Article

Exploring Strategic Directions of Pandemic Crisis Management: A Text Analysis of World Economic Forum COVID-19 Reports

Hyundong Nam ¹ and Taewoo Nam ^{2,*}

¹ Graduate School of Governance, Sungkyunkwan University, Seoul 03063, Korea; gosling@g.skku.edu

² Department of Public Administration, Sungkyunkwan University, Seoul 03063, Korea

* Correspondence: namtaewoo@skku.edu; Tel.: +82-2-760-0372

Abstract: This study aims to understand the global environment of COVID-19 management and guide future policy directions after the pandemic crisis. To this end, we analyzed a series of the World Economic Forum's COVID-19 response reports through text mining and network analysis. These reports, written by experts in diverse fields, discuss multidimensional changes in socioeconomic situations, various problems created by those changes, and strategies to respond to national crises. Based on 3897 refined words drawn from a morphological analysis of 26 reports (as of the end of 2020), this study analyzes the frequency of words, the relationships among words, the importance of specific documents, and the connection centrality through text mining. In addition, the network analysis helps develop strategies for a sustainable response to and the management of national crises through identifying clusters of words with similar structural equivalence.

Keywords: COVID-19; pandemic crisis; crisis management; text mining; network analysis

Citation: Nam, H.; Nam, T. Exploring Strategic Directions of Pandemic Crisis Management: A Text Analysis of World Economic Forum COVID-19 Reports. *Sustainability* **2021**, *13*, 4123. <https://doi.org/10.3390/su13084123>

Academic Editors:
Elena Andina-Díaz, Lindsay Welch
and Natalia Arias Ramos

Received: 12 March 2021

Accepted: 2 April 2021

Published: 7 April 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The global COVID-19 pandemic has led to social instability (value conflicts between individual liberty and social order, health issues of the minority, and the prioritization of vaccination) and economic difficulties (prolonged industrial recessions, economic downturn, and supply chain breakdowns). Many national governments have made efforts toward recovery and resilience through various countermeasures, such as institutional arrangements and digital infrastructures [1]. These efforts need guidance and direction with qualitative evidence from similar ongoing patterns of the pandemic crisis response and management [2,3]. Strategic directions for the national crisis management of COVID-19 can be derived from the analysis of insightful discussions by domain-specific experts rather than from raw data regarding the pandemic infection and expansion. For example, Corley et al. [4] identified patterns in the increase of influenza by analyzing qualitative data compiled from a collection of documents instead of structured data, thereby contributing to discovering various relations. DiMaggio [5] analyzed the linguistic context of social institutions and extracted useful information for national policy direction, thereby predicting future research trends and guiding policymakers.

As such, documents of practical research that recommend actions for coping with national pandemic crises deserve in-depth analysis of text, including the words, meanings, and contexts. Analyzing research reports that address the massive multifaceted impact of COVID-19 and strategies for post-pandemic preparation would contribute to implementing scientific administration and presenting directions for future policies [6–8]. In line with the value of a text-based analysis on pandemic-related reports, we selected the World Economic Forum's recent issue reports addressing pandemic crisis management and post-pandemic preparation among a rising number of COVID-19 research papers. The reports written by the World Economic Forum's experts seek to help national governments and leaders deeply understand and proactively respond to pandemic-creating changes in socioeconomic environments.

This study uses text mining to analyze the reports. Text mining is helpful to discover meaningful information and relationships in unstructured text data, and furthermore, to gain insight from papers of exploratory research [9–13]. Moreover, the method helps to identify the main pathways of research and advance the review of research findings [14,15].

Using the text mining method, this study aims to answer the following research questions. Since the occurrence of COVID-19, what words have appeared as keywords of pandemic crisis management and response strategies in various countries? What can be learned from the identified relationships among those words and the meanings of the relationships? What roles do keywords with centrality of highly connected relationships play?

This study determined the network relations that help predict the economic and social environments by understanding the linguistic context of the report contents, thereby suggesting new directions for crisis management and countermeasures to overcome social instability. These directions could be used to guide authorities of pandemic crisis management when investigating global trends. For text-based research, we first collected coronavirus-related reports published by the World Economic Forum. The text data of the reports were pre-processed (a morpheme analysis) and then extracted. Then, we analyzed the frequency of the extracted text, the centrality of the connection, n -gram, and the term frequency–inverse document frequency (TF–IDF), in line with the purpose of this paper. Finally, we discovered useful patterns and association rules, extract matrix values that have correlations with the extracted text, and developed a model to observe a text network environment.

This study is unique in how it employed an unstructured data-based approach, considering the specific environment of COVID-19. Reports released by recognized international organizations were also valuable to observe universal and transferrable meanings and the relationships among words used frequently. The study may contribute to building and predicting national policy directions to overcome pandemic crises from economic and social perspectives. This paper is organized as follows. Section 2 reviews the topical (pandemic crisis management) and methodological (text mining and network analysis) backgrounds. Section 3 describes the research design in terms of data and methodology. Section 4 presents the results of the text mining and network analysis. The final section provides concluding remarks.

2. Literature Review

2.1. Topical Review: Pandemic Crisis Management

COVID-19 has brought about social, economic, and health-related issues all around the world. Many countries experienced institutional and cultural limitations in responding to the pandemic crisis, which has led to long-term recessions, economic fallout, supply chain collapses, and demographic crises. Social issues raised by COVID-19 have allowed people to recognize weaknesses in various types and functions of national crisis management systems [16–18].

The entire world faces various pandemic-led problems that people have never experienced before. It is important to refer to past experiences in order to prepare for future events of massive infection, but the pandemic crisis that one cannot frequently experience qualitatively differs from emergencies that occur often (e.g., explosions, fires, or other problems caused by negligence).

In addition to inexperience, poor capability in large-scale pandemic crisis management often aggravates a variety of pandemic-led problems [19]. The global population, as well as administrative authorities of crisis response, recognizes the ubiquitous presence of wicked problems (more complex, complicated, and tangled relationships among existing problematic issues), newly generated and/or worsened by the pandemic [20]. In this sense, there is an imperative regarding COVID-19 that must solve or at least soothe pandemic-led wicked problems. In particular, the imperative would be more crucial if a threat occurs to the core values of social systems and life-sustaining functions or if urgent remedies are required under conditions of severe social uncertainty [21,22].

International organizations and national governments should develop capacities for pandemic-led crisis response and management for the imperative [23,24]. The authorities need to develop guidelines to predict unexperienced events and prepare for them [25]. Extant guidelines for pandemic crisis management turned out to be ineffective for the COVID-19 situation, where infection expanded at an unexperienced massive scope, speed, and severity. Guidelines are required to effectively present explicit knowledge for practical application and adaptation [26–28].

However, inexperience and thereby, poor response capacity led to the inability to timely provide guidelines in the event of the pandemic crisis. The absence of relevant practical knowledge about pandemic response raises the levels of ignorance and uncertainty, and thus, another dimension of the crisis appeared [29]. While the pandemic crisis itself has produced diverse issues and problems from social, economic, and cultural aspects, the recognition of inability and ignorance is a new issue and allows for setting an agenda regarding preparation for future events [30–32].

2.2. Methodological Review: Text Mining and Network Analysis

Vast amounts of unstructured data have stacked up since Web 2.0 and social networking sites produce ever-increasing amounts of text data, 80% of which is unstructured [33]. A stream of e-mails, newspapers, web articles, documents, and reports has unstructured properties. While structured data has a high value obtained through immediate analysis, there are limitations in employing quantitative approaches for unstructured data.

Text mining, as a research field, methodology, and approach, discovers significant information in unstructured texts and advances the review of academic research that explores various relationships and occurrence behaviors [34]. It basically involves a text analysis and processing sequence that extracts information with a specific purpose [35]. It creates new estimates and values by finding useful knowledge and presenting association rules and algorithms [36]. A text database is considered to be a useful source of information and knowledge. Text mining is useful in project management and policymaking, especially when it hints at a new approach to untangle various problems.

Text analysis helps collect strategic ideas for making policies, finding new relations, identifying potential useful meanings, and predicting trends in uncertain circumstances [37–42]. Methods for text mining of unstructured data have been further advanced by quantitative approaches. The application of text mining to various fields has strong potential to assist problem-solving [43] and discover important insights and rules penetrating massive amounts of text documents [44].

Such potential of text mining can be strengthened with network analysis, which enables visualization of patterns embedded in a large volume of unstructured text data. A growing number of text-based analyses have shed light on the network of relationships among words, and thus, text mining often accompanies network analysis. Network analysis basically seeks to find out the behavioral characteristics of social communication and explain structural relationships [45]. The combination of text mining and network analysis helps explore and explain the semantic networks in literature (documents and reports) related to particular themes [46,47]. Specifically, network analysis is useful for understanding overall trends and patterns of research [48,49] because identifying semantic network connections and structures informs policymakers of meaningful relationships among multiple components [50], and enables the tracking and untangling of complexity in exploring research [51]. As the connection structure is considered a transfer of thoughts through networks [52], the analysis of semantic networks helps explain the flow of the transfer and the overall trends of research [53].

3. Research Design

3.1. Data Collection

This study utilized text data drawn from a series of the World Economic Forum's COVID-19 research reports regarding national crisis response strategies, infection pre-

vention and control, surveillance case studies, epidemiological protocols, and socioeconomic response in the non-contact mode. The homepage of the World Economic Forum (www.weforum.org, accessed on 31 December 2020) publicly releases a repository of reports for creating and sharing practical and strategic knowledge regarding pandemic crisis management. These reports share timely insights and reliable knowledge about pandemic crisis management with national leaders overarching government authorities, civic organizations, and journalism. Their value also lies in highlighting and emphasizing strategic directions that the global society should pursue together to overcome the pandemic crisis from the international perspective.

We selected the World Economic Forum's reports among a growing pool of COVID-19 research reports. The World Economic Forum has offered sustainable strategies and policies for crisis management and resilience in the increasingly uncertain environment. Academics have paid keen attention to the World Economic Forum's reports as a knowledge base of problem-solving for the global society. For example, the World Economic Forum's global risk reports, healthcare infrastructure resilience reports, and tourism competitiveness reports were analyzed, and the analyses suggested strategic directions for handling incumbent issues [54–56].

Reports of interest were selected when they had relevant content related to pandemic crisis strategy and response plans. The target for data collection is the World Economic Forum's collection of COVID-19 research reports written in 2020, when people feared the fast spread of COVID-19 infections and had serious concerns from various aspects (for example, health, job, education, business, and trade), before the expansion of national vaccination. At the end of 2020, 53 reports were found with the search word "COVID-19" in the report section of the World Economic Forum's homepage (www.weforum.org/reports, accessed on 31 December 2020). Finally, 26 reports were selected for the analysis. The selection criteria were as follows: (1) selected reports must contain strategies for the response and management of the pandemic crisis, (2) brief review papers (fewer than five pages) were excluded, and (3) reports specific to particular areas of expertise were also excluded. Table 1 presents a list of the selected COVID-19 research reports.

Table 1. List of Selected Reports.

Category	The Title of Report
Crisis Management	<ul style="list-style-type: none"> Challenges and Opportunities in the Post-COVID-19 World (2020) [57] COVID-19 Risks Outlook: A Preliminary Mapping and Its Implications (2020) [58] Emerging Pathways towards a Post-COVID-19 Reset and Recovery (2020) [59] The State of the Connected World 2020 Edition (2020) [3] Winning the Race for Survival: How Advanced Manufacturing Technologies Are Driving Business-Model Innovation (2020) [60]
Economy (Employment, Trade, and Consumption)	<ul style="list-style-type: none"> Connecting Digital Economies: Policy Recommendations for Cross-Border Payments (2020) [61] Dashboard for a New Economy Towards a New Compass for the Post-COVID Recovery (2020) [62] Fostering Effective Energy Transition 2020 Edition (2020) [63] Future of Consumption in Fast-Growth Consumer Markets: ASEAN (2020) [64] How Can Trade Rules Support Environmental Action? Global Future Council on International Trade and Investment (2020) [65] Impact of COVID-19 on the Global Financial System (2020) [66] The Future of Jobs Report (2020) [67] Understanding Value in Media: Perspectives from Consumers and Industry (2020) [68] Vision Towards a Responsible Future of Consumption: Collaborative Action Framework for Consumer Industries (2020) [69]

Table 1. Cont.

Category	The Title of Report
Business and Industry	<ul style="list-style-type: none"> • Building Resilience in Manufacturing and Supply Systems in the COVID-19 Context and Beyond: Latin America Perspectives (2020) [70] • Incentivizing Responsible and Secure Innovation: A Framework for Investors and Entrepreneurs (2020) [71] • Markets of Tomorrow: Pathways to a New Economy (2020) [72] • Outbreak Readiness and Business Impact: Protecting Lives and Livelihoods across the Global Economy (2020) [73] • The Impact of COVID-19 on the Future of Advanced Manufacturing and Production: Insights from the World Economic Forum’s Global Network of Advanced Manufacturing Hubs (2020) [74]
Technology (Emerging Technologies and Related Issues)	<ul style="list-style-type: none"> • 5G Outlook Series: The Impact of Mobile Technology on the Response to COVID-19 (2020) [75] • Accelerating Digital Inclusion in the New Normal (2020) [76] • Cyber Resilience in the Electricity Ecosystem: Playbook for Boards and Cybersecurity Officers (2020) [77] • Cybersecurity Leadership Principles: Lessons learnt during the COVID-19 Pandemic to Prepare for the New Normal (2020) [78] • Global Technology Governance Report 2021: Harnessing Fourth Industrial Revolution Technologies in a COVID-19 World (2020) [79] • The Global Competitiveness Report: How Countries are Performing on the Road to Recovery (2020) [80] • Top 10 Emerging Technologies of 2020 (2020) [81]

3.2. Analysis Tools

Text mining—finding meanings that cannot be derived quantitatively—helps researchers observe and investigate social phenomena. The unstructured data extracted from the selected reports capture social phenomena related to COVID-19. Research based on text mining can detect signals and significant patterns through the exploration of various relationships and behaviors.

This study employed Textom (www.textom.co.kr, accessed on 31 December 2020) for the collection of unstructured data and the network theory-based semantic analysis of unstructured texts. Textom, as a large data-integrated processing solution, is designed for systematization and exploratory research efficiency. It is a revised and edited version of FullText, developed by Loet Leydesdorff [82]. It provides the matrix necessary for text mining and networks. It collects and analyzes various unstructured or semi-structured text data and discovers significant information [83]. The Good Software certification acquired from the Korea Information and Communication Technology Association guarantees its reliability.

3.3. Analysis Procedure

The texts in the selected reports were filtered to avoid terms that may distort the results. The text mining analysis of this study included methods of measuring various indicators, such as inverse frequency, *n*-gram, connection centrality, and structural equivalence (convergence of iteration correlation).

3.3.1. TF-IDF

The term frequency-inverse document frequency (abbreviated as *tf-idf*, TF-IDF, TF*IDF, or TFIDF) is a numerical statistic that determines how important a word is to a document in a collection or corpus [84]. TF-IDF is a value that multiplies the term frequency (TF) (the frequency of a word appearing in documents) and the inverse document frequency (IDF) (the reciprocal number of documents in which the word appears). It represents how important a particular word, *w*, is within the document, *d*. Since IDF

is the inverse of document frequency (DF) (the number of documents where the word appears), $TF\text{-}IDF(w,d)$ is the same as $TF(w,d)/DF(w)$. In this formula, the TF-IDF estimate increases proportionally to the frequency of word appearance in the document and is offset by the number of documents that contain the specific word. TF-IDF is popularly used as a weighting factor in text mining and information retrieval. Search engines employ it as an effective instrument for evaluating and ranking a document's relevance given a user query [85–87]. It is also used to filter stop words in the summarization and classification of text.

3.3.2. *n*-Gram

Broadly used in the fields of computational linguistics and probability, data compression, and communication theory, the *n*-gram is a probabilistic language model for predicting the next item in a contiguous sequence. It indicates a contiguous sequence of *n* items from the text. These items can come from phonemes, syllables, letters, or words. An *n*-gram model predicts x_i , based on $x_{i-(n-1)}, \dots, x_{i-1}$; in mathematical terms, $P(x_i | x_{i-(n-1)}, \dots, x_{i-1})$. Independent assumptions (Markov model) in text modeling posit that each word depends only on the last $n - 1$ word [88]. This assumes that the probability of a word depends on the previous item only. With this strong assumption, the *n*-gram model has merits in simplicity (massively simplifying the problem of estimating the language model from data through depending on the previous item only) and scalability (storing more context with a larger *n* and enabling small experiments to efficiently scale up) [89,90].

3.3.3. Degree Centrality

Centrality refers to a criterion of the relative importance of a vertex or node in a graph or social network [91]. Centrality indicators, as an answer to “what characterizes an important vertex?”, identify the most important vertices within a graph or network. Popular applications of centrality help identify the most influential person in a social network, key infrastructure nodes in the Internet or urban networks, and super-spreaders of disease [92–95]. The indicator is a real-valued function on the vertices of a graph or network. The values created by the function can provide a ranking that indicates the most important nodes. What “important” refers to varies with the definitions of centrality and the methods of estimation, such as degree centrality, closeness centrality, between-ness centrality, and eigenvector centrality. Centrality may be interpreted differently depending on connectivity, but the importance of centrality is basically conceived in relation to a type of flow or transfer across the network [96].

This study used the degree centrality, which refers to the number of links incident upon a node (i.e., the number of ties that a node has). In the network graph, the degree centrality identifies the most important zenith by deriving the total amount of direct links with other nodes. The degree of connectivity (the number of connected nodes) is considered a good index of centrality. The degree of centrality is determined by how much a node relates to other nodes around the criterial node.

3.3.4. CONCOR

To map complex interactions, this study uses a Convergence of Iteration Correlation (CONCOR) analysis, which measures structural equivalence based on correlation. CONCOR is used to answer the question, “How similar is the vector of similarities of Actor A to the vector of similarities of Actor B?” Because this method classifies nodes into groups according to their similarity in structural equivalence, it focuses on the correlation in the pattern of connection relationships rather than on the direct or indirect connection relationships across the network [97,98]. Among the three ways to measure structural equivalence (i.e., Pearson correlation coefficient, Euclidean distance, and/or matching), this study used the Euclidean distance [99].

CONCOR analysis begins by correlating each pair of actors. Each row of the actor-by-actor correlation matrix is extracted and correlated with each other row. This process is

iterated until the elements in the iterated correlation matrix eventually converge on a value of either +1 or −1 [100,101]. Then, CONCOR divides the data into two sets on the basis of these correlations. Within each set, in the case of more than two actors, the process is iterated. This process keeps going until all actors are divided. The end result is a binary branching tree (a final partition). In addition, we used the UCINET data visualization analysis tool to help illustrate structural equivalence [102].

4. Results

4.1. Frequency of Keywords

The text data from a total of 26 selected reports was refined through morphological analysis. As a result, the total number of words was 3987. Appendix A presents the top 100 relevant words (used in all selected reports) related to COVID-19 (more specifically, pertinent to national crisis response strategies, infection prevention and control, surveillance case studies, epidemiology protocols, and non-contact socioeconomic development), in terms of their frequency.

The conditions for crisis management and response measures in various environments related to COVID-19 overall include the words “country” (852), “market” (761), “technology” (710), “service” (620), and “company” (595). These words penetrating the reports are key to successfully managing the pandemic crisis. A primary focus for pandemic crisis management at a country level reflects “market”, “technology”, and “service.” This means that countries should make substantial efforts to recover society and the economy through the application of emerging technologies in the transition to non-contact services, as well as in preparation for post-pandemic times.

The top 25 frequent keywords include, among others, “economy” (559), “system” (515), “industry” (436), “energy” (384), “security” (317), and “supply chain” (284). These words spotlight the sustainable growth of national economies and industries in the pandemic crisis. While more frequently appearing keywords generally focus on the economic side, the new role of national government also gained keen attention in selected reports. “Governance” (449), “policy” (369), “access” (291), and “support” (214) appear in texts addressing a national approach to pandemic crisis management. In addition, these keywords put emphasis on international efforts in the context of global governance, which empowers policies for access and support, as well as international support for roles between countries.

4.2. TF-IDF

The TF-IDF value as the measure of how importantly a word is used in a particular document helps evaluate the importance of a particular document. It gives higher weight to documents with a frequently appearing specific word than to a word appearing across many documents. The results in Appendix B show the importance of the report and present the importance and inverse frequency of specific reports. Terms reflecting the importance of a particular report include “energy” (716.92), “market” (650.95), “country” (603.00), “consumption” (521.36), and “skill” (483.76). “Energy” (716.92), “skill” (483.76), “work” (460.28), “cybersecurity” (444.32), “transition” (433.25), “outbreak” (383.91), “vice” (381), “standard” (365.59), and “privacy” (349.93) also turned out to be important words in a particular report, excluding words with a high level of both frequency and TF-IDF (i.e., “market”, “country”, and “service”).

The top three words (“energy”, “consumption”, and “skill”) were importantly used in a particular report. This result is different from that of the basic frequency analysis. The indicator regarding the importance of the report suggests deeper insights on the influences and effects of pandemic crisis management than the keyword frequency analysis. For example, national policies related to energy, consumption, cybersecurity, and skills for the massive transition to the non-contact mode of work, business, and communications are importantly addressed in the selected reports. In particular, words such as “market”, “country”, and “service” that showed high scores in both word frequency and TF-IDF, are necessary for developing strategic directions.

4.3. *n*-Gram

The *n*-gram analysis predicts the next word that would appear in a given sentence through linguistic modeling. The *n*-gram indicator shows the importance of the relation between words according to the appearance of the sentence. Appendix C presents the frequency of high correlation between appearances of specific words in the COVID-19 reports. A correlation means that Word A appears after Word B and thus, the frequency indicates the number of times that “*n*” words appear like a chain. The *n*-gram value helps grasp the relationships between words in the report.

“Energy–transition”, “labor–market”, “climate–change”, “COVID-19–crisis”, and “policy–market” have higher probabilities of appearance between two words germane to pandemic crisis management. The top 10 pairwise relational frequency hints at the directions of national strategies for pandemic response and post-pandemic preparation. The relevant keywords of importance include “energy transition”, “labor market”, “climate change”, “policy for market”, “service offer”, “future market”, “national level”, and “governance framework”. These words reflect the crucial concerns of countries, businesses, and industries to overcome an unstable economy and society throughout and after the pandemic, as well as domains and areas in which societal efforts are concentrated and prioritized.

4.4. Connection Centrality

Connection centrality reflects how many connections a particular word has with others among the words drawn from the selected reports. This indicator, gauging how related the central word is to other nodes, gives insight into the importance of nodes differing from the extent of centralization. It assists researchers in understanding the key connections of the selected reports.

Appendix C presents the degree to which a particular word is central where a higher value of connection centrality by a word extracted from the reports has a higher connection node. Words with the highest connection centrality related to COVID-19 include “country”, “technology”, “market”, “company”, and “service”. These are the words significantly recognized in the results of the simple frequency and inverse frequency analyses. Additionally, the top 25 words include “challenge” (0.0712), “business” (0.0675), and “change” (0.0670), which imply the importance of new challenges and changes in businesses and industries.

4.5. CONCOR

We extracted correlated words from collected texts and classified the matrix values into groups of nodes that have similar structural equivalences. As illustrated in Figure 1, clustering measured by the value of the Euclidean distance identifies eight groups with similar structural equivalences. The factor of each group can be named in a distinct way, reflecting the result of the structural equivalence analysis and the similarity among adjacent words. The naming is based on intuitive interpretation in a way of integrating the results of the text analysis and the network analysis. The factors are titled “new environment”, “operation management”, “future strategy”, “innovation industry”, “change”, “national policy”, “disease management”, and “security”.

Figure 1. Visualization of Convergence of Iteration Correlation (CONCOR) Analysis Results.

The “new environment” factor shows the importance of “resilience” and “skill” in the reports. This cluster contains more sets of adjacent words than any other cluster. In the “operation management” factor, “governance” and “system” have connection centrality. The cluster consists of the second most sets of adjacent words. “Cyber” and “provision” showed the highest probability of appearance with other words in the “new environment” and “national policy” clusters. In the “future strategy” factor, the frequency and the connection centrality of “company” and “technology” are highly ranked. “Future” and “policy” in the “national policy” factor are most probable to appear with other words. The “innovation industry” cluster constitutes adjacent words of “industry” with high frequency and connection centrality. The “change” cluster, comprising “crisis”, “energy”, and “work”, is a group with the importance of reports with high inverse frequency. The “national policy” factor consists of words with a high value in the simplest frequency, inverse frequency, and connection centrality. This cluster includes “country”, “consumption”, “economy”, “market”, and “service”. It has the fewest sets of related adjacent words. The “disease management” factor connects adjacent keywords such as “education”, “healthcare”, “manufacture”, and “workforce”. The “security” cluster comprises “blockchain”, “border”, “interoperability”, and “protection”. All of the eight factors reflect the key issues and agendas that the global society and national governments must address and discuss for the future—not merely when facing COVID-19 but also after the pandemic crisis.

5. Discussion and Conclusions

5.1. Recapitulation and Implications of Findings

This study, based on text mining and network analysis, explored the issues and agendas of strategic efforts for resilience to social and economic instabilities caused by COVID-19. The authors collected and analyzed the World Economic Forum’s reports on national crisis response strategies, infection prevention and control, surveillance case studies, epidemiological protocols, and non-contact socioeconomic development during and after the COVID-19 pandemic. The analysis of texts derived from reliable research reports written by diverse domain experts contributes to the exploration of the relationships among the core components of social systems and helps in gaining insights for the present and future.

While some results of the analysis based on text mining confirm extant literature and the usual expectations, other new important findings were discovered, including the connection centrality of words and the probability of appearance between words. For example, “transition” and “opportunity” appear as keywords in texts mentioning strategies for overcoming the current situation. In the contents of the selected reports, responses to COVID-19 are remarkably connected with quite indirectly related agendas, such as energy transition, labor market, and climate change. In addition, “policymaking”, “service delivery”, and “future market” as keywords also indicate a country’s role in pandemic crisis management. The text mining analysis also suggests the importance of improving the governance framework at the national level.

COVID-19 gave rise to the role of technology in pandemic crisis response and various issues resulting from technology adoption and utilization. Important identified keywords include “technology”, “privacy”, “security”, and “supply chain”. This finding highlights the influence of e-government and information communication technology (ICT) in general on fostering non-contact environments for all interactions in trade, commerce, organizational management, service provision, legal enforcement, and public administration. In addition, “platform” found in the TF-IDF analysis is also meaningful for the transition to an online platform mode, and thereby establishing a more efficient and effective system. An ICT-based platform environment is pivotal for enabling non-contact socioeconomic activities.

The appearance of expected and predictable keywords may not be a novel finding, but discovering the relationships among those words provides critical insight into the preparation for unexperienced events that can refer to lessons from the existing literature. Identifying adjacent keywords can provide important insights into how to predict and solve unexpected and unexperienced problems. The network analysis examined the relationships among the derived words and visually identified eight clusters (factors named as “new environment”, “operation management”, “future strategy”, “innovation industry”, “change”, “national policy”, “disease management”, and “security”) according to the structural equivalence. This network analysis highlights “national policy” as a key factor, which is the leading role of state or national governments in overcoming difficulties and responding to socioeconomic crises (social conflict, prolonged recession, and economic fallout). A state (“country” as a keyword) should create an environment that rapidly stabilizes and recovers a society through “national policy”, in which keywords such as “country”, “economy”, “market”, and “service” frequently appear (the simple frequency, inverse frequency, and connection centrality). The appearance between words in the “national policy” cluster is also highly correlated with words in the “operation management”, “future strategy”, and “change” clusters. “Operation management”, “future strategy”, and “change” are key to national policies for effective stabilization and the development of crisis management capacities. Moreover, the illustration highlights “new environment” and “innovation industry”, which are critical to understanding and responding to unexperienced risks.

This study contributes to identifying key issues and agendas for national crisis management, focusing on texts drawn from COVID-19 reports of the World Economic Forum. The text-based data analysis provides wisdom regarding the lack of relevant understanding and knowledge for pandemic-led risks and post-pandemic uncertainty. The text and network analysis of insightful reports also provides new insight into the relationships between words and the relation-based prediction.

5.2. Research Limitations

This study has limitations in terms of methodology and data collection. Enumerating concepts in a sentence requires researchers to have a clear reference point in the determination of the connection between two concepts. It is always difficult to draw structured findings from the analysis of unstructured data. An algorithm may minimize possible errors in text mining techniques.

An increasing number of practical reports and white papers related to COVID-19 have been published in 2020 and 2021. Papers from global or international institutes other than

World Economic Forum may contain insightful arguments based on empirical or conceptual research. However, not all recent papers regarding pandemic crisis management can be collected and analyzed. This study focused on long reports that present the results of in-depth research, excluding brief articles with viewpoints. Although the United Nations, Organization for Economic Cooperation and Development (OECD), and famous public or private think tanks released impactful articles and papers on COVID-19, the World Economic Forum has established a repository of research-based (evidence-based) strategic knowledge about the pandemic crisis. This study does not aim to understand the trend of knowledge specific to particular policy domains but rather sheds light on generalizable (extensively applicable) strategic directions of sustainable preparation for the post-pandemic environment. In this sense, the World Economic Forum's reports merit analytic attention from academics. The repository of the reports is not a gathering of intermittently published papers but rather a sustainable channel for sharing practical knowledge from diverse domains and perspectives. Selecting the World Economic Forum reports was an efficient and effective way to collect relevant text data regarding strategic directions of pandemic crisis management.

Author Contributions: Conceptualization, T.N.; methodology, H.N.; software, H.N.; validation, H.N.; formal analysis, H.N.; investigation, H.N.; resources, H.N.; data curation, H.N.; writing, T.N.; visualization, H.N.; supervision, T.N.; project administration, T.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: This study was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (BK21-FOUR toward Empathic Innovation: Through Platform Governance Education and Research Programs: #4199990114294).

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

Appendix A

Table A1. Frequency Analysis.

No.	Keyword	Freq.	%	No.	Keyword	Freq.	%	No.	Keyword	Freq.	%	No.	Keyword	Freq.	%
1	country	852	1.57	25	investment	273	0.50	51	response	189	0.35	76	operation	141	0.26
2	market	761	1.40	27	challenge	260	0.48	52	administration	188	0.35	77	education	140	0.26
3	technology	710	1.31	28	innovation	255	0.47	53	network	187	0.34	78	activity	140	0.26
4	service	620	1.14	29	business	253	0.47	54	numbness	185	0.34	79	healthcare	137	0.25
5	company	595	1.10	30	cyber security	252	0.46	55	regulation	176	0.32	80	manufacture	137	0.25
6	economy	559	1.03	31	change	246	0.45	56	decision	175	0.32	81	provision	137	0.25
7	system	515	0.95	32	impact	241	0.44	57	framework	175	0.32	82	production	137	0.25
8	governance	449	0.83	33	transition	234	0.43	58	survey	170	0.31	83	benefit	135	0.25
9	industry	436	0.80	34	source	233	0.43	59	society	168	0.31	84	capital	132	0.24
10	crisis	429	0.79	35	opportunity	221	0.41	60	labor	167	0.31	85	strategy	132	0.24
11	consumption	421	0.78	36	action	220	0.40	61	model	163	0.30	86	crease	132	0.24
12	energy	384	0.71	37	effort	217	0.40	62	lead	160	0.29	87	effect	131	0.24
13	sector	380	0.70	38	outbreak	216	0.40	63	port	155	0.29	88	world	129	0.24
14	policy	369	0.68	39	measure	214	0.39	64	platform	154	0.28	89	issue	128	0.24
15	COVID-19	352	0.65	40	level	214	0.39	65	approach	154	0.28	90	solute	127	0.23
16	government	343	0.63	41	support	214	0.39	66	collaboration	151	0.28	91	employee	126	0.23
17	security	317	0.58	42	standard	214	0.39	67	term	146	0.27	92	future	125	0.23
18	resilience	303	0.56	43	demand	212	0.39	68	institute	146	0.27	93	concern	123	0.23
19	access	291	0.54	44	formation	211	0.39	69	ecosystem	145	0.27	94	state	122	0.22
20	supply chain	284	0.52	45	infrastructure	210	0.39	70	application	145	0.27	95	practice	121	0.22
21	organization	283	0.52	46	skill	207	0.38	71	community	145	0.27	96	transformation	121	0.22
22	development	280	0.52	47	process	202	0.37	72	risk	145	0.27	97	climate	121	0.22

Table A1. Cont.

No.	Keyword	Freq.	%	No.	Keyword	Freq.	%	No.	Keyword	Freq.	%	No.	Keyword	Freq.	%
23	work	280	0.52	48	vice	199	0.37	73	border	143	0.26	98	adoption	119	0.22
24	growth	279	0.51	49	employment	191	0.35	74	recovery	143	0.26	99	disease	118	0.22
25	people	275	0.51	50	privacy	189	0.35	75	search	142	0.26	100	priority	118	0.22

Appendix B

Table A2. TF-IDF Analysis.

No.	Keyword	TF-IDF	Freq. (%)	No.	Keyword	TF-IDF	Freq. (%)	No.	Keyword	TF-IDF	Freq. (%)	No.	Keyword	TF-IDF	Freq. (%)
1	energy	716.92	0.71	25	labor	349.70	0.31	51	support	277.87	0.39	76	decision	243.45	0.32
2	market	650.95	1.40	27	access	348.49	0.54	52	manufacture	276.54	0.25	77	effort	243.17	0.40
3	country	603.00	1.57	28	investment	347.33	0.50	53	opportunity	275.53	0.41	78	operation	242.77	0.26
4	consumption	521.36	0.78	29	sector	347.27	0.70	54	regulation	274.55	0.32	79	emission	242.11	0.18
5	skill	483.76	0.38	30	growth	340.89	0.51	55	model	272.07	0.30	80	carbon	241.04	0.17
6	service	482.88	1.14	31	innovation	340.30	0.47	56	challenge	265.70	0.48	81	climate	239.92	0.22
7	crisis	480.73	0.79	32	people	336.01	0.51	57	administration	265.22	0.35	82	future	239.37	0.23
8	work	460.28	0.52	33	employment	334.10	0.35	58	employee	263.85	0.23	83	port	238.27	0.29
9	economy	459.42	1.03	34	government	330.40	0.63	59	measure	263.24	0.39	84	connectivity	237.45	0.17
10	resilience	446.01	0.56	35	demand	318.86	0.39	60	provision	262.35	0.25	85	blockchain	231.88	0.12
11	cyber security	444.32	0.46	36	organization	312.97	0.52	61	level	261.47	0.39	86	search	229.92	0.26
12	technology	436.10	1.31	37	payment	309.71	0.28	62	platform	261.05	0.28	87	institute	229.44	0.27
13	transition	433.25	0.43	38	infrastructure	306.92	0.39	63	process	260.51	0.37	88	city	229.02	0.18
14	company	426.97	1.10	39	business	302.98	0.47	64	healthcare	257.93	0.25	89	project	227.99	0.01
15	system	409.30	0.95	40	border	302.28	0.26	65	lead	257.12	0.29	90	term	227.75	0.27
16	governance	399.64	0.83	41	survey	295.02	0.31	66	disease	254.25	0.22	91	workforce	226.24	0.19
17	security	392.56	0.58	42	development	291.83	0.52	67	framework	252.16	0.32	92	sustainability	226.09	0.20

Table A2. Cont.

No.	Keyword	TF-IDF	Freq. (%)	No.	Keyword	TF-IDF	Freq. (%)	No.	Keyword	TF-IDF	Freq. (%)	No.	Keyword	TF-IDF	Freq. (%)
18	industry	390.64	0.80	43	network	291.71	0.34	68	recovery	252.14	0.26	93	capital	225.51	0.24
19	supply chain	384.26	0.52	44	formation	289.47	0.39	69	collaboration	252.04	0.28	94	strategy	225.51	0.24
20	outbreak	383.91	0.40	45	action	285.67	0.40	70	ecosystem	247.71	0.27	95	transformation	222.18	0.22
21	vice	381.08	0.37	46	source	282.79	0.43	71	production	247.47	0.25	96	protection	222.12	0.02
22	policy	367.31	0.68	47	education	282.59	0.26	72	application	245.79	0.27	97	commitment	221.92	0.18
23	standard	365.59	0.39	48	response	282.23	0.35	73	society	245.53	0.31	98	interoperability	221.13	0.15
24	COVID-19	364.47	0.65	49	change	281.19	0.45	74	region	245.00	0.22	99	approach	218.79	0.28
25	privacy	349.93	0.35	50	impact	281.02	0.44	75	numbness	243.52	0.34	100	population	218.21	0.00

Appendix C

Table A3. *n*-Gram and Degree Centrality Analysis.

<i>n</i> -Gram Analysis								Degree Centrality Analysis					
No.	<i>n</i> -Gram (A)	<i>n</i> -Gram (B)	Freq.	No.	<i>n</i> -Gram (A)	<i>n</i> -Gram (B)	Freq.	No.	Keyword	Centrality	No.	Keyword	Centrality
1	energy	transition	114	26	economy	country	20	1	country	0.1570	26	growth	0.0662
2	labor	market	90	27	operation	model	20	2	technology	0.1370	27	innovation	0.0655
3	climate	change	71	28	government	business	20	3	market	0.1350	28	investment	0.0652
4	COVID-19	crisis	64	29	future	survey	19	4	company	0.1272	29	energy	0.0637
5	policy	maker	60	30	adoption	technology	19	5	service	0.1182	30	effort	0.0632
6	service	provision	57	31	company	country	18	6	system	0.1149	31	impact	0.0630
7	market	future	48	32	access	service	17	7	economy	0.1134	32	formation	0.0622
8	cyber	resilience	43	33	technology	governance	17	8	industry	0.1046	33	process	0.0620
9	disease	outbreak	42	34	risk	administration	17	9	governance	0.0953	34	level	0.0617
10	energy	system	32	35	forum	future	17	10	consumption	0.0948	35	measure	0.0605
11	border	payment	32	36	office	resilience	16	11	sector	0.0938	36	source	0.0597

Table A3. Cont.

<i>n</i> -Gram Analysis								Degree Centrality Analysis					
No.	<i>n</i> -Gram (A)	<i>n</i> -Gram (B)	Freq.	No.	<i>n</i> -Gram (A)	<i>n</i> -Gram (B)	Freq.	No.	Keyword	Centrality	No.	Keyword	Centrality
12	survey	respondent	29	37	impact	covid-19	16	12	crisis	0.0911	37	support	0.0590
13	cyber	risk	27	38	company	consumption	16	13	government	0.0858	38	demand	0.0585
14	country	energy	23	39	energy	sector	16	14	covid-19	0.0808	39	decision	0.0577
15	period	source	23	40	safety	security	16	15	policy	0.0775	40	resilience	0.0572
16	opinion	survey	22	41	security	privacy	16	16	organization	0.0740	41	infrastructure	0.0569
17	country	level	22	42	border	service	16	17	people	0.0733	42	opportunity	0.0569
18	source	forum	22	43	country	economy	16	18	development	0.0718	43	network	0.0569
19	technology	company	22	44	cyber security	culture	15	19	supply chain	0.0718	44	numbness	0.0564
20	governance	framework	22	45	movement	people	15	20	challenge	0.0712	45	action	0.0562
21	service	market	21	46	privacy	concern	15	21	access	0.0692	46	outbreak	0.0552
22	reskilling	upskilling	21	47	collaboration	company	11	22	security	0.0690	47	cyber security	0.0549
23	society	innovation	21	48	capital	investment	11	23	business	0.0675	48	vice	0.0542
24	energy	consumption	20	49	execute	office	11	24	work	0.0672	49	framework	0.0527
25	economy	society	20	50	economist	survey	11	25	change	0.0670	50	standard	0.0519

References

1. Glowacki, E.M.; Wilcox, G.B.; Glowacki, J.B. Identifying# addiction concerns on twitter during the COVID-19 pandemic: A text mining analysis. *Subst. Abus.* **2021**, *42*, 39–46.
2. Aristovnik, A.; Ravšelj, D.; Umek, L. A bibliometric analysis of COVID-19 across science and social science research landscape. *Sustainability* **2020**, *12*, 9132. [CrossRef]
3. The State of the Connected World 2020 Edition. Available online: http://www3.weforum.org/docs/WEF_The_State_of_the_Connected_World_2020.pdf (accessed on 31 December 2020).
4. Corley, C.D.; Cook, D.J.; Mikler, A.R.; Singh, K.P. Text and structural data mining of influenza mentions in web and social media. *Int. J. Environ. Res. Public Health* **2010**, *7*, 596–615. [CrossRef]
5. DiMaggio, P. Adapting computational text analysis to social science (and vice versa). *Big Data Soc.* **2015**, *2*, 2053951715602908. [CrossRef]
6. Branco, M.C.; Delgado, C.; Gomes, S.F.; Eugénio, T.C.P. Factors influencing the assurance of sustainability reports in the context of the economic crisis in Portugal. *Manag. Audit. J.* **2014**, *29*, 237–252. [CrossRef]
7. Choudhary, A.K.; Oluikpe, P.I.; Harding, J.A.; Carrillo, P.M. The needs and benefits of Text Mining applications on Post-Project Reviews. *Comput. Ind.* **2009**, *60*, 728–740. [CrossRef]
8. Lischinsky, A. In times of crisis: A corpus approach to the construction of the global financial crisis in annual reports. *Crit. Discourse Stud.* **2011**, *8*, 153–168. [CrossRef]
9. Akilan, A. Text mining: Challenges and future directions. In Proceedings of the 2015 2nd International Conference on Electronics and Communication Systems (ICECS), Coimbatore, India, 26–27 February 2015; pp. 1679–1684.
10. De Fortuny, E.J.; De Smedt, T.; Martens, D.; Daelemans, W. Evaluating and understanding text-based stock price prediction models. *Inf. Process Manag.* **2014**, *50*, 426–441. [CrossRef]
11. Gaikwad, S.V.; Chaugule, A.; Patil, P. Text mining methods and techniques. *Int. J. Comput. Appl.* **2014**, *85*, 42–45.
12. Kayser, V.; Blind, K. Extending the knowledge base of foresight: The contribution of text mining. *Technol. Forecast. Soc. Chang.* **2017**, *116*, 208–215. [CrossRef]
13. Nassirtoussi, A.K.; Aghabozorgi, S.; Wah, T.Y.; Ngo, D.C.L. Text mining for market prediction: A systematic review. *Expert Syst. Appl.* **2014**, *41*, 7653–7670. [CrossRef]
14. Aureli, S.; Medei, R.; Supino, E.; Travaglini, C. Sustainability disclosure after a crisis: A text mining approach. *Int. J. Soc. Ecol. Sustain. Dev.* **2016**, *7*, 35–49. [CrossRef]
15. Griol-Barres, I.; Milla, S.; Cebrián, A.; Fan, H.; Millet, J. Detecting Weak Signals of the Future: A System Implementation Based on Text Mining and Natural Language Processing. *Sustainability* **2020**, *12*, 7848. [CrossRef]
16. Capano, G.; Howlett, M.; Jarvis, D.S.; Ramesh, M.; Goyal, N. Mobilizing policy (in) capacity to fight COVID-19: Understanding variations in state responses. *Policy Soc.* **2020**, *39*, 285–308. [CrossRef]
17. Dobrowolski, Z. After COVID-19: Reorientation of crisis management in crisis. *Entrep. Sustain. Issues* **2020**, *8*, 799–810. [CrossRef]
18. Kuo, T.C.; Pacheco, A.M.; Iswara, A.P.; Dermawan, D.; Andhikaputra, G.; Chiang Hsieh, L.H. Sustainable Ambient Environment to Prevent Future Outbreaks: How Ambient Environment Relates to COVID-19 Local Transmission in Lima, Peru. *Sustainability* **2020**, *12*, 9277. [CrossRef]
19. Arthi, V.; Parman, J. Disease, downturns, and wellbeing: Economic history and the long-run impacts of COVID-19. *Explor. Econ. Hist.* **2021**, *79*, 101381. [CrossRef] [PubMed]
20. Yang, K. Unprecedented Challenges, Familiar Paradoxes: COVID-19 and Governance in a New Normal State of Risks. *Public Adm. Rev.* **2020**, *80*, 657–664. [CrossRef]
21. Barreiro, J.; Lopes, R.; Ferreira, F.; Brito, R.; Telhado, M.J.; Matos, J.S.; Matos, R.S. Assessing Urban Resilience in Complex and Dynamic Systems: The RESCCUE Project Approach in Lisbon Research Site. *Sustainability* **2020**, *12*, 8931. [CrossRef]
22. Ansell, C.; Boin, A.; Keller, A. Managing transboundary crises: Identifying the building blocks of an effective response system. *J. Conting. Crisis Manag.* **2010**, *18*, 195–207. [CrossRef]
23. Janssen, M.; van der Voort, H. Agile and adaptive governance in crisis response: Lessons from the COVID-19 pandemic. *Int. J. Inf. Manag.* **2020**, *55*, 102180. [CrossRef]
24. Trump, B.D.; Linkov, I. Risk and resilience in the time of the COVID-19 crisis. *Environ. Syst. Decis.* **2020**, *40*, 171–173. [CrossRef]
25. Rahman, M.; Thill, J.C.; Paul, K.C. COVID-19 pandemic severity, lockdown regimes, and people's mobility: Early evidence from 88 countries. *Sustainability* **2020**, *12*, 9101. [CrossRef]
26. Beery, T. What We Can Learn from Environmental and Outdoor Education during COVID-19: A Lesson in Participatory Risk Management. *Sustainability* **2020**, *12*, 9096. [CrossRef]
27. Carter, D.P.; May, P.J. Making sense of the US COVID-19 pandemic response: A policy regime perspective. *Adm. Theory Prax.* **2020**, *42*, 265–277. [CrossRef]
28. Titko, M.; Ristvej, J. Assessing Importance of Disaster Preparedness Factors for Sustainable Disaster Risk Management: The Case of the Slovak Republic. *Sustainability* **2020**, *12*, 9121. [CrossRef]

29. Maiorano, T.; Vagni, M.; Giostra, V.; Pajardi, D. COVID-19: Risk Factors and Protective Role of Resilience and Coping Strategies for Emergency Stress and Secondary Trauma in Medical Staff and Emergency Workers—An Online-Based Inquiry. *Sustainability* **2020**, *12*, 9004. [CrossRef]
30. Cardoso, M.A.; Telhado, M.J.; Almeida, M.D.C.; Brito, R.S.; Pereira, C.; Barreiro, J.; Morais, M. Following a step by step development of a Resilience Action Plan. *Sustainability* **2020**, *12*, 9017. [CrossRef]
31. Gao, X.; Yu, J. Public governance mechanism in the prevention and control of the COVID-19: Information, decision-making and execution. *J. Chin. Gov.* **2020**, *5*, 178–197. [CrossRef]
32. Platje, J.; Harvey, J.; Rayman-Bacchus, L. COVID-19—reflections on the surprise of both an expected and unexpected event. *CEREM* **2020**, *4*, 149–162. [CrossRef]
33. Gharehchopogh, F.S.; Khalifelu, Z.A. Analysis and evaluation of unstructured data: Text mining versus natural language processing. In Proceedings of the 2011 5th International Conference on Application of Information and Communication Technologies (AICT), Baku, Azerbaijan, 12–14 October 2011; pp. 1–4.
34. Delen, D.; Crossland, M.D. Seeding the survey and analysis of research literature with text mining. *Expert Syst. Appl.* **2008**, *34*, 1707–1720. [CrossRef]
35. Feldman, R.; Sanger, J. *The Text Mining Handbook: Advanced Approaches in Analyzing Unstructured Data*; Cambridge University Press: New York, NY, USA, 2007.
36. Huang, Z.; Li, J.; Su, H.; Watts, G.S.; Chen, H. Large-scale regulatory network analysis from microarray data: Modified Bayesian network learning and association rule mining. *Decis. Support Syst.* **2007**, *43*, 1207–1225. [CrossRef]
37. Bustikova, L.; Siroky, D.S.; Alashri, S.; Alzahrani, S. Predicting Partisan Responsiveness: A Probabilistic Text Mining Time-Series Approach. *Political Anal.* **2020**, *28*, 47–64. [CrossRef]
38. Fattori, M.; Pedrazzi, G.; Turra, R. Text mining applied to patent mapping: A practical business case. *World Pat. Inf.* **2003**, *25*, 335–342. [CrossRef]
39. Hassani, H.; Beneki, C.; Unger, S.; Mazinani, M.T.; Yeganegi, M.R. Text mining in big data analytics. *Big Data Cogn. Comput.* **2020**, *4*, 1. [CrossRef]
40. He, W. Improving user experience with case-based reasoning systems using text mining and Web 2.0. *Expert Syst. Appl.* **2013**, *40*, 500–507. [CrossRef]
41. Kim, Y.M.; Delen, D. Medical informatics research trend analysis: A text mining approach. *Health Inf. J.* **2018**, *24*, 432–452. [CrossRef]
42. Yu, L.; Wang, S.; Lai, K.K. A rough-set-refined text mining approach for crude oil market tendency forecasting. *Int. J. Knowl. Syst. Sci.* **2005**, *2*, 33–46.
43. Sumathy, K.L.; Chidambaram, M. Text mining: Concepts, applications, tools and issues—an overview. *Int. J. Comput. Appl.* **2013**, *80*, 29–32.
44. Natarajan, M. Role of text mining in information extraction and information management. *DESIDOC J. Libr. Inf. Technol.* **2005**, *25*, 31–38.
45. Scott, J. Trend report social network analysis. *Sociology* **1988**, *22*, 109–127. [CrossRef]
46. Benckendorff, P.; Zehrer, A. A network analysis of tourism research. *Ann. Tour. Res.* **2013**, *43*, 121–149. [CrossRef]
47. Chen, C.; Morris, S. Visualizing evolving networks: Minimum spanning trees versus pathfinder networks. In Proceedings of the IEEE Symposium on Information Visualization (INFOVIS) 2003, Seattle, WA, USA, 19–21 October 2003; pp. 67–74.
48. Bindu, N.; Sankar, C.P.; Kumar, K.S. From conventional governance to e-democracy: Tracing the evolution of e-governance research trends using network analysis tools. *Gov. Inf. Q.* **2019**, *36*, 385–399. [CrossRef]
49. Van den Besselaar, P.; Heimeriks, G. Mapping research topics using word-reference co-occurrences: A method and an exploratory case study. *Scientometrics* **2006**, *68*, 377–393. [CrossRef]
50. Swain, R.B.; Ranganathan, S. Modeling interlinkages between sustainable development goals using network analysis. *World Dev.* **2021**, *138*, 105136. [CrossRef]
51. Oberhardt, M.A.; Puchałka, J.; Fryer, K.E.; Dos Santos, V.A.M.; Papin, J.A. Genome-scale metabolic network analysis of the opportunistic pathogen *Pseudomonas aeruginosa* PAO1. *J. Bacteriol.* **2008**, *190*, 2790–2803. [CrossRef] [PubMed]
52. Teichert, T.A.; Schöntag, K. Exploring consumer knowledge structures using associative network analysis. *Psychol. Mark.* **2010**, *27*, 369–398. [CrossRef]
53. Tang, K.Y.; Chang, C.Y.; Hwang, G.J. Trends in artificial intelligence-supported e-learning: A systematic review and co-citation network analysis (1998–2019). *Interact. Learn. Environ.* **2021**, *29*, 1–19. [CrossRef]
54. Evans, J.; Allan, N.; Cante, N. A new insight into the world economic forum global risks. *Economic Papers. J. Appl. Econ. Policy* **2017**, *36*, 185–197.
55. Jovanović, A.; Klimek, P.; Renn, O.; Schneider, R.; Øien, K.; Brown, J.; Digennaro, M.; Liu, Y.; Pfau, V.; Jelić, M.; et al. Assessing resilience of healthcare infrastructure exposed to COVID-19: Emerging risks, resilience indicators, interdependencies and international standards. *Environ. Syst. Decis.* **2020**, *40*, 252–286. [CrossRef]
56. Mazanec, J.A.; Ring, A. Tourism destination competitiveness: Second thoughts on the World Economic Forum reports. *Tour. Econ.* **2011**, *17*, 725–751. [CrossRef]
57. Challenges and Opportunities: In the Post COVID-19 World. Available online: http://www3.weforum.org/docs/WEF_Challenges_and_Opportunities_Post_COVID_19.pdf (accessed on 31 December 2020).

58. COVID-19 Risks Outlook: A Preliminary Mapping and Its Implications. Available online: http://www3.weforum.org/docs/WEF_COVID_19_Risks_Outlook_Special_Edition_Pages.pdf (accessed on 31 December 2020).
59. Emerging Pathways towards a Post COVID-19 Reset and Recovery. Available online: http://www3.weforum.org/docs/WEF_Emerging_Pathways_towards_a_Post-COVID-19_Reset_and_Recovery_2020_final.pdf (accessed on 31 December 2020).
60. Winning the Race for Survival: How Advanced Manufacturing Technologies Are Driving Business-Model Innovation. Available online: http://www3.weforum.org/docs/WEF_Winning_The_Race_For_Survival_2020.pdf (accessed on 31 December 2020).
61. Connecting Digital Economies: Policy Recommendations for Cross-Border Payments. Available online: http://www3.weforum.org/docs/WEF_Connecting_Digital_Economies_2020.pdf (accessed on 31 December 2020).
62. Dashboard for a New Economy towards a New Compass for the Post-COVID Recovery. Available online: http://www3.weforum.org/docs/WEF_Dashboard_for_a_New_Economy_2020.pdf (accessed on 31 December 2020).
63. Fostering Effective Energy Transition 2020 Edition. Available online: http://www3.weforum.org/docs/WEF_Fostering_Effective_Energy_Transition_2020_Edition.pdf (accessed on 31 December 2020).
64. Future of Consumption in Fast-Growth Consumer Markets: ASEAN. Available online: http://www3.weforum.org/docs/WEF_Future_of_Consumption_in_Fast_Growth_Consumer_Markets_ASEAN_2020.pdf (accessed on 31 December 2020).
65. How Can Trade Rules Support Environmental Action? Global Future Council on International Trade and Investment. Available online: http://www3.weforum.org/docs/WEF_GFC_Briefing_on_Trade_and_Environment_Report_2020.pdf (accessed on 31 December 2020).
66. Impact of COVID-19 on the Global Financial System. Available online: http://www3.weforum.org/docs/WEF_Impact_of_COVID_19_on_the_Global_Financial_System_2020.pdf (accessed on 31 December 2020).
67. The Future of Jobs Report 2020. Available online: http://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf (accessed on 31 December 2020).
68. Understanding Value in Media: Perspectives from Consumers and Industry. Available online: http://www3.weforum.org/docs/WEF_Understanding_Value_in_Media_Perspectives_from_Consumers_and_Industry_2020.pdf (accessed on 31 December 2020).
69. Vision towards a Responsible Future of Consumption: Collaborative Action Framework for Consumer Industries. Available online: http://www3.weforum.org/docs/WEF_Vision_Towards_a_Responsible_Future_of_Consumption_2020.pdf (accessed on 31 December 2020).
70. Building Resilience in Manufacturing and Supply Systems in the COVID-19 Context and beyond: Latin America Perspectives. Available online: http://www3.weforum.org/docs/WEF_Resilience_in_manufacturing_and_supply_systems_LATAM_2020.pdf (accessed on 31 December 2020).
71. Incentivizing Responsible and Secure Innovation: A framework for Investors and Entrepreneurs. Available online: http://www3.weforum.org/docs/WEF_Incentivizing_Secure_and_Responsible_Innovation_A_framework_for_investors_and_entrepreneurs_2020.pdf (accessed on 31 December 2020).
72. Markets of Tomorrow: Pathways to a New Economy. Available online: http://www3.weforum.org/docs/WEF_Markets_of_Tomorrow_2020.pdf (accessed on 31 December 2020).
73. Outbreak Readiness and Business Impact: Protecting Lives and Livelihoods across the Global Economy. Available online: http://www3.weforum.org/docs/WEF%20HGI_Outbreak_Readiness_Business_Impact.pdf (accessed on 31 December 2020).
74. The Impact of COVID-19 on the Future of Advanced Manufacturing and Production: Insights from the World Economic Forum's Global Network of Advanced Manufacturing Hubs. Available online: http://www3.weforum.org/docs/WEF_AMHUB_Insight_Paper_2020.pdf (accessed on 31 December 2020).
75. 5G Outlook Series: The Impact of Mobile Technology on the Response to COVID-19. Available online: http://www3.weforum.org/docs/WEF_Global_Accelerator_Program_5G_Outlook_Report_2020.pdf (accessed on 31 December 2020).
76. Accelerating Digital Inclusion in the New Normal. Available online: http://www3.weforum.org/docs/WEF_Accelerating_Digital_Inclusion_in_the_New_Normal_Report_2020.pdf (accessed on 31 December 2020).
77. Cyber Resilience in the Electricity Ecosystem: Playbook for Boards and Cyber Security Officers. Available online: http://www3.weforum.org/docs/WEF_Cyber_Resilience_in_the_Electricity_Ecosystem_Playbook_for_Boards_and_Cybersecurity_Officers_2020.pdf (accessed on 31 December 2020).
78. Cybersecurity Leadership Principles: Lessons Learnt during the COVID-19 Pandemic to Prepare for the New Normal. Available online: http://www3.weforum.org/docs/WEF_Cybersecurity_leadership_principles_for_the_Covid_19_pandemic_2020.pdf (accessed on 31 December 2020).
79. Global Technology Governance Report 2021: Harnessing Fourth Industrial Revolution Technologies in a COVID-19 World. Available online: http://www3.weforum.org/docs/WEF_Global_Technology_Governance_2020.pdf (accessed on 31 December 2020).
80. The Global Competitiveness Report: How Countries Are Performing on the Road to Recovery. Available online: http://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2020.pdf (accessed on 31 December 2020).
81. Top 10 Emerging Technologies of 2020. Available online: http://www3.weforum.org/docs/WEF_Top_10_Emerging_Technologies_2020.pdf (accessed on 31 December 2020).
82. Leydesdorff, L. *The Challenge of Scientometrics: The Development, Measurement, and Self-Organization of Scientific Communications*; Universal-Publishers: Irvine, CA, USA, 2001.

83. Sung, Y.A.; Kim, K.W.; Kwon, H.J. Big Data Analysis of Korean Travelers' Behavior in the Post-COVID-19 Era. *Sustainability* **2021**, *13*, 310. [\[CrossRef\]](#)
84. Christian, H.; Agus, M.P.; Suhartono, D. Single document automatic text summarization using term frequency-inverse document frequency (TF-IDF). *ComTech* **2016**, *7*, 285–294. [\[CrossRef\]](#)
85. Iwendi, C.; Ponnar, S.; Munirathinam, R.; Srinivasan, K.; Chang, C.Y. An efficient and unique TF/IDF algorithmic model-based data analysis for handling applications with big data streaming. *Electronics* **2019**, *8*, 1331. [\[CrossRef\]](#)
86. Havrland, L.; Kreinovich, V. A simple probabilistic explanation of term frequency-inverse document frequency (tf-idf) heuristic (and variations motivated by this explanation). *Int. J. Gen. Syst.* **2017**, *46*, 27–36. [\[CrossRef\]](#)
87. Trstenjak, B.; Mikac, S.; Donko, D. KNN with TF-IDF based framework for text categorization. *Procedia Eng.* **2014**, *69*, 1356–1364. [\[CrossRef\]](#)
88. Nadkarni, P.M.; Ohno-Machado, L.; Chapman, W.W. Natural language processing: An introduction. *J. Am. Med. Inf. Assoc.* **2011**, *18*, 544–551. [\[CrossRef\]](#)
89. Çiltık, A.; Güngör, T. Time-efficient spam e-mail filtering using n-gram models. *Pattern Recognit. Lett.* **2008**, *29*, 19–33. [\[CrossRef\]](#)
90. Halevy, A.; Norvig, P.; Pereira, F. The unreasonable effectiveness of data. *IEEE Intell. Syst.* **2009**, *24*, 8–12. [\[CrossRef\]](#)
91. Gómez, D.; Figueira, J.R.; Eusébio, A. Modeling centrality measures in social network analysis using bi-criteria network flow optimization problems. *Eur. J. Oper. Res.* **2013**, *226*, 354–365. [\[CrossRef\]](#)
92. Yustiawan, Y.; Maharani, W.; Gozali, A.A. Degree centrality for social network with opsahl method. *Procedia Comput. Sci.* **2015**, *59*, 419–426. [\[CrossRef\]](#)
93. Umadevi, V. Case study—centrality measure analysis on co-authorship network. *JGRCS* **2013**, *4*, 67–70.
94. Agryzkov, T.; Tortosa, L.; Vicent, J.F.; Wilson, R. A centrality measure for urban networks based on the eigenvector centrality concept. *Env. Plan B Urban Anal. City Sci.* **2019**, *46*, 668–689. [\[CrossRef\]](#)
95. Liu, J.G.; Lin, J.H.; Guo, Q.; Zhou, T. Locating influential nodes via dynamics-sensitive centrality. *Sci. Rep.* **2016**, *6*, 21380. [\[CrossRef\]](#)
96. Borgatti, S.P. Centrality and network flow. *Soc. Netw.* **2005**, *27*, 55–71. [\[CrossRef\]](#)
97. Chen, C.H. Generalized association plots: Information visualization via iteratively generated correlation matrices. *Stat. Sin.* **2002**, *12*, 7–29.
98. Lafosse, R.; ten Berge, J.M. A simultaneous CONCOR algorithm for the analysis of two partitioned matrices. *Comput. Stat. Data Anal.* **2006**, *50*, 2529–2535. [\[CrossRef\]](#)
99. Batagelj, V.; Ferligoj, A.; Doreian, P. Direct and indirect methods for structural equivalence. *Soc. Netw.* **1992**, *14*, 63–90. [\[CrossRef\]](#)
100. Breiger, R.L.; Boorman, S.A.; Arabie, P. An algorithm for clustering relational data with applications to social network analysis and comparison with multidimensional scaling. *J. Math Psychol.* **1975**, *12*, 328–383. [\[CrossRef\]](#)
101. Richards, W.; Seary, A. Eigen analysis of networks. *J. Soc. Struct.* **2000**, *1*, 1–17.
102. Otte, E.; Rousseau, R. Social network analysis: A powerful strategy, also for the information sciences. *J. Inf. Sci.* **2002**, *28*, 441–453. [\[CrossRef\]](#)