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New Trends in Smart Cities: The Evolutionary Directions Using Topic Modeling and Network Analysis

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Abstract: The COVID-19 pandemic has affected smart city operations and planning. Smart cities, where digital technologies are concentrated and implemented, face new challenges in becoming sustainable from social, ecological, and economic perspectives. Using text mining methodologies of topic modeling and network analysis, this study aims to identify keywords in the field of smart cities after the pandemic and provide a future-oriented perspective on the direction of smart cities. A corpus of 1882 papers was collected from the Web of Science and Scopus databases from December 2019 to November 2022. We identified six categories of potential issues in smart cities using topic modeling: "supply chain", "resilience", "culture and tourism", "population density", "mobility", and "zero carbon emission". This study differs from previous research because it is a quantitative study based on text mining analysis and deals with smart cities, given the prevalence of COVID-19. This study also provides insights into the development of smart city policies and strategies to improve urban resilience during the pandemic by anticipating and addressing related issues. The findings of this study will assist researchers, policymakers, and planners in developing smart city strategies and decision-making in socioeconomic, environmental, and technological areas.

Keywords: smart cities; COVID-19; sustainability; text mining; topic modeling; network analysis

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1. Introduction

How are smart cities growing? Urbanization increased from 17.95% in 1978 to 54.7% in 2016 and is expected to increase by 70% by 2030 [1]. Urbanization and industrialization have increased slum populations and various economic, environmental, and social issues. Countries face many problems, including infrastructure issues such as roads, water, and sanitation systems, traffic congestion, and a lack of resources. Cities are becoming increasingly larger and more populous. Due to the rapid development of information and communication technology (ICT), cities have been able to mitigate the impact of global economic and environmental crises [2]. Smart cities aim to achieve sustainable economic growth and improve the quality of life and value for citizens living in the city through intelligent management of the information gathered from ICT-based city infrastructure. The concept of smart cities is becoming a global urban phenomenon and is improving the quality of life [3]. Thus, smart cities have become an attractive concept for city managers, policymakers, and strategic planners [2,4].

A comprehensive and complex approach is required to consider user needs and the environment. For example, the development of automobiles and the use of technology in cities has increased the importance of connectivity and proximity. Artificial intelligence (AI) and Internet of Things (IoT) are used to improve cities in areas such as smart home automation, smart vehicle management systems, and smart waste management. The application of smart city technologies in various industries, such as agriculture, biology, home appliances, and automobiles, is reflected in corporate strategies and national policies. Cities worldwide are transforming into sustainable cities. According to the literature, not only smart cities but also sustainable cities operate on circular economy models [5–7]. For instance, research organizations and businesses are developing technologies and services to increase the efficiency of environmental energy resources. Governments have developed policies and institutions to promote carbon neutrality and reduce transportation demand. Citizens of smart cities consume technologies and services and take action to preserve ecosystems and reduce pollution. Research organizations, businesses, governments, and citizens are the key stakeholders in smart cities. Hence, to understand smart cities, it is necessary to have technical knowledge and contextual knowledge of complex systems consisting of multiple interacting layers and nodes [8].

The COVID-19 pandemic of December 2019 has shocked the world. It has brought about many changes and modifications in human life, including social life, public safety, and health. Various infectious diseases have been reported in the past, including Middle East Respiratory Syndrome (MERS-CoV) and Severe Acute Respiratory Syndrome (SARS-CoV). MERS-CoV infects humans via camels, SARS-CoV via civet cats or raccoons, cholera via contaminated water, and Zika virus through mosquitoes [9]. Viruses are managed by reducing their contact with virus vectors. COVID-19, however, differs from previous viruses in that it spreads through general contact with people. The response was a lockdown in cities and regions.

Border closures, remote work, school closures, and social distancing have altered lifestyles [9]. With social distancing, the home was recognized as a space to prevent the spread of viruses and as a place for resting and recharging. There were increased indoor activities and the transformation of the city into a center for cultural and artistic activities. Residential environments were also given attention as quarantine measures were strengthened for ventilation, lighting, and housing density. With the closure of borders and travel restrictions, the use of metaverse technologies increased rapidly. Global value chains became vulnerable during the pandemic, and many countries and companies experienced economic crises [10]. Consequently, many countries have developed an interest in cities to address social, economic, and environmental issues associated with urban life and infectious diseases [11]. Almost no literature existed on cities and pandemics before the COVID-19 pandemic [12]. The impact of COVID-19 has underscored the importance of technology not only for maintaining city functions but also for promoting welfare, such as education, living, and social connectivity among residents [12,13]. ICTs, IoT, and AI-based technologies have contributed to urban restoration by resolving issues such as urban mobility and logistics [14]. According to the World Health Organization (WHO), AI is crucial for resolving virus-induced crises [15].

Despite this, there is debate regarding the vulnerability of cities to future uncertain pandemics considering of COVID-19. Undoubtedly, a smart city is a key factor in building an inclusive and resilient city [14]. Therefore, in the future, urban resilience—the ability to respond to unpredictable external shocks—will become a key concept in smart cities. The concept of urban resilience refers to a city's ability to adjust quickly to external conditions, recover quickly, and remain functional despite external shocks [16]. As the OECD noted, cities and countries can manage the pandemic crisis using smart city capabilities. The fragility of cities has been highlighted because of the pandemic, but researchers have noted that the smart city model represents a city for sustainable and inclusive growth [17].

Smart cities are necessary for urban sustainability, strengthening urban resilience to infectious diseases, responding to climate change, and improving the quality of life in cities. To develop and operate smart cities, it is imperative to understand the impact of the COVID-19 pandemic on cities and examine the key lessons learned. As ICTs develop, physical, social, and environmental changes occur, urbanization accelerates, and epidemics spread. Smart city development and policies must shift. The importance of sustainability is increasing. Technology-driven smart cities are transforming into sustainable cities where the city functions as a platform. New technologies have been introduced in both the public and private sectors, and the goal of a sustainable smart city is to improve the lives of global citizens and address social and environmental issues. In what direction should a sustainable smart city move?

This study addresses the following research questions:

RQ1: What are the research trends in smart cities?

RQ2: After COVID-19, how has smart city research been trending?

RQ3: To ensure a sustainable future for the city and improve the quality of human life, what direction should a smart city take?

This study aims to (1) identify keywords and keyword connections in smart cities and (2) identify the potential direction for smart city research after COVID-19. By discussing these topics, we aim to prepare for an uncertain future, increase urban resilience, and provide insights into a sustainable smart city model.

Smart cities are a global research field that requires current and future scientific research. Previous studies are primarily bibliographic in terms of the concept, characteristics, and trends of smart cities. A bibliographic analysis examined 4409 papers on smart cities on the Web of Science (WoS) [18]. One study selected 35 smart city-related publications and descriptively analyzed what smart cities should do to become sustainable [2]. Another study identified key dimensions of smart cities through a bibliographic analysis of 1354 documents [19]. A bibliographic analysis of smart cities and governance has also been conducted based on Scopus and other recent publications [20]. A recent study analyzed the literature on smart cities and public health to address the social reality and problems associated with smart cities [21]. Specifically, their study examined topic modeling using Latent Dirichlet Allocation (LDA) in bibliometrics. LDA research has recently emerged in the field of smart cities, and most studies have focused on technologies.

This study differs from previous research because it is a quantitative study based on text mining analysis and deals with smart cities in the context of COVID-19 [21–23]. A recent study identified themes such as smart city governance, economy, environment, transport, and energy in the literature on smart cities using big data analytics solutions [24]. Since COVID-19, research in the field of smart cities has generally focused on qualitative research or review studies rather than LDA studies. However, new concepts regarding smart cities can be uncovered from unstructured data by mining them from the vast literature on smart cities. In other words, previously unknown knowledge was sought from the text data [25]. Using a clustering algorithm, we identified unknown categories of smart cities in a new environment and presented semantic interpretations of these categories. By doing so, we aim to prepare for an uncertain future and provide insights into maintaining urban functions without disrupting the daily lives or economic activities of city residents during crises, such as epidemics. This study aims to understand and analyze the linguistic context of sustainable smart cities. This study is expected to provide researchers, policymakers, and planners with information that can be used to make decisions and develop strategies related to the socioeconomic, environmental, and technological aspects of smart cities after the pandemic.

A literature review of smart cities and their methodology is discussed in detail in Section 2. Section 3 describes the data collection and design. Section 4 presents the frequency analysis results, term frequency-inverse document frequency (TF-IDF) analysis, connection centrality analysis, *n*-gram analysis, and topic modeling analysis. Finally, a comprehensive discussion of the implications of this study and its limitations is presented in Section 5.

2. Theoretical Background

2.1. Topical Review: Smart City

"Smart city" has been used as a synonym, and there are differences in the definitions of digital city, sustainable city, information city, virtual city, ubiquitous city, and hybrid city [26]. Smart cities are defined differently depending on how each country perceives the environment and urban problems and how it designs and operates its infrastructure. According to the European Commission (EC), smart cities play an important role in realizing sustainable cities [27]. According to the International Telecommunications Union (ITU), an ICTs agency under the United Nations (UN), 116 smart city concepts have been defined by scholars and organizations [28]. As a whole, the ITU defines "A smart sustainable city (SSC) as an innovative city that uses ICTs and other means to improve quality of life, the efficiency of urban operation and services, and competitiveness while ensuring that it meets the needs of present and future generations concerning economic, social and environmental aspects" [28]. Ultimately, each of these initiatives aims to increase economic prosperity, ecological sustainability, and the efficiency of citizens. In addition, Table 1 shows smart city definitions by various scholars.

Table 1. Definitions of smart city.

Source	Definitions
Yigitcanlar (2016)	An ideal form to build the sustainable cities of the 21st century, in the case that a balanced and sustainable view on economic, societal, environmental, and institutional development is realized [29].
BIS (2013)	The UK Department for Business, Innovation and Skills (BIS) considers smart cities a process rather than a static outcome, in which increased citizen engagement, hard infrastructure, social capital and digital technologies make cities more livable, resilient, and better able to respond to challenges [30].
Barrionuevo et al. (2012)	Being a smart city means using all available technology and resources in an intelligent and coordinated manner to develop urban centers that are at once integrated, habitable, and sustainable [31].
Guan (2012)	A smart city, according to ICLEI, is a city that is prepared to provide conditions for a healthy and happy community under the challenging conditions that global, environmental, economic, and social trends may bring [32].
Lazaroiu and Roscia (2012)	A city that represents the future challenge, a city model where the technology is in service to the person and to his economic and social life quality improvement [33].
Zhao (2011)	A city that improves the quality of life, including ecological, cultural, political, institutional, social, and economic components without leaving a burden on future generations [34].
Chen (2010)	Smart cities will take advantage of communications and sensor capabilities sewn into the cities' infrastructures to optimize electrical, transportation, and other logistical operations supporting daily life, thereby improving the quality of life for everyone [35].
Paskaleva (2009)	A city that takes advantages of the opportunities offered by ICT in increasing local prosperity and competitiveness—-an approach that implies integrated urban development involving multi-actor, multi-sector, and multi-level perspectives [36].
Giffinger et al. (2007)	A city well performing in a forward-looking way in economy, people, governance, mobility, environment, and living, built on the smart combination of endowments and activities of self-decisive, independent, and aware citizens [37].
Bowerman et al. (2000)	A city that monitors and integrates conditions of all its critical infrastructures including roads, bridges, tunnels, rails, subways, airports, seaports, communications, water, power, even major buildings, can better optimize its resources, plan its preventive maintenance activities, and monitor security aspects while maximizing services to its citizens [38].

There are six components of a smart city: a smart economy (spirit of innovation, entrepreneurship, economy, productivity, labor flexibility), smart citizens (quality level, lifelong learning, social and ethnic diversity, flexibility, creativity, globalism and open mind, smart city projects, synergies through partnerships and cooperation), smart governance (participation in decision making, public and social services, transparent governance), smart environment (attractiveness of natural conditions, pollution, environmental protection, sustainable resource management, future usability), smart mobility (regional accessibility, global accessibility, sustainable innovative safe transportation system), and smart living (cultural facilities, medical conditions, personal safety, housing quality, educational facilities, attractiveness of tourist destinations, social cohesion) [39].

As urbanization continues, cities face many challenges and demands from citizens and the global community. The UN attempts to resolve social and economic issues such as global sustainability, the transition to a low-carbon society, population aging, and resource depletion. All UN members are committed to working together to achieve the Sustainable Development Goals (SDGs) by 2030. Sustainable development entails meeting current generations' needs without compromising future generations [40]. In addition to eradicating poverty, the 17 SDGs consider environmental concerns, social inequality, and economic development. The 11th goal focuses on cities. This goal aims to create inclusive, safe, resilient, and sustainable cities and residences. Based on this background, smart city projects have gained considerable traction in recent years. Urbanization has led to rapid economic growth. However, ecological destruction, economic inequality, and climate change have emerged, and the world has begun to consider the sustainability of cities. Therefore, sustainable cities focus on developing environmentally and economically sustainable smart cities [41]. For a city to become sustainable, it depends on the interactions among countries, cities, and industries in global networks [42]. These relationships work together to achieve relevant goals, such as reducing the impact of climate change and improving air and water quality. In addition, city residents' goals, such as quality of life, life satisfaction, education, work, health, culture, and leisure, should be pursued together.

Cities are living organisms where human activities occur. For cities to be sustainable, there must be a connection between the economy, society, and nature that activates the socioeconomic system without harming the natural environment [2]. The concepts of "smart city" and "sustainable city" are the most intelligent and outstanding future cities. Cities continue to grow while facing economic, social, and environmental crises [2,43]. It has been argued that the way to address socioeconomic, environmental, and governance challenges is to build a sustainable smart city [2,44–46]. With the aid of ICTs, urban residents can not only solve urban problems but also benefit from these technologies. However, it is challenging to create a city in which people, society, and the environment live in harmony using technology alone [2,4]. It is possible to create sustainable smart cities when policy, social, and environmental capital are invested together to influence each other positively [2,47].

2.2. Methodological Review: Topic Modeling and Smart City

The text mining approach was developed for natural language processing (NLP) and used to extract information from unstructured data [48]. It includes analyzing text, extracting information suitable for a specific purpose, and generating new estimates and values by presenting rules and algorithms [49,50]. A text-based database is like a knowledge source that contains useful information. Academic research in text mining studies the relationship and occurrence of behaviors through texts. It assists in discovering ideas or new relationships, identifying potential meanings, and formulating policies or strategies [50]. The text mining techniques used in this study include network analysis and topic modeling.

Network analysis helps reveal structural relationships by examining behavioral characteristics [51]. Network analysis, a visual analytic approach, is a text-based approach that reveals relationships between words in related documents and examines and describes semantic networks [52,53]. Network analysis complements a researcher's subjective judgment by analyzing objective data [50]. It has the advantage of tracking the complexity of semantic network connections and identifying flows between different components to identify overall trends and patterns in research [50].

Topic modeling involves technologies such as LDA, latent semantic analysis (LSA), and nonnegative matrix factorization (NMF), among which LDA is the most widely used [54,55]. LDA is a probabilistic method for determining the latent topics in a document using Bayesian inference. Topic modeling analyzes a corpus of vast documents to identify hidden topics and patterns. That is, vector values of words are obtained and grouped into related terms, from which topics can be inferred [56]. As vector values can be used to measure semantic similarity between words, analyzing relationships between concepts becomes easier and more effective. And the number of topics is very critical in topic modeling. Increasing the number of topics may lead to semantic consistency errors. Selecting the wrong number of topics can lead to inaccurate results and misinterpretations. For this reason, choosing the correct number of topics is crucial to obtain reliable results. It is common for researchers to make qualitative determinations [57–60].

Previous studies using text mining analysis in smart cities focused mainly on predicting the trends and patterns related to specific technologies or industries. Sharma et al. (2022) conducted a topic modeling analysis using LDA on a corpus of 8320 articles on the IoT in smart cities published between 2010 and 2020 [55]. Researchers presented IoT trends in smart cities based on ten topics, including technologies to regulate the electric energy consumption of buildings, security systems using blockchain, and smart home and healthcare solutions using machine learning [55]. There is a study using topic modeling to solve the problem of road space allocation in smart cities based on a bibliographic analysis of traffic and roads [61]. Thus, "dynamic space allocation on a regional scale", "temporary urban space solutions", "intermittent lane allocation", "dynamic space allocation on a municipal scale", "policies toward dynamic space allocation", and "sustainable transportation policy" were discussed [61]. They also discussed future research directions for analyzing the role of smart roads in adapting to the effects of COVID-19 on travel behavior. Topic modeling and time-series analysis has also been used to define and categorize the technology groups associated with sustainable smart cities [42]. Researchers presented a strategic approach for achieving sustainable smart cities through technology. As a result, the approach identified four topics: "networks and devices", "smart energy and smart vehicles", "smart water", and "telecommunications and smart services" [42]. Other scholars used topic modeling to classify smart mobility into "transportation paradigm", "change, sharing, automation, and electrification", "ICT technologies", "sustainability and safety", and "social inclusiveness and quality of life" [62]. Some studies use LDA in smart cities and categorize it into "building and monitoring", "citizen-centered innovation and sustainability", "big data and algorithms", "privacy and user location information", "energy and smart grid", "IoT and cloud", "data and decision-making support", and "transportation problems and efficiency" [63]. In addition, text mining studies have been conducted on micro-mobility to develop smart service systems and sustainable city planning [64,65].

Research on smart cities has shown that they are developing rapidly. Smart cities were initiated to improve city efficiency by expanding technological infrastructure throughout the city [65]. However, for the future development and operation of sustainable smart cities, we should not focus solely on the application and expansion of technology. It is important to pursue sustainability to solve urban problems and improve citizens' lives. The COVID-19 pandemic has shown that technology alone cannot solve urban problems, the degradation of citizens' lives, and social inequalities.

3. Materials and Methods

3.1. Data Collection

We collected published documents from 1 December 2019, to 30 November 2022, using the Scopus and WoS databases. We manually downloaded the data on the second week of 2022 December by applying a query to the database. To extract publications containing smart city and COVID-19 written in English, the following query was applied to the title, abstract, and keywords: (("sustainable city" OR "smart city" OR "sustainable urban" OR "smart urban") AND (COVID-19)). Table 2 presents the data collection strategies used in the study.

Selecting documents or parts of papers to collect text data is important for text mining application research. The database excludes document types, such as corrections, data papers, reprints, and reviews, as they may be duplicated. Articles were the only type of document. This study collected text mining-based analysis data from articles rather than reports [66]. We conducted text mining using the title, abstract, and keywords. The main reason is that the full text contains significant noise, including information not directly related to the study [64]. In other word, by focusing on the title, abstract, and keywords, we can filter out the "noise" and focus on the more relevant and salient aspects of the paper. Additionally, titles, abstracts, and keywords should provide a concise overview of the paper's content, goals, and conclusions. It is easier to analyze because it follows a standard format across different journals or disciplines. In contrast, full-text analysis is more complex and requires more preprocessing by the researcher due to variations in form and structure. By restricting sections, researchers can process more papers more efficiently and with less time and effort.

Table 2. Data collection strategy.

Field	Option Introduced	
Queries	"COVID-19" AND ("sustainable city" OR "smart city" OR "sustainable urban" OR "smart urban")	
Language	English	
Document type	Article	
Content of data	Title, abstract, keywords	
Period	1 December 2019~30 November 2022 (Researchers searched and downloaded it on December 2nd week.)	
Database	Web of Science	SCOPUS
Collected items	820 items	1062 items

We used the Excel program for manual preprocessing because it allowed us to identify and remove errors and outliers easily. This was performed to ensure the accuracy and reliability of the data set before further text-mining analyses. The details of the preprocessing process are described in Section 3.2.1. We then applied more sophisticated text mining techniques to analyze the data further, such as frequency analysis, TF-IDF, connection centrality, *n*-gram, and topic modeling. These total processes took about three months to complete but provided valuable insights. The details of the text mining techniques are described in Section 3.2.2.

3.2. Data Preprocessing and Analysis Tool and Techniques

3.2.1. Preprocessing

Data preprocessing is required to apply topic modeling to collect text data. It is the process of removing unnecessary information from the text data. Undesirable words and characters were removed from the corpus to improve the quality of the collected data. It is an imperative part of NLP and significantly contributes to the reliability of analysis results. Data preprocessing makes information more accurate and suitable for data analysis [67]. In this study, we conducted the following preprocessing steps: lowercase, tokenization, stopword removal, and stemming, as common processes in topic modeling.

First, uppercase letters were converted into lowercase letters. Then, tokenization was performed to separate the words into consecutive terms by removing all spaces and punctuation. Tokenization is a preprocessing technique that separates and transforms a text corpus into smaller units (words and phrases) called tokens. The next step is the stopwords removal process. We filter stopwords such as prepositions, articles, conjunctions, prepositions, and punctuation, such as meaningless periods, commas, or question marks. Stopword removal speeds up computation by reducing vocabulary size [68]. Lastly, a stemming process was conducted. This step converts plural words or words with similar meanings into single stemmed words (nouns). For example, the word "cities" is converted to "city". In the case of "educate" or "educated", which have the same meaning but differ in form, it replaces them with the single form "education". The stemming process improves the interpretability of the corpus without affecting LDA outcomes [67,69].

3.2.2. Analysis Tools and Techniques

This study used various text mining analysis such as frequency analysis, TF-IDF, connection centrality, *n*-gram, and topic modeling.

The TF-IDF statistic measures the importance of words within a document, calculated based on frequency and inverse frequency [70]. TF-IDF is calculated by multiplying TF, the frequency of a word in a document, and IDF, the reciprocal of the frequency of occurrence. Evaluating the relevance of words in a document can be an effective tool for ranking and filtering stop words during text processing and classification [71]. TF is defined as $tf(t,d)$, representing the frequency of document t within a particular document d. If the frequency of word t used in a particular document d is denoted by $f(t,\ d)$, document frequency (DF) can be denoted by $f(t,d) \equiv tf(t,d)$. Using IDF helps determine if a term is a common word or an unfamiliar word based on the amount of information provided by the term. IDF is calculated by taking the log of the number of documents and dividing it by the corresponding word DF. Taking a log makes it possible to prevent the value from growing to infinity. Generally, the higher the IDF value, the less familiar the word is. In a formula, N represents the total number of documents, and $|\{d \in D : t \in d\}|$ represents the numbers of documents containing the term t.

$$idf(t,\ D) = \log \frac{N}{|\{d \in D : t \in d\}|} \tag{1}$$

The formula of TF-IDF in Equation (2).

$$tfidf(t,d,D) = tf(t,d) \cdot idf(t,D) \tag{2}$$

Connection centrality indicates the most important vertices in a network; the most influential words in the network are those with the highest connection centrality [72]. Centrality is determined by the number of links connecting a node. It means that, in terms of measuring how much a ventral word is interconnected with another word, the greater the number of connected words, the greater the centrality of the relationship. Equation (3) calculates the value of connection centrality.

$$C_D(P_k) = \sum_{i=1}^{n} d(p_k, p_i) \tag{3}$$

n: the number of nodes
$d(p_k, p_i)$: the number of paths that exist between node p_k and p_i

An *n*-gram is a technique for examining words that appear simultaneously and is widely used in computational linguistics, probability, data compression, and communication theory [50]. Co-occurrence frequency is a measure of how often words occur consecutively. Furthermore, the *n*-gram can infer the content of a relationship between words and improve the quality of text analysis by predicting the next word [73,74]. This study used network visualization to interpret the relationships between words, the *n*-gram results, and other indicators.

We conducted topic modeling using LDA. Topic modeling is a clustering method used to identify potential themes within a collection of documents [56]. An algorithm for estimating parameters relating to unknown topics is based on mathematical recognition of the semantic structure of text data [54,75]. The advantage of LDA is minimizing subjective bias in text analysis since mathematical algorithms are used to analyze the text automatically. The latent themes are confirmed through the number of derived topics, the topic size, the terms that comprise the topic, the distance between the topics, and the λ value. The λ value becomes higher, suitable for identifying topics composed of meaningful words [76,77]. And as discriminant validity increases, topics become clearer. Discriminant validity refers to the appearance of discrimination between measures when different concepts are measured. When there is a close distance between two topics or if the topics intersect, discriminant validity is poor, and the terms constituting the topic are similar [50,77]. In addition, the larger the size of the topic, the more frequently and systematically that it is considered a crucial topic [77]. Accordingly, this study classified topics into six types and refined the overlapping keywords in the topic modeling results.

In addition, our LDA model is formally described as the following equation in [56].

$$p(\beta_{1:K},\ \theta_{1:D}, \varkappa_{1:D}, \omega_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(\varkappa_{d,n}|\theta_d \right) p(\omega_{d,n}|\beta_{1:K}, \varkappa_{d,n})) \quad (4)$$

Equation (4) calculates the joint distribution of observed words for each topic and the distribution of hidden topics for each document. More specifically, this equation is defined with D representing the total documents in the corpus, K as the total number of topics (a hyperparameter), and N as the word count in the d^{th} document. The observed variable is $\omega_{d,n}$ which is the n^{th} word in the d^{th} document. With this variable, all latent variables, except α and η, are estimated. β_κ corresponds to the K^{th} topic vector, with a length equal to the total corpus word count. θ_d is a vector that illustrates the topic proportions in the d^{th} document, while $\varkappa_{d,n}$ assigns the relevant topic to the n^{th} word in the d^{th} document. $\omega_{d,n}$ is the observed word, which is influenced by both β_κ and $\varkappa_{d,n}$. LDA employs an inference process to estimate latent variables based on $\omega_{d,n}$ assuming that words in a document are generated through a combination of topic word distribution and document topic distribution. Ultimately, the topic word distribution and document topic distribution are estimated using $\omega_{d,n}$. To maximize the posterior $p(\varkappa,\ \varphi,\ \beta \mid \omega)$, we must determine $\varkappa$, φ and β. $p(\omega)$ calculates the probability of each word's (ω) occurrence, considering all latent variable possibilities $\varkappa$, φ and β.

Textom and NetMiner 4.3 software were used in this study. Textom is a modified version of the Full Text by Loet Leydesdorff that provides a matrix for text mining [78]. A social network analysis tool called NetMiner was used to create and visualize networks between the extracted words. We used it to visualize the results of an n-gram analysis; using network visualizations, we seeked to gain a better understanding of the relationships between nodes intuitively.

4. Results

A final dataset of 1882 papers was used for the analysis. Since December 2019, when COVID-19 occurred, the number of publications on COVID-19 and smart cities increased dramatically, particularly in 2020 (see Figure 1). A total of 820 papers were collected from WoS under the current query, most of which were categorized into Environmental Sciences (308), Green Sustainable Science and Technology (260), Environmental Studies (237), Public Environmental Occupational Health (66), and Urban Studies (63). A total of 1062 papers were collected from Scopus under the current query, and most of these papers were related to the Social Sciences (560), Environmental Science (408), engineering (326), energy (285), and Computer Science (201).

4.1. Word Frequency

Text-type data were preprocessed and morphologically analyzed to refine the words in the text. The frequency of words in a document refers to the total number of words that appear in that document. Words other than nouns were excluded from the analysis because the word extraction was based on nouns.

A total of 6649 words were included in the analysis. The top 50 keywords that appeared most frequently in the theses are listed in Table 3. According to researchers, the top 10 keywords most frequently mentioned about smart cities and COVID-19 are "transport" (1575), "policy" (1385), "mobility" (1188), "population density" (1166), "supply chain" (1106), "carbon emission" (1089), "tourism" (1047), "change" (1008), "planning" (975), and "air" (974). As smart cities and COVID-19 are discussed simultaneously, and the papers published after the outbreak of COVID-19 are datasets, it is evident that most keywords are related to smart cities and infections.

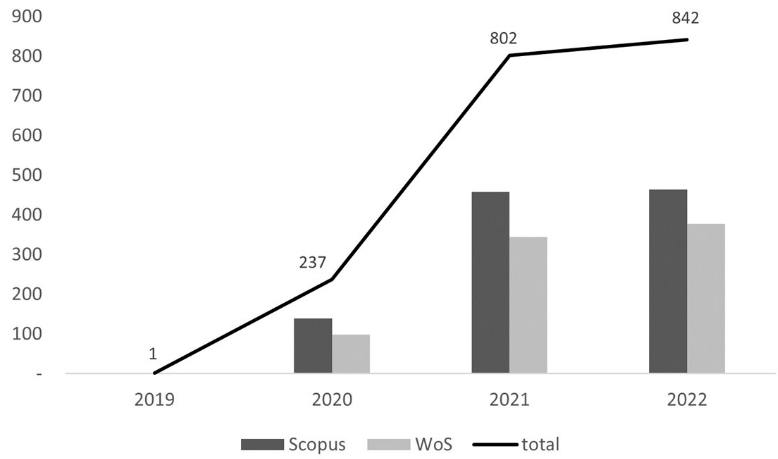

Figure 1. Year publications on COVID-19 and smart cities.

Table 3. Word frequency analysis result.

No.	Keyword	Freq.	%	No.	Keyword	Freq.	%
1	transport	1575	1.37%	26	water	661	0.57%
2	policy	1385	1.2%	27	network	626	0.54%
3	mobility	1188	1.03%	28	resilience	619	0.54%
4	population density	1166	1.01%	29	sign	616	0.53%
5	supply chain	1106	0.96%	30	challenge	600	0.52%
6	carbon emission	1089	0.95%	31	crisis	587	0.51%
7	tourism	1047	0.91%	32	formation	580	0.50%
8	change	1008	0.88%	33	life	551	0.48%
9	planning	975	0.85%	34	waste	543	0.47%
10	air	974	0.85%	35	travel	532	0.46%
11	level	956	0.83%	36	household	529	0.46%
12	technology	945	0.82%	37	region	524	0.45%
13	pollutant	940	0.82%	38	goal	520	0.45%
14	quality	913	0.79%	39	economy	518	0.45%
15	community	877	0.76%	40	work	513	0.44%
16	lockdown	847	0.74%	41	process	506	0.44%
17	sustainability	842	0.73%	42	accessibility	500	0.43%
18	environment	837	0.73%	43	response	497	0.43%
19	governance	755	0.65%	44	infection	483	0.42%
20	disease	735	0.64%	45	construction	449	0.39%
21	risk	676	0.59%	46	production	428	0.37%
22	energy	675	0.58%	47	climate	409	0.35%
23	space	669	0.58%	48	infrastructure	406	0.35%
24	strategy	665	0.58%	49	education	404	0.35%
25	behavior	665	0.58%	50	spread	403	0.35%

Using the keywords “population density” (1166), “transport” (1575), “mobility” (1188), “supply chain” (1106), “space” (669), “behavior” (665), “network” (626), “challenge” (600), “formation” (580), “life” (551), “household” (529), “accessibility” (500), “construction” (449), and “infrastructure”, it can be inferred that citizens’ lives are a research topic for smart cities. Keywords like “policy” (1385), “planning” (975), “level” (956), “technology” (945), “community” (877), “sustainability” (842), “government” (837), “strategy” (665), “goal” (520), and “economy” (518) were used to identify research topics related to government goals, policies, and strategies for smart city development and operation. Keywords like “carbon emission” (1089), “air” (974), “pollutant” (940), “quality” (913), “environment” (837), “water” (661), “waste” (543), and “climate” (409) suggest that the environment is becoming a research topic of interest as the world considers it critical for sustainable cities and lives. The keywords “tourism” (1047), “lockdown” (847), “disease” (735), “risk” (676), “work” (513), “infection” (483), and “spread” (403) can be seen as keywords related to the impact of smart cities.

4.2. TF-IDF

TF-IDF analysis was used to supplement the limitations of frequency analysis in text analysis. We applied TF-IDF to identify words of relative importance in multiple documents because frequency analysis does not provide this information [79]. When the number of documents containing a word in a specific document decreased, the TF-IDF value increased. Therefore, it can be used to discover clues that are not accessible through word frequencies.

According to the analysis, there were many documents containing keywords such as “supply chain”, “tourism”, “carbon emission”, “transport”, “air”, “pollution”, “mobility”, “water”, “population density”, and “energy”. There was a slight difference in rank compared with the top 50 results of TF-IDF and the top 50 results of word frequency. “Water”, “Energy”, “Waste”, “Resilience”. “Household” and “Education” ranked higher in TF-IDF than by word frequency, with a difference exceeding 10 units. Many studies are related to the natural environment and energy use in smart cities. There was no mention of “nitrogen dioxide”, “student”, “security”, “traffic”, and “heritage” in word frequency; however, they were found to be present in TF-IDF. While “process”, “response”, “production”, “infrastructure”, and “spread” appeared in the word frequency, they did not appear in the top 50 of TF-IDF. Table 4 presents the top 50 TF-IDF analysis results, which helped us understand the subject and context.

Table 4. TF-IDF analysis result.

No.	Keyword	TF-IDF	No.	Keyword	TF-IDF
1	supply chain	2570.44	26	behavior	1227.12
2	tourism	2541.11	27	governance	1207.14
3	carbon emission	2501.74	28	environment	1189.32
4	transport	2349.36	29	travel	1181.52
5	air	2107.49	30	disease	1173.23
6	pollutant	2047.07	31	sustainability	1170.85
7	mobility	2035.08	32	sign	1132.57
8	water	1926.19	33	formation	1047.30
9	population density	1736.52	34	education	1043.61
10	energy	1658.90	35	economy	1043.03
11	waste	1638.36	36	student	1038.42
12	quality	1516.76	37	infection	1027.53

Table 4. *Cont.*

No.	Keyword	TF-IDF	No.	Keyword	TF-IDF
13	lockdown	1505.10	38	crisis	1023.12
14	policy	1488.10	39	accessibility	1014.82
15	technology	1418.59	40	region	1003.47
16	community	1383.93	41	strategy	1001.45
17	resilience	1345.12	42	security	958.27
18	planning	1325.04	43	construction	955.19
19	nitrogen dioxide	1302.70	44	climate	952.78
20	space	1285.99	45	work	946.64
21	change	1270.59	46	goal	938.96
22	network	1263.00	47	traffic	932.45
23	household	1252.96	48	challenge	919.60
24	level	1241.61	49	life	913.83
25	risk	1236.13	50	heritage	912.87

4.3. Connection Centrality

The connection centrality of a word is determined by the number of links it has with other words in text data. It provides insight into keywords by measuring how related they are to other nodes. The connection centrality value increases as the degree of the connection node increases (see Table 5). By observing connection centrality, word frequency and TF-IDF results differed in ranking.

Table 5. Connection centrality analysis result.

No.	Central Word	Centrality	No.	Central Word	Centrality
1	air	0.253	26	risk	0.099
2	transport	0.252	27	tourism	0.096
3	pollutant	0.236	28	reduction	0.093
4	carbon emission	0.226	29	sign	0.091
5	policy	0.213	30	space	0.089
6	quality	0.206	31	region	0.085
7	mobility	0.188	32	network	0.082
8	lockdown	0.181	33	challenge	0.081
9	change	0.175	34	infection	0.081
10	population density	0.160	35	traffic	0.080
11	level	0.155	36	formation	0.076
12	supply chain	0.146	37	life	0.076
13	planning	0.137	38	crisis	0.075
14	disease	0.134	39	resilience	0.074
15	environment	0.133	40	economy	0.074
16	nitrogen dioxide	0.124	41	goal	0.073
17	water	0.123	42	response	0.073
18	technology	0.115	43	accessibility	0.071

Table 5. *Cont.*

No.	Central Word	Centrality	No.	Central Word	Centrality
19	sustainability	0.114	44	waste	0.069
20	community	0.111	45	household	0.069
21	energy	0.104	46	work	0.069
22	strategy	0.104	47	process	0.069
23	governance	0.102	48	climate	0.067
24	behavior	0.102	49	spread	0.067
25	travel	0.101	50	production	0.066

The keyword "air" has the highest connection centrality value at 0.253. Next, "transport" is 0.252, "pollutant" is 0.236, "carbon emission" is 0.226, "policy" is 0.213, "quality" is 0.206, "mobility" is 0.188, "lockdown" is 0.181, and "change" is 0.175, "population density" is 0.160. These keywords form the core of this study, as indicated by their connection centralities.

4.4. *n*-Gram

An *n*-gram analysis aims to predict the words appearing after a particular word in each sentence. It refers to the importance of the relationships between words in a sentence structure [50]. There is a correlation between words *a* and *b*. Table 6 lists the order in which words occur in the frequency distribution with a high correlation. *n*-grams helped identify the co-occurrence of words in this study.

Table 6. *n*-gram analysis result.

No.	*n*-Gram (A)	*n*-Gram (B)	Freq.	No.	*n*-Gram (A)	*n*-Gram (B)	Freq.
1	air	pollutant	446	26	waste	disposal	46
2	air	quality	395	27	mobility	planning	46
3	climate	change	227	28	bicycle	share	43
4	travel	behavior	138	29	water	supply chain	42
5	quality	life	99	30	infection	risk	42
6	goal	SDGs	97	31	disease	transmission	42
7	pollutant	air	95	32	transport	sector	42
8	mobility	transport	90	33	quality	lockdown	41
9	water	quality	84	34	spread	virus	41
10	communication	technology	81	35	governance	policy	41
11	transport	policy	79	36	internet	IoT	40
12	formation	communication	77	37	co2	carbon emission	40
13	transport	mobility	77	38	quality	air	39
14	originality	value	71	39	disease	spread	39
15	water	consumption	69	40	mobility	policy	38
16	lockdown	air	66	41	human	SARS	38
17	tourism	industry	60	42	mobility	pattern	38
18	machine	learning	59	43	risk	assessment	38

Table 6. *Cont.*

No.	*n*-Gram (A)	*n*-Gram (B)	Freq.	No.	*n*-Gram (A)	*n*-Gram (B)	Freq.
19	greenhouse	gas	56	44	quality	pollutant	37
20	energy	consumption	54	45	policy	transport	36
21	traffic	congestion	53	46	wind	speed	36
22	transport	planning	53	47	spread	disease	35
23	policy	policymaker	50	48	challenge	opportunity	35
24	energy	efficiency	48	49	pollutant	disease	35
25	carbon emission	reduction	47	50	change	mobility	35

A pandemic crisis and content related to human life and quality may often appear together with terms such as "air-pollution", "air-quality", "quality-life", or "quality-lockdown". Concerning climate change, "climate-change", "water-quality", "water-consumption", "water supply chain", "carbon emission-reduction", "energy-efficiency", and "CO2-carbon emission" are key considerations. The terms "goal-SDGs", "policy-policy maker", "government-policy", and "challenge-opportunity" refer to the government's policies toward achieving a sustainable urban environment. The keywords "mobility-transport", "communication-technology", "transport-policy", "machine-learning", "traffic congestion", "transport-planning", "mobility-planning", "bicycle-share", "transport-sector", "mobility-pattern", and "change-mobility" are indicative of specific strategies for establishing and operating sustainable smart cities.

4.5. Topic Modeling

A topic modeling algorithm extracts topics from the extracted text data based on correlations. This study clustered topics related to smart cities and COVID-19 through topic modeling. For topic modeling, it is necessary to determine the number of topics. Users can arbitrarily set the number of topics. When the number of topics was too low, different topics were mixed within one subject group, whereas overlapping topics were encountered when the number was too high. We gradually changed the number of topics to determine an appropriate number. Six topics were identified as minimally coexisting; therefore, six topics were derived, with frequently occurring keywords for each topic. The results of selecting the six topics that semantically encompassed each topic and keyword in the text data are presented in Table 7. To categorize keywords by topic, words with high λ values were sorted. The topics were categorized as Topic A (13%), Topic B (13.6%), Topic C (22.7%), Topic D (10.8%), Topic E (18.1%), and Topic F (21.8%). Topic 3, Topic 4, and Topic 6 comprise the largest topics. There is some distance between Topic 4 and the other topics. A topic distance map is shown in Figure 2.

The analysis results were divided into quadrants. No topic belonged entirely to the first quadrant. Topic D was in the second quadrant. In Topic D, words such as "waste", "disease", "healthcare", "life", and "work" were mentioned, and population density is a major potential issue when considering COVID-19 and smart cities. Topics B, C, and E were in the third quadrant. Topic B comprised keywords such as "resilience", "sustainability", "level", "community", and "change". The second-largest topic is Topic C, which displays keywords such as "tourism", "travel", and "heritage". Therefore, a comprehensive view of culture and tourism is necessary. Topic E contains keywords such as "transport", "carbon emission", "technology", and "mobility". We confirm that topic E encompasses both the third and second quadrants. Quadrants A and F are included in the fourth quadrant. As shown in topic A, "supply chain" has the largest λ value, and keywords such as "water", "energy", "consumption", "governance", and "farm" are identified. It is possible to examine the relationship between supply and demand in smart cities during the COVID-19 pandemic. The largest topic is Topic F, which contains keywords such as "air", "pollutant", "quality", "lockdown", and "nitrogen dioxide". There is a need to pay particular attention to the pollution issues caused by infectious diseases and urbanization.

Table 7. Topic modeling analysis result.

Topic	Keyword	λ	Topic	Keyword	λ
Topic (A)	supply chain	0.047	Topic (D)	population density	0.014
	water	0.023		waste	0.013
	energy	0.018		disease	0.010
	lockdown	0.017		mobility	0.009
	consumption	0.010		healthcare	0.007
	governance	0.009		life	0.007
	household	0.008		work	0.007
	farm	0.007		vehicle	0.007
	risk	0.007		assessment	0.007
Topic (B)	resilience	0.015	Topic (E)	transport	0.018
	sustainability	0.015		carbon emission	0.015
	level	0.012		technology	0.015
	community	0.012		mobility	0.012
	change	0.011		network	0.010
	crisis	0.011		governance	0.008
	space	0.010		community	0.007
	environment	0.009		infection	0.007
	mobility	0.009		region	0.006
Topic (C)	tourism	0.026	Topic (F)	air	0.027
	transport	0.026		pollutant	0.026
	mobility	0.016		quality	0.017
	travel	0.010		carbon emission	0.011
	behavior	0.009		lockdown	0.010
	change	0.009		energy	0.010
	economy	0.007		nitrogen dioxide	0.010
	heritage	0.007		strategy	0.008
	planning	0.007		disease	0.008

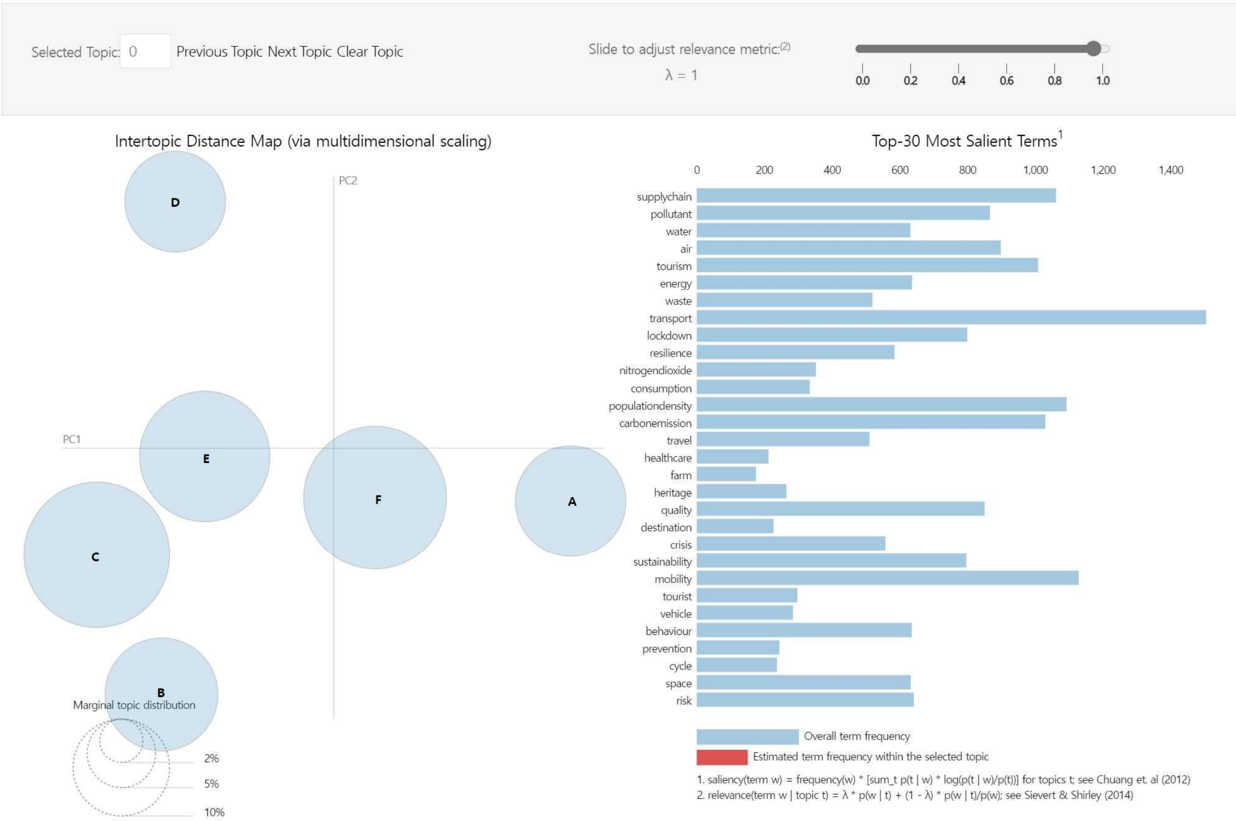

Figure 2. Inter-topic distance map (via multidimensional scaling) [80,81].

5. Concluding Remarks

5.1. Discussion and Implication

The researchers in this study drew two main conclusions. First, a network visualization technique can be used to observe the relationships between words more efficiently. We comprehensively evaluated the word frequency, connection centrality, and *n*-gram analysis, as illustrated in Figure 3. Network visualization is effective in identifying the sequential relationships and directions of words. The circle size indicates the frequency and a larger circle indicates a higher frequency of occurrence. In the circle, the color becomes darker when the centrality value is higher. "Transport", "quality", "pollutant", "air", "policy", and "planning" are the keywords that have the most centrality and is colored in the darkest shades. The arrows indicate the direction of the next word mentioned after it appears. The thickness of a node indicates the frequency of keyword co-occurrence. By analyzing the network of words, it was possible to confirm the potential connections between words. The purpose of this study is to consider social problems and prepare countermeasures to address them. When we consider the meanings of connected words, we can develop alternative solutions to social problems.

We can see that the keyword "disease" is linked to keywords associated with COVID-19. In addition to having a direct influence on "infection", "spread", "transmission", "outbreak", and "monitoring", this flow is also related to "disease-infection-prevention". Further, the arrow that leads to "disease-monitoring-human" implies that many papers focus on understanding the effects of diseases on humans. There is a high co-occurrence of "disease" with "pollutant", a keyword with a strong centrality and direct relationship. The keyword "pollutant" is highly co-occurring with "quality" and "air" and has a very high connection centrality. As can be seen, this keyword is associated with "climate", "challenge", "carbon emission", "life", "traffic", and "road". As a health risk, air pollution is also a global issue requiring cooperation among cities worldwide. Thus, based on this keyword, it can be concluded that we must prepare for air pollution and climate change caused by urban and industrial development, along with contagious diseases that spread through the air, to maintain quality of life and sustainable human life.

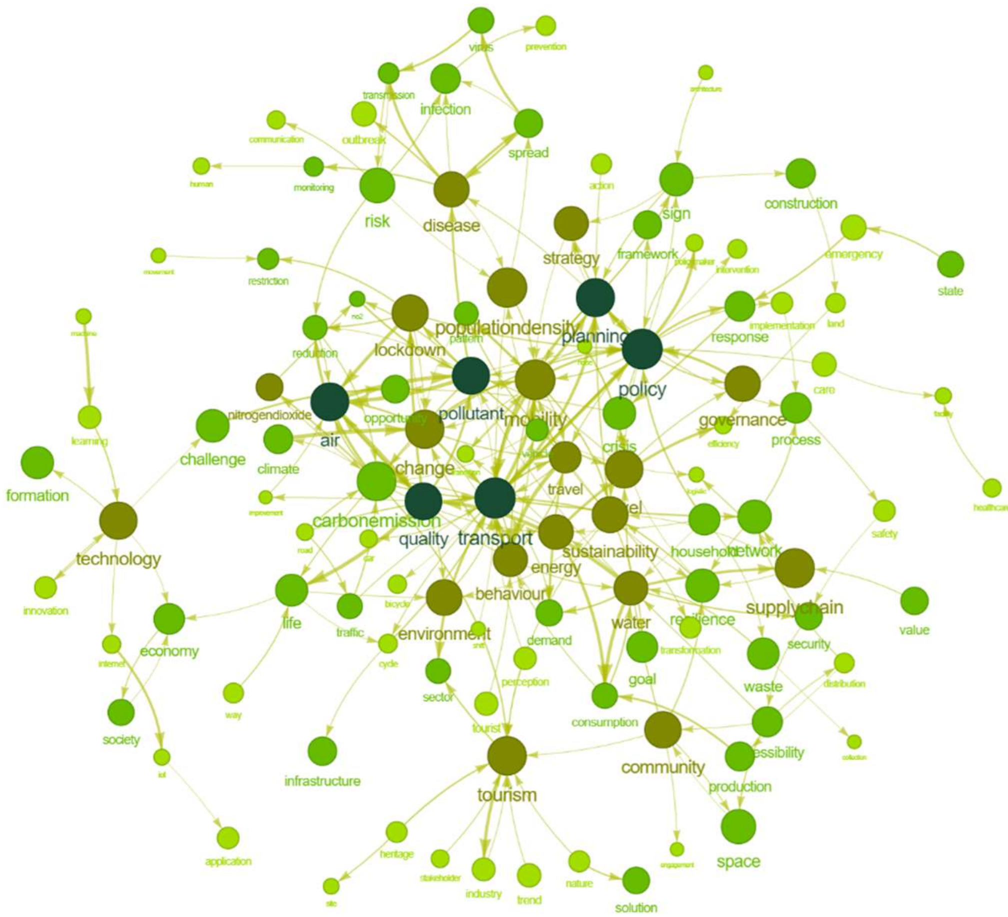

Figure 3. Visualization of *n*-gram analysis results.

The keyword "policy" is linked to other keywords. As we follow the arrow out of "policy", we find "strategy", "framework", "reaction", "sign", "policymaker", "governance", "process", "action", and "implementation". These keywords were necessary for policy implementation. There exists a direct or indirect flow of keywords with related terms. By observing the direction of the arrow in "policy", you can observe the flow of keywords related to housing and industry, such as "transport", "water", "energy", "household", "work", and "travel". Prior to COVID-19, the Smart City policy was based on the development and application of technology to cities for the convenience and prosperity of citizens. However, the COVID-19 pandemic paralyzed daily life and economic activities in densely populated cities by forcing schools and workplaces to close and movement between cities to cease. Therefore, we conclude that the development and operation of smart cities should be accompanied by policies that consider the possibility of unexpected crises, such as epidemics, in the future.

Second, we conducted topic modeling using text data acquired from recent publications related to smart cities following the COVID-19 pandemic. Topic modeling not only identifies research trends based on keyword searches for each topic but also identifies future potential issues that need to be considered. We have experienced the impact of the pandemic on people and cities. Unknown infectious diseases will continue to exist in the future. Smart city policies and alternatives that can reduce socioeconomic damage and maintain human and urban life must be available in infected environments. Based on the six topics derived from the analysis, potential issues and solutions for smart cities are presented below.

Topic A: Smart cities' challenge: supply chain.

Despite their limited resources and infrastructure, cities accommodate a large population. Smart cities are being developed and operated as advanced intelligent cities with sustainable energy sources, such as water and air, and new technologies. This includes related solutions and infrastructure, such as transport, health, administration, and energy. Many industries are involved in developing and operating smart cities, resulting in higher productivity levels for communities, businesses, and countries. Several threats have been posed to the structure of global supply chains since COVID-19. For example, we have experienced the threat of city and country lockdowns, which have caused semiconductor shortages. The lack of standardization among technology vendors has made it difficult for cities and data platforms to communicate effectively during the pandemic [82]. Smart cities are places where production and consumption are centralized, connected to a global network, and complex. Hence, the sustainability and viability of the supply chain structure should be considered for sustainable smart cities [83]. These potential issues were derived from the keywords clustered in Topic A (water, energy, lockdown, consumption, governance, household, farm, and risk). In the future, production and consumption networks concentrated in cities should be redesigned to fit people rather than technology.

Topic B: Smart city resilience.

During the pandemic, the use of digital technology in cities intensified and became more widespread. With digital technologies, people, businesses, and governments have been able to adapt to the new environmental conditions during lockdowns. Studies on the relationship between smart cities and urban resilience during COVID-19 have revealed no evidence to support the claim that smart cities are more resilient [84]. As long as the city provides medical, educational, transportation, and other services, it can be sustainable if it is designed as a smart city resilient to potentially dangerous situations such as infectious diseases. The digital divide between rich and poor residents in smart cities has increased because of COVID-19 [84]. Ideally, smart technologies should contribute to sustainability, inclusiveness, and resident well-being. With the keywords clustered in Topic B (resilience, sustainability, level, community, change, crisis, space, environment, mobility), we asserted the need to create smart city policies that increase their happiness index, strengthen technological and material foundations, and solve social problems.

Topic C: Culture and tourism in smart cities.

The pandemic has affected many industries, particularly tourism. Productivity has declined in these cities and communities because of international travel bans, closures between regions, and restrictions on transportation, accommodations, and festivals [85]. Scholars have evaluated tourism outcomes and researched citizen behavior after COVID-19 [86,87]. Economic hardship for communities has been a major effect of the pandemic on tourism and hospitality. Before the COVID-19 outbreak, advancing technologies contributed to the perception of smart cities becoming more common by improving residents' quality of life. Because of this pandemic, safety and health have become increasingly important. Consumers seek fast and reliable services through e-hospitalities and e-tourism [88]. Cultural tourism experienced a significant change during the pandemic when virtual reality was quickly applied to the industry. In museums, advanced technologies such as AI and VR are being used to provide a greater appreciation of cultural heritage. Bangtan Sonyeondan (BTS) held a virtual reality showcase at UNESCO headquarters in Paris, France, in 2021. Potential issues were derived from keywords (tourism, transport, mobility, travel, behavior, change, economy, heritage, and planning) clustered in Topic C. It is recommended that more secure digitalized urban designs and smart tourism policies be prepared. To transform into sustainable smart tourism, tourism companies must study how residents behave and live during a pandemic.

Topic D: Densely populated areas: smart cities.

We discussed potential issues based on the keywords (population density, waste, disease, mobility, healthcare, work, vehicle, and assessment) grouped in Topic D. Urbanization has created technological and economic added value but has also resulted in paradoxical problems such as inequality, poverty, health, and unemployment. The concept of "smart cities" is popular among urban economists and policymakers. However, implementing smart city systems has resulted in several social and economic problems. Lockdowns and social distancing implemented by the government during the COVID-19 pandemic have decreased mobility and civil liberties [89]. Consequently, the high population density in cities has accelerated the spread of infectious diseases. Whether digitized smart cities have lower infection rates than others has yet to be proven [90]. In a densely populated city, the spatial characteristics and habits of the residents play an important role in society [89]. Due to the pandemic outbreak, people have become concerned about the population density in cities. However, we should focus on inequality rather than population density [91]. The pandemic has increased the need for a telemedicine system that was previously restricted by medical law. Social inequality has become an issue due to inadequate medical services and limited access to medical institutions. Physical and mental health are invaluable factors for maintaining happiness and well-being. Therefore, it is important to approach the urbanization problem of smart cities from a value perspective.

Topic E: Mobility in smart cities.

Smart city transport systems have improved citizens' quality of life and promoted urban mobility. Globally, smart city policies have been implemented to increase economic benefits by increasing the use of energy-efficient and environmentally friendly vehicles. This creates challenges in urban traffic design, including climate change, air quality, and congestion. With an increase in remote working since the COVID-19 outbreak, traffic usage has decreased, reducing CO2 emissions, air pollution, and traffic congestion [92]. In the long term, the pandemic has changed people's daily lives and work, leading to a significant reduction in fossil fuel consumption [93]. Thus, COVID-19 contributed to the development of smart cities. As a result of the keywords clustered in Topic E (transport, carbon emissions, technology, mobility, network, governance, community, infection, and region), the study identified the potential issues described above. A pandemic could provide an opportunity to develop responsible and environmentally friendly urban transportation [89]. For example, the American National Association of City Transportation Officials (NACTO) stated that solutions such as bike lanes, safe transit lanes, pick-up and delivery zones, and outdoor dining places should be created [94]. Accordingly, future research should explore the positive impacts of the pandemic on transportation systems in the design of smart cities.

Topic F: Zero carbon emission in smart cities.

Rapid urbanization has resulted in severe air pollution. To address the problem of urbanization, countries worldwide have supported the development of technology-based smart cities. Unlike developed countries with air-cleaning zones or systems, low-income countries are threatened by social and economic burdens caused by air pollution [95]. Residents have been exposed to natural and anthropogenic air pollution during the pandemic. The risk of infectious diseases being transmitted through aerosols has been found to be higher than through air pollution owing to urbanization [96]. Globally, the air quality improved significantly during the lockdown. Air pollution is not a local phenomenon, so national initiatives and strategies are required through multi-sectoral coordination and synchronization between countries and cities [97]. Improving the air quality in smart cities involves implementing disparate technologies and stakeholders from various sectors. The keyword clusters (air, pollutants, quality, carbon emissions, lockdown, energy, nitrogen dioxide, strategy, and disease) appeared in Topic F during the discussion of these potential issues. Consequently, it emphasizes the importance of building trust among stakeholders across the air quality value chain and of developing globally standardized air quality policies. Therefore, countries should implement green transportation policies and green infrastructure, establish air quality monitoring systems, enforce environmental regulations, and raise public awareness of environmental pollution. However, this is not country-specific. Establishing cooperation between countries and approaching this issue from an international perspective is necessary.

This is particularly relevant in the post-COVID-19 era when smart cities face ever-evolving challenges and opportunities. Thus, smart cities should identify keywords related to COVID-19 and other unexpected events to address these issues. Our study identified topics such as supply chains, resilience, culture and tourism, population density, mobility, and zero carbon emissions. The topics identified in various studies have presented comprehensive words. Consequently, smart cities can be more resilient and sustainable by anticipating and addressing issues related to the derived topics.

The emergence of expected and predictable keywords may not represent a new phenomenon. However, discovering the relationships between words in existing studies provides lessons for new events that may be applied to future research. To predict and solve unexpected problems, smart cities worldwide could become more sustainable by identifying adjacent keywords related to smart cities after COVID-19. Through topic modeling analysis results and potential issues, we discussed the practical implications of this study. We also have highlighted practical implications in that they provide insights into innovative policies and strategies for smart cities in new environments, considering uncertain future risks. In addition, this study has academic implications because it collected and analyzed smart city studies after COVID-19 using a topic modeling approach. In this study, the structured results were derived from unstructured data analysis. We extracted interpretable topics from extensive text documents related to smart cities during the COVID-19 pandemic.

5.2. Future Studies

This study aimed not to understand trends in the pandemic crisis but to illuminate the strategic direction of smart cities in the post-pandemic era. There is a limit to the underused subject areas that may occur depending on the number of topics and subjective interpretations. Therefore, future research should adopt a topic modeling approach for various areas and industries. Due to socioeconomic instability, a pandemic caused by infectious diseases poses a greater threat to low-income individuals. Further research on the relationship between infectious diseases and smart cities should focus on the impact of smart cities on children, the elderly, refugees, and migrant workers.

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