Article

Issues and Agendas of Pandemic Crisis Management: A Text Analysis of World Economic Forum COVID-19 Reports

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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 3,897 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, network analysis helps develop strategies for sustainable response to and management of national crises through identifying clusters of words with a similar structural equivalence.

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

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 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 [47]. These efforts need guidance and direction with qualitative evidence from similar ongoing patterns of pandemic crisis response and management [5,77]. Strategic directions for national crisis management for 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. [28] identified patterns in the increase of influenza through analyzing qualitative data compiled from a collection of documents instead of structured data, thereby contributing to discovering various relations. DiMaggio [34] analyzed the linguistic context of social institutions and extracted useful information for national policy direction, thereby predicting future research trends and guiding policy makers.

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 [14,24,62]. In line with the value of a text-based analysis on pandemic-related reports, we selected 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 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, gain insight from papers of exploratory research [4,33,42,57,60,66]. Moreover, the method helps to identify the main pathways of research and advance the review of research findings [7,48].

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 determines 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 inverse 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 employs an unstructured data-based approach considering the specific environment of COVID-19. Reports released by recognized international organizations are 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 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 [17,35,59].

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 often-experienced 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 [6,68]. 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 [93]. 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 [9,74].

International organizations and national governments should develop capacities for pandemic-led crisis response and management for the imperative [55,85]. The authorities need to develop guidelines to predict unexperienced events and prepare for them [72]. 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 [10,19,83]. 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 appears [63]. While the pandemic crisis itself produces diverse issues and problems from social, economic, and cultural aspects, the recognition of inability and ignorance is a new issue and allows setting an agenda regarding preparation for future events [18,43,71].

2.2 Methodological Review: Text Mining and Social 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 [20]. A stream of e-mails, newspapers, web articles, documents, and reports have unstructured properties. While structured data has high value, as determined through an 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 [76]. It basically involves a text analysis and processing sequence that extracts information with a specific purpose [39,51]. It creates new estimates and values by finding useful knowledge and presenting association rules and algorithms [3]. A text database is considered to be a useful source of information and knowledge. Text mining is useful in project management and policy making, especially when it hints at a new approach to untangle various problems.

Text analysis helps collect strategy ideas for making policies, finding new relations, identifying potential useful meanings, and predicting trends in uncertain circumstances [16,24,38,49,50,58,94]. 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 [79] and discover important insights and rules penetrating massive amounts of text documents [67].

A growing number of text-based analyses have shed light on the network of relationships among words and thus, social network analysis accompanies text mining. The social network analysis seeks to find out the characteristics of network behaviors and explain structural relationships [75]. Mitchell [65] denoted it as "an attempt to explain humans' social behavior as a characteristic of the network of relationships they have." It enables observation of the structure and pattern of connection relations [8]. The analysis method focuses on a social structure consisting of a gathering of social actors or diverse patterns of social interactions among multiple gatherings. This behavioral connection structure is considered as a transfer of thoughts and behaviors through social networks [25,36]. In technical words, a social network analysis finds the location and structure of nodes, their influence, and the groups and communities they belong to. It also interprets their meaning. However, objective interpretation requires caution because the nodes and connection relations are interpreted in a subjective manner. As a result, researchers should be careful when examining the network structure and measuring its influence.

Identifying network connections among multiple factors is useful for informing policymakers of meaningful relationships [81] as well as tracking and understanding complexity in exploring research [69]. In particular, a social network analysis helps determine the overall trends and patterns of research [61,87]. If unstructured data restricts the use of objective and quantitative approaches, researchers would be able to detect patterns, recognize trends, and gain insights through applying a network analysis to such data [11,13,23,61].

3. Research Design

3.1 Data Collection

This study utilizes text data drawn from a series of World Economic Forum's COVID-19 research reports regarding national crisis response strategies, infection prevention and control, surveillance case studies, epidemiological protocols, and socioeconomic response in the non-contact mode. The homepage of the World Economic Forum publicly releases a repository of reports for creating and sharing practical and strategic knowledge regarding pandemic crisis management (www.weforum.org/reports). 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.

Reports of interest were selected when they have relevant contents related to 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. Finally, 26 reports were selected for the analysis. The selection criteria are as follows: 1) selected reports must contain strategies for the response and management of the pandemic crisis, 2) brief review papers (less than five pages) are excluded, and 3) reports specific to particular areas of expertise are also excluded. Table 1 presents the list of selected COVID-19 research reports.

Table 1. The List of Selected Reports

Category	The title of report
Crisis management	• *Challenges and Opportunities Post COVID-19* 2020 [21] • *COVID-19 Risks Outlook Special Edition Pages* 2020 [29] • *Emerging Pathways towards a Post COVID-19 Reset and Recovery 2020 Final* 2020 [37] • *The State of the Connected World 2020* [78] • *Winning the Race for Survival 2020* [92]
Economy (Employment, Trade, and Consumption)	• *Connecting Digital Economies 2020* [27] • *Dashboard for a New Economy 2020* [32] • *Fostering Effective Energy Transition 2020 Edition Future of Jobs 2020* [40] • *GFC Briefing on Trade and Environment Report 2020* [52] • *Impact of COVID-19 on the Global Financial System 2020* [53] • *Future of Consumption in Fast Growth Consumer Markets ASEAN 2020* [41] • *Understanding Value in Media Perspectives from Consumers and Industry 2020* [86] • *Vision Towards a Responsible Future of Consumption 2020* [88]
Business and Industry	• *AMHUB Insight Paper 2020* [82] • *HGHI Outbreak Readiness Business Impact 2020* [70] • *Incentivizing Secure and Responsible Innovation: A Framework for Investors and Entrepreneurs 2020* [54] • *Markets of Tomorrow 2020* [64] • *Resilience in Manufacturing and Supply Systems LATAM 2020* [15]
Technology (Emerging Technologies	• *Global Accelerator Program 5G Outlook Report 2020* [1] • *Global Technology Governance 2020* [46] • *The Global Competitiveness Report 2020* [45]

and Related Issues)	• *Top 10 Emerging Technologies 2020* [84] • *Accelerating Digital Inclusion in the New Normal Report 2020* [2] • *Cyber Resilience in the Electricity Ecosystem Playbook for Boards and Cyber Security Officers 2020* [30] • *Cyber security leadership principles for the COVID-19 Pandemic 2020* [31]

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 danger signals and significant patterns through exploring various relationships and behaviors.

This study employs Textom (www.textom.co.kr) 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. 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 [80]. Good Software certification acquired from the Korea Information and Communication Technology Association guarantees its reliability.

3.3 Analysis Procedure

Table 2 describes the process of the text analysis. The texts in the selected reports are filtered to avoid terms that may distort the results. The text mining analysis of this study includes methods of measuring various indicators such as inverse frequency, connection centrality, *n*-gram, and structural equivalence.

Table 2. Steps of the Analysis

Steps	Tasks
Step 1	• Download the relevant reports in a PDF format and convert them to a TXT format. • Attach the converted TXT text to each line in Excel spreadsheet as a paragraph structure for each category.
Step 2	• Delete stop words necessary for a morpheme analysis (manually eliminate and replace hyphenated words with the composition of the words specified in the dictionary. • Remove the methods, methodology and reference sections and text citations.
Step 3	• Convert all capital letters to lowercase.
Step 4	• Remove commonly-used stop words from punctuation marks, numbers, and language (e.g., “ ”, %, number, that, next, and, between, etc.).
Step 5	• Extract nouns (including synthetic nouns) to understand clear trends when conducting a morpheme analysis.
Step 6	• Arrange the text corpus and process related terms in a database. • Analyze frequency, inverse frequency, connection centrality, and *n*-gram
Step 7	• Visualize the correlations among keywords processed in the database or the matrix value (Euclidian distance) by UCINET software, which enables a structural equivalence analysis.

3.2.1 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 [73]. TF-IDF is a value that multiplies TF (the frequency of a word appearing in documents) and IDF (the reciprocal number of documents in which the word appears). It represents how important a particular word, w, is within document d. Since IDF is the inverse of DF (document frequency or the number of documents where the word appears), TF-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 including 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. It is also used to filter stop words in the summarization and classification of text.

3.2.2 *n*-gram

Broadly used in the fields of computational linguistics and probability, data compression, and communication theory, 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 text. These items can come from phonemes, syllables, letters, or words. An n-gram model predicts x_i based on $x_{i-(n-1)},\ldots,x_{i-1}$: in mathematical terms, $P(x_i \mid x_{i-(n-1)},\ldots,x_{i-1})$. Independent assumptions (Markov model) in text modeling posit that each word depends only on the last n–1 words [26]. 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).

3.2.3 Degree Centrality

Centrality refers to a criterion of the relative importance of a vertex or node in a graph or social network [89,90]. 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. 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 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.

This study uses 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.

3.2.4 CONCOR

To map complex interactions, this study uses a CONCOR (CONvergence of iteration CORrealtion) 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?" Since 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 [22]. Among the three ways to measure structural equivalence (i.e., Pearson correlation coefficient, Euclidean distance, and/or matching), this study uses the Euclidean distance.

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 [91]. 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, the UCINET data visualization analysis tool helps illustrate structural equivalence.

4. Results

4.1 Frequency of Keywords

The text data from a total of 26 selected reports was refined through a morphological analysis. As a result, the total number of words was 3,987. 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 such words as “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 in a country level reflects “market”, “technology”, and “service.” This means that countries should make substantial efforts to recover society and economy through the application of emerging technologies in the transition to non-contact services as well as in the preparation of post-pandemic times.

The top 25 frequent keywords encompass “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 [12]. The results in Appendix B show the importance of the report and present the importance and inverse frequency of specific reports. Conditions 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) turned out to be important words in a particular report, except for 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”) are 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 [44,56]. Appendix C presents the frequency of high correlation between appearances of specific words in the COVID-19 reports. The 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 while in and after the pandemic as well as domains and areas on 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 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 to understand 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 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 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

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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”.

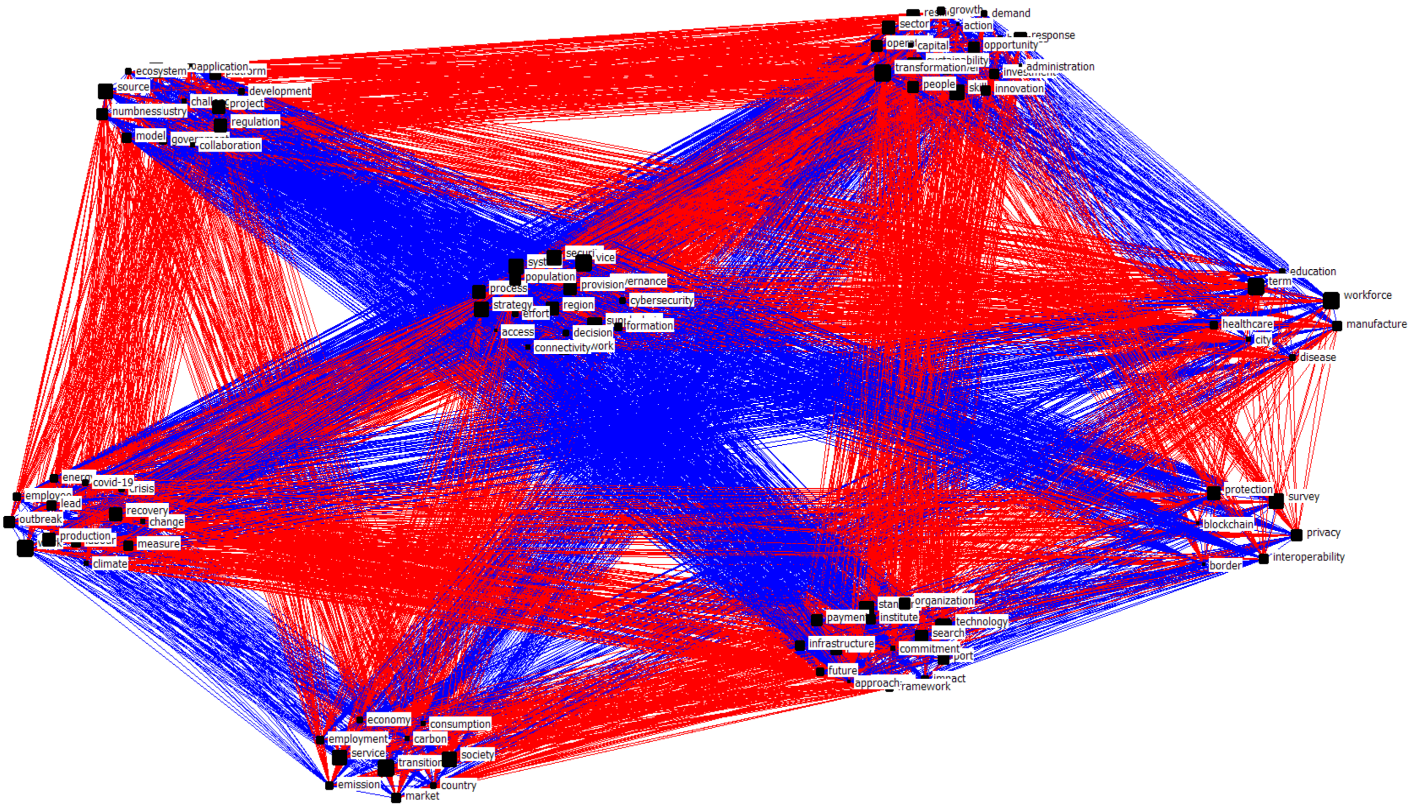

Figure 1. Visualization of CONCOR Analysis Results

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 explores the issues and agendas of strategic efforts for resilience to social and economic instabilities caused by COVID-19. The authors collected and analyzed 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 exploring the relationships among the core components of social systems and 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, policy making, 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 preparation for unexperienced events that can refer to lessons from 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 crisis (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 that between 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 development of crisis management capacities. Moreover, the illustration pays attention to "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. Papers from global or international organizations other than the World Economic Forum may contain insightful arguments based on research. However, not all recent papers regarding pandemic crisis management can be collected and analyzed. Although the United Nations, OECD, and famous think-tanks release important papers on this topic, the World Economic Forum has established a repository of strategic knowledge about the pandemic crisis. The repository is not a gathering of intermittently published papers but rather a channel for sharing practical knowledge from diverse domains and perspectives. Selecting the World Economic Forum reports is an efficient and effective way to collect relevant text data.

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Appendix A. 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	eco system	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
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. TF-IDF

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

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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
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	eco system	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. *n*-gram and Degree Centrality

n-gram analysis								Degree centrality analysis					
No	*n*-gram (A)	*n*-gram (B)	Freq	No	*n*-gram (A)	*n*-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
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

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