and 2011 (10 years ago). The data are collected in URLs, titles, and contents of SNS (Twitter, YouTube, and Facebook) that contain these words after search for "smartcity" and "smartcities" in the TEXTOM. Keyword search was performed through English, a universal language.

For the collected data, duplicate URLs and contents were first removed, then only nouns were extracted, and the extracted text information was preprocessed. First, a normalization or separation operation was performed to convert uppercase letters to lowercase letters or to

remove spaces between two words used as the same word to form a single word. In addition, morpheme analysis, which simplifies text to a meaningful minimum unit, and word refining works, to remove special characters and words including search keywords such as "smartcity" and "smartcities" and meaningless words in the analysis (conjunctions, unit noun, numeral, preposition, etc.), were also carried out. As a result, 22,080 keywords in 2011, 25,025 keywords in 2016, and 36,843 keywords in 2020 were collected.

4. RESULTS

4.1. Frequency Analysis

Before performing Semantic Network Analysis, this study identified the most used smart city-related keywords on SNS through frequency analysis. As a result of frequency analysis up to the top 20 (Table 1), the keywords most frequently mentioned on SNS related to the smart city in 2011 were mainly identified as keywords related to "technology" (network, system, IoT, application, technology, computer, algorithm). On the other hand, in 2016, the ranking of "technology" relevant keywords decreased slightly, "policy" relevant keywords (project, develop, busy, management) began to appear, and most recently (2020), "policy and business" related keywords (mission, summit, govern, project, infrastructure) and keywords related to "India", an emerging smart city powerhouse (dholera, india, airport), became prominent.

Table 1. Frequency Analysis Result

2011			2016				2020			
Rank	Word	N	Rank	Word	N	+-	Rank	Word	N	+-
1	network	518	1	network	573	-	1	project	453	▲3
2	system	443	2	system	525	-	2	technology	330	▲1
3	IoT	302	3	technology	366	▲1	3	develop	206	▲5
4	application	273	4	IoT	349	▼1	4	mission	189	▲63
5	technology	239	5	project	312	▲17	5	solution	179	▲9
6	computer	231	6	application	299	▼2	6	covid	141	new
7	service	227	7	service	276	-	7	summit	131	▲93
8	performance	218	8	computer	238	▼2	8	infrastructure	129	▲25
9	algorithm	197	9	develop	235	▲8	9	capital	128	▲14
10	conference	187	10	performance	232	▼2	10	system	125	▼8
11	process	178	11	conference	216	▼1	11	dholera	115	▲16
12	formation	177	12	formation	209	-	12	govern	114	▲33
13	data	172	13	energy	208	▲1	13	busy	112	▲6
14	energy	155	14	solution	198	▲5	14	market	111	▲45
15	source	152	15	algorithm	197	▼6	15	service	110	▼8
16	analysis	130	16	source	178	▼1	16	airport	109	▲317
17	develop	125	17	process	173	▼6	17	innovate	104	▲29
18	method	121	18	busy	165	▲32	18	energy	102	▼5
19	traffic	119	19	analysis	156	▼3	19	platform	97	▲30
20	solution	118	20	management	153	▲3	20	india	94	▲15

† '+-' refers to rank increase and decrease compared to previous point in time

4.2. Semantic Network Analysis

Semantic Network Analysis is a technique for identifying network relationships through the following procedures: Centrality, Structural Equivalence, and Correlation. Centrality is measured by 'Centrality Analysis' that quantifies the centrality of the specific word in the network, and Structural Equivalence is measured through 'CONCOR (CONvergence of interaction CORrelation) analysis' that groups nodes with the same or similar relationship. And the correlation between networks is measured through 'QAP (Quadratic Assignment Procedure) analysis' using Pearson's correlation coefficient. Therefore, this study also sequentiallyperformed semantic network analysis procedures such as centrality, structural equivalence, and QAP.

To conduct a semantic network analysis, a matrix (50X50) between each smart city keyword network in 2011, 2016, and 2020 was formed. The network size of the matrix is determined by the number of nodes, and the higher the number of nodes, the more complex the network structure; therefore, this study established the network size with node 50, which is widely used in prior studies. Later, network analysis indicators such as centrality, structural equivalence, and Quadratic Assignment Procedure (QAP) correlation were analyzed. The calculation formula for semantic network analysis is shown in Table 2.

Table 2. The calculation formula for semantic network analysis

Semantic Network Analysis		Calculation Formula
Centrality	Degree Centrality	$C_D(N_i) = \sum_{j=1}^{g} x_{ij}, i \neq j$ $C_D(N_i) = The\ degree\ centrality\ of\ node\ i$ $\sum_{i=1}^{g} x_{ij} = The\ number\ of\ degree\ between\ a\ node\ i\ and\ (g-1)\ other\ nodes$ $g = The\ number\ of\ nodes$
	Closeness Centrality	$C_c(N_i) = \frac{1}{[\sum_{j=1}^{g} d(N_i, N_j)]}, i \neq j$ $C_c(N_i) = The\ closeness\ centrality\ of\ node\ i$ $\sum_{j=1}^{g} d(N_i, N_j) = The\ sum\ of\ shortest\ path\ distances\ between\ node\ i\ and\ node\ j$ $g = The\ number\ of\ nodes$
	Betweenness Centrality	$C_B(N_i) = \sum_{j<k} \frac{g_{jk}(N_i)}{g_{jk}}$ $he\ number\ of\ shortest\ path\ between\ node\ j$ and $node\ k$ $= The\ number\ of\ paths \in cluding\ node\ i$ $among\ the\ shortest\ paths\ between\ node\ j$ and $node\ k$
	Eigenvector Centrality	$C_E(N_i) = \lambda \sum_{j} x_{ij} e_j$ $C_E(N_i) = The\ Eigenvector\ Centrality\ of\ node\ i$ $\lambda = Eigenvalue\ (proportional\ constant)$
Structural Equivalence	CONCOR Analysis	$r_{ij} = \frac{\sum(x_{ki} - \bar{x}_{\cdot i})(x_{kj} - \bar{x}_{\cdot j}) \sum(x_{ik} - \bar{x}_{i\cdot})(x_{jk} - \bar{x}_{j\cdot})}{\sqrt{\sum(x_{ki} - \bar{x}_{\cdot i})^2 (x_{ik} - \bar{x}_{i\cdot})^2 \sum(x_{ik} - \bar{x}_{i\cdot})^2 (x_{jk} - \bar{x}_{j\cdot})^2}}$ $r_{ij} = The\ structural\ equivalence\ used\ in\ the$ CONCOR $analysis$ $x_{ik} = The\ value\ of\ the\ relationship\ when\ node\ i\ is\ connected\ to\ node\ k$ $\bar{x}_{i\cdot} = The\ aberage\ value\ of\ i\ row\ relationship$ $\bar{x}_{\cdot i} = The\ aberage\ value\ of\ i\ column\ relationship$
QAP Correlation		$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$ $\rho_{XY} = Pearson\ product - moment\ correlation\ coefficient$ $cov(X,Y) = covariance\ of\ variables\ x\ and\ y$ $\sigma_X = standard\ deviation\ of\ x$ $\sigma_Y = standard\ deviation\ of\ y$ *Based on the Pearson Correlation Coefficient

(1) Centrality

The centrality index suggested by Freeman (2008) was used to identify keywords with high centrality among smart city-relevant keywords of SNS. According to Freeman (2008), centrality is measured by the indicators of Degree Centrality, Closeness Centrality, Betweenness Centrality, and Eigenvector Centrality. 'Degree Centrality' indicates the degree of a link connected to a node, and 'Closeness Centrality' indicates the degree of connection by applying the concept of distance between a specific word and other words within the entire network. Moreover, 'Betweenness Centrality' refers to the degree of connection as a medium of specific words among network words, and 'Eigenvector Centrality' refers to the degree of connectivity in the entire network.

Therefore, in this study, each analysis was conducted by subdivision into degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality, result of the centrality analysis is as follows (refer to Appendix Table 1, Appendix Table 2, Appendix Table 3).

First, in degree centrality, which indicates the number of links connected to nodes in 2011, we found that "technology" keywords such as 'network', 'system', 'IoT', 'application', 'technology' and others were highly ranked and those words were the keywords used to express smart cities on SNS. In addition, closeness centrality, which indicates the distance from smart city keywords within the entire network, showed that "consultation or computing" related keywords were high in the order of office, conference, gram, event, project, infrastructure, memory, and others. The betweenness centrality, which acts as a mediator among network words, showed that words related to "technology and smart city formation processes" such as 'IoT', 'process', 'formation', and 'network', lead smart city-related agendas and discourse on SNS. The eigenvector centrality, which implies the degree of connection hidden in the entire network, accounted for a large proportion in the order of network, system, application, and data, confirming that these words will be influential in representing smart cities on SNS in the future.

In 2016, "technology" related keywords ranked high in the order of network, system, technology, and IoT in the degree centrality, which shows the keywords for smart city on SNS, as in 2011. In addition, the closeness centrality, which shows words that have a great influence on the agenda and discourse about smart cities on SNS, confirmed that "India and policy" related keywords such as 'dholera', 'capital', 'conference', 'india', 'office' and 'govern' have a greater influence. In betweenness centrality, which shows medium words between smart city keywords and words that enrich discussions on social media, words related to "smart city business", such as 'development', 'system', 'people', 'project', 'application' and 'infrastructure' were ranked high. In addition, the eigenvector centrality, which shows influence representing smart cities on social media in the future, showed that words similar to those of 2011 were found to occupy a high ranking such as 'network', 'system', 'application' and 'performance'.

In the degree centrality, which indicates the number of links connected to nodes in 2020, "business" related keywords such as 'project', 'technology', 'develop', and 'mission' were ranked high, and for the closeness centrality, indicating the distance from smart city keywords within the entire network, keywords related to "emerging smart city" such as 'islamabad', 'lahore' and 'dholera' were found to be high. In the betweenness centrality, which plays a mediating role between network words, words related to "development" and "smart city project" such as 'project', 'develop', 'people' and 'airport', were ranked high, and in the eigenvector centrality, which shows the degree of connection hidden in the entire network, it was found that keywords related to "policy and business" such as 'project', 'mission', 'develop' and 'summit' occupy a large proportion.

(2) Structural Equivalence

CONCOR (CONvergence of interaction CORrelation) was performed to confirm the structural equivalence of identifying characteristics and patterns by clustering smart city keywords on SNSs. CONCOR analysis is a representative analysis technique of structural equivalence, which repeatedly performs correlation analysis and clusters keywords with similarity (TEXTOM, 2021). For optimal clustering, we performed a correlation analysis between nodes several times until the cluster was derived using the UCINET program. The "Attribute Group" which determines the level of the cluster, and the "Scrunch Factor" which determines the density between words, were set to the same levels 2 and 7 at each 2011, 2016, and 2020 time points. This is because clustering is performed as shown in Figure 2, Figure 3, and Figure 4 only when the level is set as above, and clustering is not performed at other levels.

The results of the CONCOR analysis are shown in Tables 3, 4, and 5. Figure 2, 3, and 4 show the visualization of the CONCOR analysis using NetDraw of UCINET. All four dense clusters were derived from 2011, 2016, and 2020 data, but despite the analysis at the same level, it was confirmed that the clusters of words were somewhat scattered indistinctly in 2011 (refer to Figure 2) compared to 2016 (refer to Figure 3) and 2020 (refer to Figure 4). In Figures 3 and 4, the clusters are well-bound, meaning that the relationship between the keywords is clear, whereas, in Figure 2, it means that th ere are many unbound outlier points in the cluster.

In addition, naming was performed to determine the characteristics of each cluster. For naming, we considered the overall common properties of the words represented by multiple keywords, along with the words with the largest node strength in the cluster. The intensity of the node is shown as the size of the point in the figure that visualizes the CONCOR analysis. As a result, Cluster 1 in 2011 was named "IoT Technology in Smart City" based on 'IoT' with the highest node strength and the characteristics of words such as 'sensor', 'security' and 'technology'. Cluster 2 was named "Computing-based Smart City" considering the characteristics of various computing technology-related words that apply to smart cities, such as 'computer', 'machine', 'storage' and 'memory', along with 'system' with the largest nodes. Cluster 3 has the strongest 'network' node, but words such as 'algorithm', 'model', 'method' and 'detection' have the characteristics of machine learning, so it is named "Smart

City and Machine Learning". Cluster 4 is named "Smart City and Urban Management" based on the characteristics of the overall cluster words because there are no strong nodes (refer to Figure 2 and Table 3). Overall, the structural equivalence results of 2011 showed technology-oriented words such as IoT, computing and machine learning as characteristics of smart cities.

Table 3. 2011 CONCOR Analysis Results

Cluster	Composed Nodes
1 IoT Technology in Smart City	IoT, service, formation, sensor, software, security, technology, challenge, architecture, sign, vice, approach, develop, analysis, traffic, communicate (16 nodes)
2 Computing-based Smart City	system, schedule, scale, platform, source, energy, memory, performance, application, storage, multi, computer, strategy, time, framework, machine (16 nodes)
3 Smart City and Machin Learning	network, method, algorithm, problem, detection, model, cluster (7 nodes)
4 Smart City and Urban Management	management, infrastructure, project, solution, environment (5 nodes)

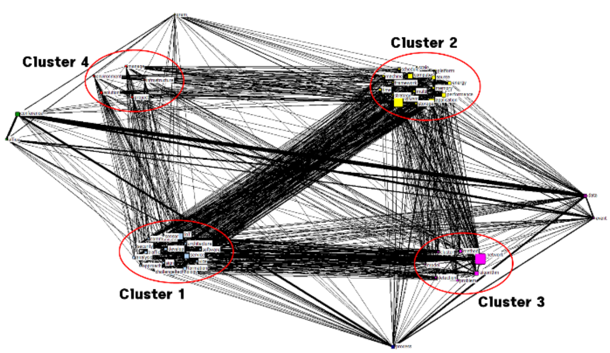

Figure 2. 2011 CONCOR Analysis Results

Cluster 1, the largest cluster of words in the 2016 results, was named the "US Smart City Challenge" by combining words such as 'traffic', 'technology', 'software', 'approach', 'environment' and 'solution' together with smart city in 2016. The US Smart City Challenge is a smart city project in the U.S., which has been in full swing since 2016, and aims to solve environmental and urban problems through traffic innovation that incorporates technology. Cluster 2 was named "Smart City's Application and Performance" based on strong nodes such as 'system', 'application' and 'performance'. Cluster 3 was named "Smart City in India" based on words such as 'india', 'dholera', and 'develop', along with 'system' with the largest node strength. Cluster 4 was named "International Conference in Smart Cities 2016" in Malaga, Spain, June 2016, considering the cluster words such as 'conference', 'event', 'process' and 'office' together with smart city in 2016 (refer to Figure 3 and 4). It was confirmed that the structural equivalence of smart city keywords on SNS in 2016 shows the characteristics of smart city-related projects and conferences conducted in various countries, as well as the application of smart city policies and performance.

Table 4. 2016 CONCOR Analysis Results

Cluster	Composed Nodes
1 US Smart City Challenge	network, IoT, technology, software, infrastructure, service, approach, communicate, sensor, architecture, method, environment, algorithm, people, security, analysis, sign, solution, traffic, fomation, vice, people (22 nodes)
2 Smart City's Application and Performance	system, application, performance, management, busy, source, computer, memory, time, storage, platform, multi, machine, energy, problem (15 nodes)
3 Smart City in India	project, develop, innovate, capital, india, holera, govern (7 nodes)
4 International Conference in Smart Cities 2016	conference, office, message, process, event, gram (6 nodes)

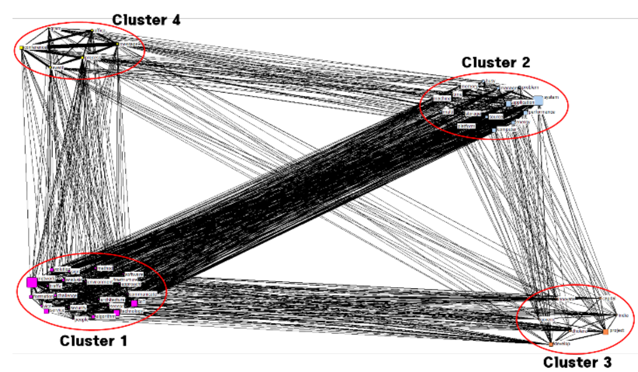

Figure 3. 2016 CONCOR Analysis Results

In 2020, Cluster 1 was named the "Smart City Platform" because although technology's node is the largest, the components, which underly the smart city, such as 'citizen', 'people', 'community', 'service', 'network', 'platform', 'manage', 'source', 'support', and 'formation' are clustered. Cluster 2 was named the "World Smart City Award 2020" by combining the words of 2020 smart city and 'award', 'initiative', 'transport', 'mobility', 'energy', 'market', 'partner', and 'govern'. The World Smart City Awards 2020 is a global event that discovers and awards cities that implement innovative and pioneering projects and initiatives in various smart city fields such as transportation, environment, and governance. In Cluster 3, 'project' had the largest node strength, and was named "Projects of Smart City Emerging Countries" by combining the words such as 'dholera', 'islamabad', 'lahore', 'develop', and 'airport'. Cluster 4 was also named "Smart Cities India Expo 2020" by synthesizing the words of 2020 smart city and 'india', 'mission', and 'summit' (refer to Figure 4 and Table 5). The structural equality in 2020 showed the characteristics of various events similar to 2016, but compared to 2016, when only India appeared, some cities in India and Pakistan were clustered into nodes, showing the rise of emerging countries implementing similar programs. In addition, it was confirmed that various smart city components were gathered to form a single platform.

Table 5. 2020 CONCOR Analysis Results

Cluster	Composed Nodes
1 Smart City Platform	technology, solution, platform, management, policy, industry, source, IoT, network, world, busy, service, park, opportunity, sensor, support, formation, challenge, citizen, people, community (21 nodes)
2 World Smart City Awards 2020	infrastructure, system, event, sign, govern, company, initiative, transport, market, partner, mobility, energy, award, innovate (14 nodes)
3 Projects of Smart City Emerging Countries	project, develop, dholera, islamabad, lahore, airport, capital, build, economy, percent (10 nodes)
4 Smart Cities India Expo 2020	mission, summit, covid, india, author (5 nodes)

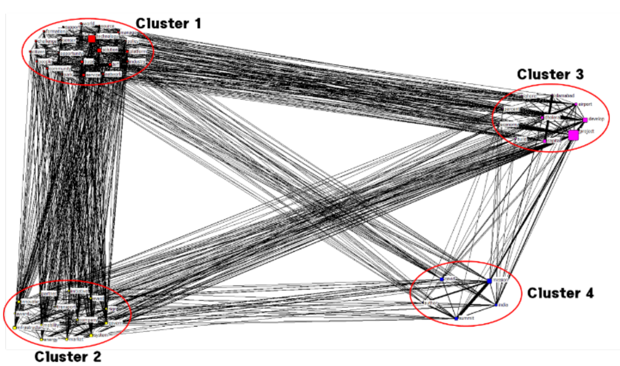

Figure 4. 2020 CONCOR Analysis Results

(3) QAP (Quadratic Assignment Procedure) Correlation

The keyword data used in semantic network analysis are not random samples from the population, and since each individual observation is interdependent, general statistical tests cannot be performed. Therefore, in semantic network analysis, QAP correlation analysis, which is a permutation test, is used for statistical significance test (Hubert, 1987; Krackhardt, 1987). The permutation test is a method of generating and statistically testing sample statistical distributions based on the assumption that null hypotheses are true from randomly arranged sample data and is a nonparametric test technique that does not assume theoretical distributions such as normal, t, and F distributions. In other words, QAP correlation analysis is an analysis method that statistically tests the null hypothesis that there is no correlation between networks, and the degree of correlation between networks is measured through Pearson's correlation coefficient.

The QAP correlation requires matrix data with two matrices. Therefore, this study was intended to conduct QAP correlation analysis through keyword network matrices in 2011, 2016, and 2020 and to quantify the significance and association of network changes according to the trend of the times.

As a result of the correlation analysis (refer to Table 6), the study found that after 5,000 matrix rearrangements (5,000 permutations), all networks between 2011, 2016, and 2020 had some correlation significance under the null hypothesis that there was no correlation between networks. The correlation coefficient between the keyword networks in 2011 and 2016 was 0.246, the correlation coefficient between the keyword networks in 2011 and 2020 was 0.225, and the correlation coefficient between 2016 and 2020 was 0.205. Although the correlation coefficient value was not overall high, it was confirmed that the correlation between 2011 and 2016 was relatively higher than that at other times.

Table 6. QAP Correlation Analysis Results

Division	2011	2016	2020
2011	1.000	-	-
2016	0.246***	1.000	-
2020	0.225***	0.205***	1.000

† $*p<0.05$, $**p<0.01$, $***p<0.001$.

This study conducted a cross-sectional network analysis in 2011, 2016, and 2020, but through the results of the QAP correlation analysis, it was confirmed that the years influence each other and are somewhat mutually related.

4.3. Discussion

The results of the analysis are summarized as follows: First, it was confirmed through frequency analysis that technology-oriented keywords appeared the most in relation to smart cities in 2011. In addition, the centrality analysis results showed that "technology", "consultation or computing", "technology and smart city formation process" and "network and structure" were ranked high, while the CONCOR analysis results showed characteristics such as "IoT technology", "computing-based", "machine learning" and "urban management". These results show that the smart city discussions circulating around SNS in 2011 were mainly centered on technology. Since 2010, most countries have moved away from traditional city management to smart cities (POSCO, 2021). In particular, in 2011, various types of smart cities were planned in various countries around the world as an investment in urban infrastructure was accelerated based on physical devices incorporating technologies. Such technologies included sensor networks, IoT systems, artificial intelligence, and machine learning, led by global superpowers (GreenBiz, 2021). Therefore, it can be interpreted that people were also interested in these changes in the city and actively discussed them on SNS.

Results of frequency analysis in 2016 showed that most keywords related to "policy", but, results of centrality analysis in 2016 showed that keywords such as "technology", "India and policy”, “smart city business” and “network and structure” were high. In the CONCOR analysis, characteristics such as “US smart city challenge”, “smart city application and performance”, “India” and “international conferences” were derived as a result. In 2016, similar to 2011, technology and network-related keywords formed central characteristics, but keywords such as India and smart city-related policies or businesses also emerged. This shows that India has established itself as an influential word in people’s discussions when it announced the Smart City Mission in 2015 (Ferrer, 2017; Aijaz, 2021).

In 2020, keywords related to “policy and project” and “India” were ranked high in frequency analysis results, while keywords related to “project”, “emerging countries” and “development or project” were ranked high in centrality analysis results. According to the results of the CONCOR analysis, characteristics such as “platform”, “smart city awards”, “emerging countries” and “smart city expo in India” were derived. In 2020, policies and businesses were becoming an issue on social media not only in India, but also in a variety of emerging smart city countries. One of the reasons India continued to be mentioned on social media in 2020 is that India has conducted a four-round smart city challenge process until 2018, and the Noida International Greenfield Airport Project was selected among the World’s 100 Strategic Global Infrastructure Projects (selected as 100 trendy projects that shape the global market). It seems that these issues and news are being shared through SNS, as many emerging countries are executing large and small businesses and events as part of their smart city policies.

As such, the results of 2011, 2016, and 2020 were all related to each other, certain similarities were derived, and the characteristics of these analysis results were statistically identified through QAP correlation analysis. In the QAP correlation analysis results, some correlations were found between 2011, 2016, and 2020. In particular, the network correlation between 2011 and 2016 was relatively high. This can be understood as a result of supporting a similar derivation of keyword characteristics at both points in 2011 and 2016 in frequency analysis, centrality analysis, and CONCOR analysis. Meanwhile, considering that the word ‘covid’ was derived from influential words in 2020, it is confirmed that COVID-19 is also influencing people’s discussion of smart cities.

5. CONCLUSIONS

This study sought to identify the people’s understanding and perceptions of smart cities that express on social media. In particular, this study to analyze keywords related to smart cities circulated in SNSs to solve research questions such as what the common perception of people related to smart cities is, and how it is changing over time; various channels (Twitter, Facebook, and YouTube) of social media were utilized in the analysis to compensate for the limitations of the analysis period of data, which were mainly used in prior studies, and were very short-term and transverse. Furthermore, several points of view were analyzed, not just one, by identifying the changes in people’s perception of smart cities according to the different time periods by dividing them into recent past, five years ago, and ten years ago.

As a result, first, it was confirmed that the smart city policy that started in the mid-1990s showed that people’s understanding and perception of smart city was not clear until about 10 years ago, and that smart city was understood mainly by focusing on technology (refer to Figure 2 and Table 3). However, as time passed, it was confirmed that the themes became clear from around 2016 (refer to Figure 3 and Table 4), which seems to be a result of the expansion of people’s understanding as various countries participate in the smart city. The fact that people’s understanding and perception of smart cities have not expanded until 20 years after the introduction of smart cities around the world means that the existing smart city policy was a top-down approach that made it difficult for people to feel.

Second, from 2011 to 2016 and 2020, it was confirmed that smart city keywords showed a change from technology-oriented characteristics to more policy-oriented and segmented businesses and events. In addition, it was confirmed that the rise of emerging countries in smart-city initiatives became more prominent in recent times. Through the results of the analysis, people’s interests in the smart cities on SNS was identified, and this suggested a policy implication that should be used to establish policies that reflect the needs and opinions of citizens in planning smart cities.

Third, as a result of this study, the themes and issues of smart cities at each time were summarized, with technology-oriented characteristics in 2011, India and policy-oriented characteristics in 2016, and policy or business-oriented characteristics with emerging countries in 2020. Actually, in 2011, Barcelona hosted the Smart City Expo, and cities in Latin America and the Caribbean (e.g. Buenos Aires in Latin America) have planned technology-oriented smart cities (Bouskela et al., 2016). The 2016 results are also seen part of the ‘Smart City Mission’ policy announced by India in June 2015 (India Ministry of Housing and Urban Affairs, 2021). The results of 2020 match the facts that the ranking of the Global Smart City Index in European countries, which have implemented smart city policies for a long time, has fallen whereas such countries as Singapore, India, Helsinki, and Zurich have risen rapidly (IMD, 2021).

Fourth, it was concluded that keywords related to “technology” “emerging countries” and “policy and project” were characteristics of smart cities that have been discussed over the past 10 years and peoples’ understanding at an international level. These results are similar to previous studies (Angelidou, 2017), but such characteristics as emerging countries and projects reflect the characteristics of SNS that share event or conference information. In addition, the fact that representative keywords do not represent short-term characteristics, but are long-term characteristics that integrate the characteristics of the 10 years from 2011 to 2020 is also seen as a significant result of this study. Short-term identification of national, urban, and government-specific opinions and the latest trends in relation to smart cities are important, but it is also important to identify smart cities in the overall context, considering the long-term trend and global dimensions. For countries that are beginning to plan smart cities, it is more important to understand the overall nature of smart cities than the fragmentary aspects that represent specific space or time. In this context, the findings of this study are expected to help emerging countries, in the smart city planning phase, understand the nature and trends of smart cities, and to provide the leading countries with guidance for more sustainable technological development in establishing smart cities policies in the future.

Finally, the study reveals that there are some limitations to the generalization of the study because it does not include non-english speakers or those who do not use SNS, given that the smart city keyword is set in english and the majority of people are young. Furthermore, this study examines network analysis of 2011, 2016, and 2020 which was conducted cross-sectionally. This study expects to expand the future scope and predict the opinions of smart cities by analyzing time-series and longitudinal keyword data in the future.

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APPENDIX

Appendix Table 1. 2011 Centrality Results

NO.	Degree		Closeness		Betweenness		Eigenvector	
1	network	1725.00	office	85.00	IoT	8.29	network	0.35
2	system	1528.00	conference	79.00	process	7.96	system	0.32
3	IoT	998.00	gram	69.00	formation	7.76	application	0.25
4	application	1055.00	event	65.00	network	7.49	data	0.24
5	technology	633.00	project	63.00	data	7.38	performance	0.24
6	computer	925.00	infrastructure	62.00	service	6.49	conference	0.23
7	service	762.00	memory	61.00	technology	6.42	IoT	0.23
8	performance	927.00	challenge	61.00	develop	5.84	computer	0.22
9	algorithm	702.00	detection	59.00	traffic	5.16	process	0.21
10	conference	875.00	storage	58.00	system	4.98	service	0.18
11	process	780.00	solution	57.00	application	4.98	algorithm	0.16
12	formation	570.00	sign	57.00	computer	4.98	traffic	0.15
13	data	888.00	strategy	57.00	machine	4.94	formation	0.14
14	energy	573.00	problem	56.00	approach	4.73	technology	0.14
15	source	575.00	sensor	56.00	performance	4.35	event	0.14
16	analysis	469.00	framework	56.00	model	4.18	source	0.13
17	develop	338.00	method	55.00	communicate	4.04	energy	0.13
18	method	382.00	schedule	55.00	event	3.75	office	0.12
19	traffic	525.00	cluster	55.00	schedule	3.63	analysis	0.12
20	solution	287.00	scale	55.00	gram	3.16	storage	0.11
21	multi	455.00	security	55.00	software	3.11	schedule	0.11
22	project	163.00	algorithm	54.00	multi	2.75	multi	0.11
23	manage	407.00	energy	54.00	analysis	2.58	manage	0.10
24	problem	366.00	machine	54.00	project	2.58	time	0.10
25	memory	335.00	time	54.00	source	2.55	communicate	0.10
26	machine	387.00	platform	54.00	platform	2.48	software	0.09
27	architecture	374.00	analysis	53.00	vice	2.31	vice	0.09
28	vice	370.00	traffic	53.00	manage	2.31	sensor	0.09
29	office	415.00	manage	53.00	challenge	2.23	method	0.09
30	approach	349.00	architecture	53.00	environment	2.13	memory	0.09
31	event	473.00	environment	53.00	method	2.05	machine	0.09
32	storage	398.00	service	52.00	energy	2.03	architecture	0.09
33	detection	324.00	performance	52.00	architecture	2.01	detection	0.09
34	software	345.00	source	52.00	time	1.93	problem	0.08
35	schedule	425.00	develop	52.00	sign	1.83	approach	0.08
36	sign	267.00	multi	52.00	algorithm	1.82	develop	0.08
37	time	377.00	vice	52.00	security	1.79	cluster	0.08
38	communicate	370.00	communicate	52.00	sensor	1.75	environment	0.07
39	cluster	309.00	data	51.00	framework	1.59	scale	0.07
40	environment	308.00	approach	51.00	cluster	1.52	security	0.07
41	infrastructure	223.00	software	51.00	solution	1.43	solution	0.07
42	sensor	327.00	model	51.00	detection	1.34	sign	0.07
43	gram	198.00	network	50.00	scale	1.28	platform	0.07
44	model	234.00	system	50.00	problem	1.26	model	0.06
45	platform	274.00	application	50.00	conference	1.16	framework	0.06
46	framework	238.00	technology	50.00	strategy	1.15	strategy	0.05
47	challenge	169.00	computer	50.00	storage	0.80	gram	0.05
48	scale	287.00	process	50.00	infrastructure	0.75	infrastructure	0.05
49	strategy	228.00	formation	50.00	memory	0.63	challenge	0.04
50	security	288.00	IoT	49.00	office	0.39	project	0.04

Appendix Table 2. 2016 Centrality Results

NO.	Degree		Closeness		Betweenness		Eigenvector	
1	network	1677.00	dholera	87.00	develop	11.94	network	0.36
2	system	1549.00	capital	81.00	system	11.05	system	0.34
3	technology	887.00	conference	73.00	people	10.42	application	0.25
4	IoT	941.00	india	72.00	project	9.39	performance	0.23
5	project	511.00	office	71.00	application	9.05	computer	0.22
6	application	991.00	govern	68.00	infrastructure	8.88	IoT	0.21
7	service	793.00	message	67.00	technology	8.20	technology	0.20
8	computer	840.00	memory	65.00	busy	7.82	service	0.20
9	develop	572.00	gram	65.00	platform	7.78	conference	0.19
10	performance	821.00	algorithm	60.00	sign	7.60	process	0.19
11	conference	920.00	event	60.00	service	7.49	message	0.17
12	formation	607.00	time	60.00	formation	7.49	formation	0.16
13	energy	600.00	multi	59.00	solution	6.86	source	0.15
14	solution	466.00	challenge	59.00	manage	6.85	traffic	0.15
15	algorithm	539.00	storage	59.00	communicate	6.67	energy	0.15
16	source	656.00	sensor	59.00	event	6.60	algorithm	0.14
17	process	767.00	method	58.00	software	5.12	event	0.13
18	busy	422.00	machine	58.00	analysis	5.06	analysis	0.12
19	analysis	477.00	architecture	58.00	IoT	5.02	manage	0.12
20	manage	474.00	innovate	58.00	challenge	4.68	storage	0.12
21	traffic	495.00	performance	57.00	innovate	4.64	sensor	0.12
22	capital	128.00	traffic	57.00	network	4.52	vice	0.11
23	message	705.00	problem	57.00	process	4.34	solution	0.11
24	sign	365.00	environment	57.00	source	3.75	office	0.11
25	event	520.00	vice	56.00	computer	3.38	develop	0.11
26	dholera	162.00	project	55.00	approach	3.38	communicate	0.10
27	office	460.00	infrastructure	55.00	security	3.35	multi	0.10
28	method	322.00	security	55.00	environment	3.27	security	0.10
29	vice	408.00	computer	54.00	energy	3.07	time	0.10
30	multi	411.00	energy	54.00	message	3.01	software	0.10
31	challenge	267.00	source	54.00	problem	2.98	busy	0.09
32	infrastructure	332.00	busy	54.00	performance	2.88	architecture	0.09
33	problem	333.00	sign	54.00	office	2.88	memory	0.09
34	india	180.00	approach	54.00	traffic	2.66	approach	0.09
35	security	390.00	platform	54.00	machine	2.64	environment	0.09
36	software	348.00	network	53.00	vice	2.40	sign	0.09
37	storage	421.00	solution	53.00	gram	2.40	method	0.08
38	machine	329.00	process	53.00	method	2.30	machine	0.08
39	environment	339.00	analysis	53.00	india	2.17	project	0.08
40	approach	340.00	people	53.00	storage	1.94	problem	0.08
41	architecture	377.00	communicate	53.00	sensor	1.66	platform	0.08
42	memory	304.00	IoT	52.00	govern	1.43	infrastructure	0.07
43	sensor	399.00	manage	52.00	time	1.38	challenge	0.06
44	govern	143.00	software	52.00	multi	1.37	gram	0.05
45	innovate	176.00	system	51.00	architecture	1.22	people	0.03
46	people	170.00	application	51.00	algorithm	1.13	innovate	0.03
47	gram	231.00	service	51.00	conference	0.84	govern	0.02
48	platform	318.00	formation	51.00	memory	0.54	india	0.02
49	communicate	380.00	technology	50.00	capital	0.47	capital	0.02
50	time	349.00	develop	50.00	dholera	0.09	dholera	0.02

Appendix Table 3. 2020 Centrality Results

NO.	Degree		Closeness		Betweenness		Eigenvector	
1	project	811.00	islamabad	87.00	project	25.53	project	0.41
2	technology	629.00	lahore	87.00	develop	24.61	mission	0.34
3	develop	560.00	dholera	85.00	people	21.61	develop	0.31
4	mission	509.00	author	80.00	airport	17.59	summit	0.25
5	solution	465.00	award	76.00	solution	14.83	technology	0.24
6	covid	224.00	summit	75.00	market	13.70	capital	0.21
7	summit	360.00	economy	73.00	busy	13.13	solution	0.20
8	infrastructure	386.00	sign	72.00	infrastructure	12.71	infrastructure	0.18
9	capital	358.00	capital	70.00	technology	10.20	govern	0.16
10	system	316.00	india	70.00	formation	10.10	author	0.16
11	dholera	224.00	transport	70.00	source	9.71	dholera	0.16
12	govern	301.00	build	70.00	mobility	9.64	service	0.15
13	busy	292.00	park	69.00	covid	9.37	airport	0.15
14	market	303.00	percent	68.00	world	9.15	islamabad	0.15
15	service	355.00	opportunity	67.00	policy	8.54	india	0.15
16	airport	324.00	support	67.00	initiative	7.64	market	0.14
17	innovate	245.00	mission	66.00	manage	7.31	system	0.14
18	energy	174.00	event	65.00	innovate	7.24	busy	0.14
19	platform	208.00	challenge	65.00	opportunity	7.24	covid	0.12
20	india	220.00	sensor	65.00	india	6.96	innovate	0.11
21	IoT	156.00	partner	65.00	service	6.69	industry	0.11
22	manage	214.00	covid	64.00	system	6.43	citizen	0.10
23	citizen	215.00	IoT	64.00	energy	6.42	manage	0.10
24	people	182.00	platform	63.00	capital	6.37	formation	0.09
25	network	180.00	citizen	63.00	industry	6.36	company	0.08
26	mobility	164.00	world	63.00	govern	6.36	platform	0.08
27	company	181.00	market	62.00	support	6.34	energy	0.08
28	industry	237.00	network	61.00	community	6.25	people	0.08
29	formation	206.00	company	61.00	platform	6.04	transport	0.08
30	initiative	147.00	initiative	61.00	partner	5.92	network	0.07
31	world	114.00	govern	60.00	network	5.90	initiative	0.07
32	sign	124.00	community	60.00	citizen	5.89	sign	0.07
33	event	127.00	policy	60.00	company	5.69	park	0.07
34	challenge	113.00	system	59.00	mission	5.21	community	0.06
35	community	148.00	innovate	59.00	build	4.99	mobility	0.06
36	economy	86.00	energy	59.00	percent	4.96	sensor	0.06
37	author	200.00	industry	59.00	event	4.41	source	0.06
38	sensor	145.00	formation	59.00	sign	4.25	IoT	0.06
39	policy	107.00	source	59.00	IoT	4.23	lahore	0.06
40	islamabad	220.00	service	58.00	economy	3.89	challenge	0.05
41	park	140.00	manage	58.00	challenge	3.77	world	0.05
42	transport	159.00	mobility	58.00	sensor	3.44	support	0.05
43	source	131.00	airport	56.00	summit	3.33	event	0.05
44	lahore	76.00	solution	55.00	transport	2.88	policy	0.05
45	build	82.00	busy	55.00	park	2.21	economy	0.05
46	opportunity	97.00	technology	54.00	author	1.65	percent	0.05
47	support	113.00	infrastructure	54.00	award	1.04	partner	0.04
48	percent	94.00	people	53.00	islamabad	0.91	opportunity	0.04
49	partner	106.00	develop	51.00	lahore	0.69	build	0.04
50	award	58.00	project	50.00	dholera	0.67	award	0.03