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Analyzing Trends in Digital Transformation Korean Social Media Data: A Semantic Network Analysis

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Abstract: This study explores the impact of digital transformation on Korean society by analyzing Korean social media data, focusing on the societal and economic effects triggered by advancements in digital technology. Utilizing text mining techniques and semantic network analysis, we extracted key terms and their relationships from online news and blogs, identifying major themes related to digital transformation. Our analysis, based on data collected from major Korean portals using various related search terms, provides deep insights into how digital evolution influences individuals, businesses, and government sectors. The findings offer a comprehensive view of the technological and social trends emerging from digital transformation, including its policy, economic, and educational implications. This research not only sheds light on the understanding and strategic approaches to digital transformation in Korea but also demonstrates the potential of social media data in analyzing the societal impact of technological advancements, offering valuable resources for future research in effectively navigating the era of digital change.

Keywords: digital transformation; online news; blog; big data; text mining; semantic network analysis; CONCOR analysis

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1. Introduction

The digital era's boom has ushered in a paradigm shift known as the "digital transformation", which significantly impacts various societal sectors, including business, education, and governance [1,2]. This shift transcends mere technological upgrades, signifying a comprehensive overhaul of organizations, culture, and operations [1]. As our society becomes increasingly digitalized, with a rise in public and private services based on such technologies, the ability to adapt to variable situations has become crucial [2].

In the face of inevitable digital transformation across most industries, companies facing a challenging internal and external business environment, especially those with limited resources, have been compelled to seek breakthroughs via open innovation in corporate and business models [3,4]. Accelerated by pandemics or radical technological innovations, businesses have had to continuously evolve and adjust their innovation strategies to maintain their operations [5].

Additionally, digital transformation in business dismantles barriers among people, businesses, and objects, enabling the creation of new products and services and the genesis of new ventures [6]. It emphasizes the construction of new business models, processes, and software and systems that lead to increased revenue, competitive advantage, and higher efficiency [6].

In this context, social media becomes a vital tool for capturing public sentiment and social trends. Especially regarding the digital transformation, the role of these platforms in shaping public discourse is crucial. Considering Korea's high social media penetration rate in harmony with traditional values and technological advancements, it presents an opportunity to gauge the social and individual impacts of the digital transformation.

Within the context of social media, semantic network analysis holds particular importance. It enables mapping how ideas, trends, and sentiments interconnect and evolve over time within digital conversations. Researchers can gain insights into public opinion, emerging trends, and the cultural zeitgeist of specific communities or societies by examining these networks [6,7]. This approach not only enhances our understanding of the dynamics of digital communication but also offers practical applications across various domains, from marketing to political science, providing a lens through which to view the complex tapestry of human thought and expression in the digital realm [7–9].

This study applies semantic network analysis techniques to social media data from Korea, focusing on the keyword "digital transformation" to analyze the relationships between keywords and phrases within social media posts. This method reflects systematic and meta-analytical techniques previously employed, with an emphasis on distilling core ideas from extensive data. Moreover, the research integrates perspectives based on social media, particularly within the non-Western context of Korea, to provide insights into the concept of digital transformation.

2. Related Studies

2.1. Digital Transformation

Digital transformation involves using new digital technologies such as social media, mobile technologies, analytics, or embedded devices to enable key business improvements, including enhanced customer experience, streamlined operations, or new business models [10]. It represents the use of technology to fundamentally improve a company's performance or reach, encompassing changes related to the application of digital technologies in all aspects of human society [11,12].

Digital technologies can be seen as key assets for leveraging organizational innovation, considering their disruptive nature and inter-organizational and systemic effects [13]. To achieve successful digital transformation, changes must occur at various levels within an organization, including the exchange of resources and capabilities, adaptation of core businesses, restructuring of processes and structures, and practical implementation of a digital culture [14–17].

It is argued that digital transformation needs to capture both technology-centric and actor-centric perspectives [18]. For leveraging the technology-centric view, the literature on technological disruptions was included and merged with research on digital transformation [18]. Regarding the actor-centric perspective, intrinsic implications were derived from the field of entrepreneurship, which is seen as capable of adding valuable insights into action-driven innovation and renewal processes within the framework [18].

The rapid development of various digital technologies enables the transformation into digital service, thereby facilitating the accelerated growth of the service industry through digital transformation [19,20]. Considered foundational technologies for digitalization, IoT (Internet of Things), cloud computing, and Big Data analytics provide service firms with the capacity to develop customer-oriented business models [21,22]. Manufacturing companies are also shifting their primary focus to ecosystems that integrate products with services to maximize customer value [20].

The recent trend is evolving the world into a single competitive market through one platform [23]. Consequently, suppliers and buyers strive to secure a competitive advantage by offering more choices in an increasingly fierce market [23]. As a result, digital transformation becomes a key strategic force that can enable innovation for creating customer value [23].

2.2. Big Data and Semantic Network Analysis

The term "Big Data" has attracted considerable attention since the early 21st century, with various researchers attempting to establish a widely accepted definition. One of the most common definitions introduced the challenge of Big Data through the 3Vs: volume (large amounts of data), velocity (rapid data streams), and variety (heterogeneous con-

tent) [24]. Big Data has been defined as large volumes of structured or unstructured data, indicating that traditional data processing technologies struggle to manage and process it due to the data's complexity and volume [25].

From a corporate perspective, the same information is required across various aspects such as customers, their needs, competition, products, distribution channels, service providers, and laws, making Big Data analytics necessary for making informed decisions [26]. Mobile marketing and social media platforms can extend knowledge by incorporating detailed personal information such as geographical location, time, interests, and gender [26].

Data exist almost everywhere in business and everyday life, and their volume is continuously increasing [26]. With the growing amount of data, scalability issues have become apparent, leading to increased processing times [27,28]. However, combining traditional algorithms with Big Data technologies has played a role in mitigating these scalability issues [27,29].

Among various Big Data analytics techniques, semantic network analysis is a method that models semantic relationships represented by graphs with nodes and edges [30]. Semantic networks can be automatically extracted from unstructured text data and used as a medium for visual text analysis, incorporating information retrieval and text mining techniques to extract relationships within the text [31–33].

Compared to traditional methods of text data analysis, semantic network analysis allows for the objective and accurate understanding of the structural relationships between individual words and the overall context, with relatively less reflection of the researcher's subjective thoughts [34,35]. In a semantic network model, nodes represent semantic or lexical units, while edges denote the associations and similarities, co-occurrences, or intensity between them [36,37]. Representing relationships with graphs that have labeled nodes and edges enables the identification of semantic relationships, patterns, and similarities between words regarding a specific topic, making it easier to discover insights [34,38]. Therefore, semantic network analysis can be actively used to explore the qualitative aspects or intrinsic meanings of issues by focusing on relationships within online Big Data, such as news on portal sites or posts on social media.

Data from various social media posts, news, and blogs on internet portal sites have become major sources supplying the raw materials necessary for Big Data analysis. Therefore, this paper aims to identify public perceptions related to digital transformation and discover widely recognized trends using text mining techniques and semantic network analysis.

3. Method

In this study, we analyzed the key thoughts of Korean users on digital transformation using text mining techniques and semantic network analysis on Big Data collected from the internet. Text mining is the process of extracting meaningful information from unstructured text data, exploring core themes and trends from multiple perspectives. Furthermore, to understand the relationships between the extracted keywords, semantic network analysis was utilized. This paper outlines an analytical process to comprehend the semantics between words related to digital transformation in online news articles and blogs, based on the degree of their co-occurrence. The overall process is illustrated in Figure 1.

3.1. Data Collection

For the semantic network analysis conducted in this research, a search was performed on Korea's two major portals, Naver [38] and Daum [39], using the keyword "digital transformation" to collect data from online news and blogs. Based on this, 1236 online news articles from Naver News and 1137 blog posts from both Naver and Daum blogs were collected as the data for analysis.

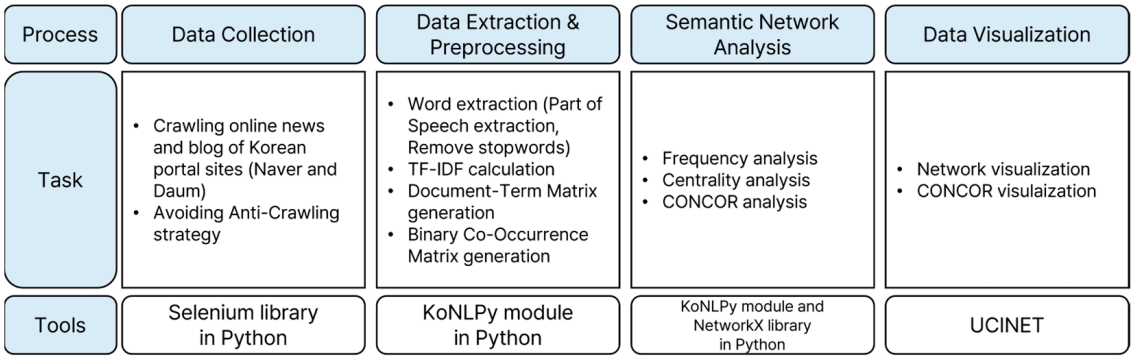

Figure 1. Data collection and analysis process for digital transformation.

Online news article texts were collected exclusively from Naver, as most Korean news articles can be accessed through it. However, given the occurrence of various news outlets providing identical articles, duplicates were removed from the collected news articles using cosine similarity on the texts. Since Naver and Daum blogs rarely contain posts with identical content on both platforms, no duplicate checks were conducted when collecting data from these blogs. Although the collection period was not specified, it was confirmed that over 90% of the data originated from within the last ten years.

During the collection process, it was observed that some websites had anti-crawling features. To circumvent these, the Selenium library, implemented in Python for automating web browser interactions, was utilized. The data thus collected were processed using the BeautifulSoup library and stored in the form of DataFrames using the Pandas library.

3.2. Data Extraction and Preprocessing

The extraction and preprocessing of the data were performed using KoNLPy, a Python open-source library for natural language processing of the Korean language [40]. Utilizing KoNLPy, only nouns, verbs, and adjectives were selected as Korean unigrams, and stopwords, which are commonly used or insignificant words, were excluded to filter the data. The refined list of words was then used to calculate their TF-IDF (Term Frequency-Inverse Document Frequency) values, enabling the identification and weighting of the most relevant words within the dataset.

TF-IDF formally measures how the occurrence of a given word is concentrated in relatively fewer documents. It is calculated by multiplying two metrics: the word frequency in a document and the inverse document frequency of the word across a set of documents. This value is primarily used to gauge similarity within documents, in addition to assessing the relevance of a document in search queries and the importance of specific words in search results [41,42]. TF-IDF helps in highlighting words that are distinctive to certain documents, thereby facilitating more accurate and meaningful analysis of textual data.

After sorting the extracted TF-IDF word list in descending order, the top 50 words were selected as nodes for the semantic network analysis. During the selection of words, unrelated terms such as “person” and “society” were excluded, and semantically similar words were consolidated. For example, the frequency of “core” was combined with the frequency of “center”, a similar term.

Based on the 50 selected words, a Document-Term Matrix (DTM) was created, representing the frequency of each word across various articles and blogs. DTM enables the quantification of the relationship between words and documents. Subsequently, a Co-Occurrence Matrix (COM) was constructed to represent the relationships of word co-occurrences across all documents. Due to the complexity of the analysis with the generated COM, all values were binarized by changing values higher than the median of all elements to 1 and those lower to 0, resulting in a binary matrix. This process simplifies dense values to 1 and 0, creating a looser relationship for network analysis. The semantic network analysis utilized this binary-structured keyword COM.

3.3. Semantic Network Analysis and Visualization

To discover the relationships among the top 50 words related to digital transformation, a semantic network analysis was conducted. This leverages the data mining techniques for unstructured Big Data analysis, a method distinct from social network analysis, which identifies the structural characteristics of social phenomena [43]. The co-occurrence relationships among the refined words within social media data were intuitively visualized using NetDraw 2.175, a network visualization software, with the previously created keyword COM [44].

To examine the connection structure of words related to digital transformation, the Python open-source package NetworkX [45] was utilized. Four types of network centrality metrics [46] were calculated using NetworkX for the keyword COM as follows:

1. Degree centrality, which calculates the number of nodes connected to a specific node, indicating the node's activity or popularity within the network;
2. Betweenness centrality, measuring a node's mediating role within the network, indicating its importance in facilitating information flow between other nodes;
3. Closeness centrality, calculating the inverse of the average distance to all other nodes, indicating how close a node is to all other nodes in the network, which can suggest its accessibility or centrality in the network's communication pathways;
4. Eigenvector centrality, a measure of a node's influence in the network, indicating not just how many connections a node has but also how important those connections are.

To identify mutually exclusive subgroups within the semantic network, a CONCOR (Convergence of Iterated Correlations) analysis was performed. CONCOR is based on structural equivalence, iteratively dividing nodes into subsets and then analyzing the Pearson correlation to identify groups with a certain level of similarity before forming clusters that include these groups [47]. This method is commonly used to find clusters of similar keywords and to identify the co-occurrence relationships between words across all possible terms [48]. UCINET 6.0 [49] was utilized to conduct the CONCOR analysis, and the results were visualized using NetDraw.

4. Results

4.1. The Frequencies of Keywords Related to Digital Transformation

The results of the word frequency analysis from online news articles and blogs, showing the top 50 words, are presented in Tables 1 and 2. The top five keywords from online news articles were "Education", "Innovation", "Corporation", "Information", and "Artificial Intelligence", highlighting a focus on how digital changes impact education, business innovation, and the integration of AI across sectors. Blogs, however, put "Artificial Intelligence", "Corporation", "Education", "Data", and "Innovation" at the forefront, indicating a stronger emphasis on the technical aspects of digital transformation, such as AI and data utilization, while still valuing education and innovation. This nuanced difference between online news articles and blogs suggests varying degrees of engagement with digital transformation themes across different platforms, but both recognize the importance of education and innovation in adapting to and capitalizing on digital advancements.

Table 1. Frequencies of 50 keywords related to digital transform in online news.

Rank	Keyword	Freq.	Rank	Keyword	Freq.
1	Education	2975	26	Nation	1137
2	Innovation	2643	27	Strategy	1068
3	Corporation	2437	28	Cooperation	1057
4	Information	2120	29	New	942
5	Artificial Intelligence	2093	30	Smart	937
6	Project	1955	31	Human Resources	852
7	Data	1942	32	Operation	831

Table 1. *Cont.*

Rank	Keyword	Freq.	Rank	Keyword	Freq.
8	Future	1830	33	Citizens	820
9	Support	1822	34	Study	791
10	Government	1816	35	Student	786
11	Global	1770	36	Leading	764
12	Field	1710	37	Professor	756
13	Metaverse	1644	38	Competence	745
14	Policy	1548	39	Investment	741
15	Construction	1502	40	Training	695
16	Region	1478	41	Contents	684
17	Platform	1460	42	Institution	668
18	Promotion	1458	43	Tech	657
19	Era	1444	44	Bio	646
20	Center	1394	45	School	639
21	Service	1363	46	Finance	544
22	Economy	1274	47	Cloud	543
23	Development	1267	48	Infrastructure	462
24	Society	1253	49	Software	439
25	Plan	1158	50	Personal Information	429

Table 2. Frequencies of 50 keywords related to digital transform in blogs.

Rank	Keyword	Freq.	Rank	Keyword	Freq.
1	Artificial Intelligence	2975	26	New	1137
2	Corporation	2643	27	System	1068
3	Education	2437	28	Society	1057
4	Data	2120	29	Government	942
5	Innovation	2093	30	Market	937
6	Era	1955	31	Nation	852
7	Metaverse	1942	32	Cloud	831
8	Project	1830	33	Region	820
9	Service	1822	34	Study	791
10	Field	1816	35	Professor	786
11	Support	1770	36	Citizens	764
12	Future	1710	37	Corona	756
13	Global	1644	38	Online	745
14	Change	1548	39	Space	741
15	Information	1502	40	Human Resources	695
16	Development	1478	41	Personal Information	684
17	Platform	1460	42	Business	668
18	Construction	1458	43	Finance	657
19	Center	1444	44	Big Data	646
20	Strategy	1394	45	Leading	639
21	Economy	1363	46	Research	544
22	Smart	1274	47	Infrastructure	543
23	Promotion	1267	48	Industrial Revolution	462
24	Plan	1253	49	Software	439
25	Policy	1158	50	Science and Technology	429

4.2. Analysis of Centralities of Keywords Related to Digital Transform

In Section 4.1, we initially present the raw frequency results as shown in Tables 1 and 2. These results depict the unmodified occurrence of keywords across our dataset with common stopwords filtered out. Following this initial analysis, we apply the TF-IDF method to refine these frequencies, thereby highlighting words that hold unique significance within our corpus. The relationships and centrality of these keywords are then explored in greater depth using a Document-Term Matrix (DTM) and a binary-structured Co-Occurrence Matrix (COM).

Table 3 presents the results of the network centrality analysis from the keyword COM for online news articles. The keyword "Innovation" had the highest degree of association with other keywords, resulting in the highest degree centrality, followed by "Education", "Artificial Intelligence", "Support", and "Data". The order of betweenness centrality was high for "Data", "Education", "Innovation", "Support", and "Artificial Intelligence". Closeness centrality was high for "Innovation", "Education", "Artificial Intelligence", "Support", and "Data", in that order. Eigenvector centrality was high for "Innovation", "Artificial Intelligence", "Support", "Education", and "Corporation".

Table 3. Centralities of keywords related to digital transformation from news network.

Rank	Keyword	Cd [1]	Keyword	Cb [2]	Keyword	Cc [3]	Keyword	Ce [4]
1	Innovation	0.938776	Data	0.06154	Innovation	0.940408	Innovation	0.200111
2	Education	0.897959	Education	0.050155	Education	0.904239	Artificial Intelligence	0.195975
3	Artificial Intelligence	0.877551	Innovation	0.049585	Artificial Intelligence	0.887178	Support	0.194377
4	Support	0.877551	Support	0.035948	Support	0.887178	Education	0.192973
5	Data	0.857143	Artificial Intelligence	0.032176	Data	0.870748	Corporation	0.191475
6	Corporation	0.836735	Corporation	0.027202	Corporation	0.854917	Data	0.18877
7	Global	0.795918	Global	0.026213	Global	0.824919	Global	0.185881
8	Project	0.77551	Government	0.019029	Project	0.810697	Future	0.185531
9	Future	0.77551	Future	0.016818	Future	0.810697	Project	0.184892
10	Government	0.77551	Project	0.015426	Government	0.810697	Field	0.184361
11	Information	0.755102	Information	0.015374	Information	0.796956	Government	0.183366
12	Field	0.755102	Metaverse	0.015002	Field	0.796956	Information	0.18166
13	Metaverse	0.714286	Policy	0.013719	Metaverse	0.770826	Promotion	0.179538
14	Policy	0.714286	Field	0.01159	Policy	0.770826	Policy	0.176005
15	Promotion	0.714286	Citizens	0.011204	Promotion	0.770826	Metaverse	0.175198
16	Construction	0.693878	Construction	0.010303	Construction	0.758394	Platform	0.174759
17	Platform	0.693878	Development	0.009443	Platform	0.758394	Center	0.17228
18	Service	0.673469	Platform	0.008512	Service	0.746356	Service	0.172084
19	Center	0.653061	Promotion	0.007452	Center	0.734694	Construction	0.171971
20	Development	0.653061	Service	0.006708	Development	0.734694	Nation	0.170091
21	Nation	0.653061	Society	0.004792	Nation	0.734694	Region	0.166259
22	Region	0.632653	Nation	0.004159	Region	0.723391	Society	0.165359
23	Society	0.632653	Region	0.003406	Society	0.723391	Economy	0.164331
24	Economy	0.612245	Center	0.00286	Economy	0.71243	Development	0.163565
25	Era	0.591837	Era	0.001982	Era	0.701797	Era	0.159499
26	Strategy	0.571429	Study	0.001756	Strategy	0.691477	Strategy	0.156086
27	Plan	0.510204	Economy	0.001665	Plan	0.662259	Plan	0.141053
28	Cooperation	0.469388	Human Resources	0.001255	Cooperation	0.644115	Cooperation	0.13411
29	New	0.469388	Strategy	0.001233	New	0.644115	New	0.132824
30	Citizens	0.469388	Leading	0.001116	Citizens	0.644115	Citizens	0.127351
31	Human Resources	0.44898	School	0.001047	Human Resources	0.626939	Human Resources	0.122508
32	Investment	0.408163	Student	0.000984	Investment	0.61869	Investment	0.113464
33	Smart	0.367347	Tech	0.000834	Smart	0.602826	Smart	0.105321
34	Operation	0.326531	Plan	0.000646	Operation	0.587755	Operation	0.095075
35	Bio	0.326531	Bio	0.000354	Bio	0.587755	Bio	0.090109
36	Leading	0.265306	Investment	0.000338	Leading	0.566511	Competence	0.073346
37	Study	0.244898	Training	4.05×10^{-5}	Study	0.559767	Leading	0.071322
38	Professor	0.244898	New	3.87×10^{-5}	Professor	0.559767	Contents	0.07119
39	Competence	0.244898	Cooperation	3.15×10^{-5}	Competence	0.559767	Professor	0.070857
40	Contents	0.244898	Smart	0	Contents	0.553181	Training	0.064338

Table 3. *Cont.*

Rank	Keyword	Cd [1]	Keyword	Cb [2]	Keyword	Cc [3]	Keyword	Ce [4]
41	Student	0.22449	Operation	0	Student	0.546749	Study	0.058304
42	Training	0.22449	Professor	0	Training	0.546749	Student	0.052909
43	School	0.204082	Competence	0	School	0.540464	Institution	0.049241
44	Tech	0.183673	Contents	0	Institution	0.534323	Cloud	0.048228
45	Institution	0.163265	Institution	0	Tech	0.534323	School	0.044269
46	Cloud	0.163265	Finance	0	Cloud	0.534323	Infrastructure	0.042801
47	Infrastructure	0.142857	Cloud	0	Infrastructure	0.528319	Tech	0.040939
48	Finance	0.081633	Infrastructure	0	Finance	0.511091	Finance	0.02403
49	Personal Information	0.040816	Software	0	Personal Information	0.470204	Personal Information	0.010226
50	Software	0	Personal Information	0	Software	0	Software	1.45×10^{-13}

[1] Cd: degree centrality. [2] Cb: betweenness centrality. [3] Cc: closeness centrality. [4] Ce: eigenvector centrality.

In the analysis of network centrality from the keyword COM for blogs, as detailed in Table 4, "Artificial Intelligence" emerged as the most centrally connected term, exhibiting the highest degree of association with other keywords. This centrality was closely followed by the terms "Data", "Corporation", "Innovation", and "Service", in that order. Furthermore, "Artificial Intelligence" also led in betweenness centrality, suggesting its role as a pivotal bridge within the network. This pattern was similarly observed in closeness centrality, with "Artificial Intelligence", "Data", "Corporation", "Innovation", and "Service" ranking high, indicating their close connections within the network. Additionally, "Artificial Intelligence", "Data", "Corporation", "Service", and "Development" were found to have high eigenvector centrality, highlighting their influence across the network.

Table 4. Centralities of keywords related to digital transformation from blog network.

Rank	Keyword	Cd [1]	Keyword	Cb [2]	Keyword	Cc [3]	Keyword	Ce [4]
1	Artificial Intelligence	0.918367	Artificial Intelligence	0.092258	Artificial Intelligence	0.918802	Artificial Intelligence	0.193392
2	Data	0.877551	Data	0.041167	Data	0.881299	Data	0.192609
3	Corporation	0.857143	Education	0.031264	Corporation	0.863673	Corporation	0.191275
4	Innovation	0.816327	Corporation	0.028714	Innovation	0.830455	Service	0.18964
5	Service	0.816327	Information	0.018267	Service	0.830455	Development	0.189048
6	Development	0.816327	Innovation	0.017399	Development	0.830455	Innovation	0.18838
7	Education	0.795918	Support	0.017302	Education	0.814786	Metaverse	0.187632
8	Metaverse	0.795918	Development	0.014583	Metaverse	0.814786	Construction	0.186105
9	Support	0.795918	Service	0.013366	Support	0.814786	Promotion	0.186105
10	Construction	0.795918	Construction	0.012719	Construction	0.814786	Support	0.185267
11	Promotion	0.795918	Promotion	0.012719	Promotion	0.814786	Project	0.184539
12	Project	0.77551	Metaverse	0.010805	Project	0.799698	Smart	0.184539
13	Smart	0.77551	Center	0.009584	Smart	0.799698	Education	0.18388
14	Field	0.755102	Project	0.009436	Field	0.785158	Field	0.183307
15	Center	0.755102	Smart	0.009436	Center	0.785158	Center	0.18085
16	Information	0.734694	Citizens	0.008668	Information	0.771137	Information	0.175311
17	Platform	0.693878	Strategy	0.00794	Platform	0.744546	Platform	0.174807
18	Strategy	0.693878	Field	0.006863	Strategy	0.744546	Strategy	0.171625
19	System	0.693878	Future	0.005236	System	0.744546	System	0.171384
20	Global	0.653061	System	0.005218	Global	0.719728	Global	0.163418
21	Future	0.632653	Global	0.004499	Future	0.707929	Plan	0.159692
22	Plan	0.632653	Plan	0.003899	Plan	0.707929	Future	0.157281
23	Era	0.571429	Platform	0.003363	Era	0.674745	Government	0.151141
24	Government	0.571429	Era	0.002008	Government	0.674745	Nation	0.148339
25	Citizens	0.571429	Government	0.00083	Citizens	0.674745	Era	0.147639

Table 4. *Cont.*

Rank	Keyword	Cd [1]	Keyword	Cb [2]	Keyword	Cc [3]	Keyword	Ce [4]
26	Nation	0.55102	Change	0.000604	Nation	0.664364	Citizens	0.145619
27	Policy	0.530612	Society	0.000582	Policy	0.654298	Policy	0.143094
28	Economy	0.510204	Economy	0.000514	Economy	0.644532	Economy	0.137371
29	Society	0.489796	Nation	0.000448	Society	0.635054	Cloud	0.134165
30	Cloud	0.489796	Policy	0.000377	Cloud	0.635054	Society	0.130427
31	Market	0.469388	Cloud	0.000157	Market	0.62585	Market	0.129527
32	Infrastructure	0.44898	Market	7.91×10^{-5}	Infrastructure	0.61691	Infrastructure	0.124915
33	Online	0.428571	New	0	Online	0.608221	Online	0.120143
34	Leading	0.408163	Region	0	Leading	0.599773	Leading	0.114433
35	Change	0.387755	Study	0	Change	0.591557	Region	0.104145
36	Region	0.367347	Professor	0	Region	0.583563	Change	0.101043
37	Study	0.326531	Corona	0	Study	0.568206	Study	0.094029
38	Big Data	0.285714	Online	0	Big Data	0.553637	Big Data	0.082636
39	New	0.244898	Space	0	New	0.539796	Finance	0.070776
40	Corona	0.244898	Human Resources	0	Corona	0.539796	Corona	0.070504
41	Finance	0.244898	Personal Information	0	Finance	0.539796	New	0.065627
42	Space	0.183673	Business	0	Space	0.520285	Space	0.051164
43	Business	0.102041	Finance	0	Business	0.496364	Business	0.029595
44	Human Resources	0.081633	Big Data	0	Human Resources	0.48521	Human Resources	0.023802
45	Personal Information	0.061224	Leading	0	Professor	0.474546	Personal Information	0.016215
46	Professor	0.040816	Research	0	Personal Information	0.469388	Professor	0.011912
47	Research	0.020408	Infrastructure	0	Research	0.469388	Research	0.006106
48	Industrial Revolution	0	Industrial Revolution	0	Industrial Revolution	0	Industrial Revolution	3.72×10^{-15}
49	Software	0	Software	0	Software	0	Software	3.72×10^{-15}
50	Science and Technology	0	Science and Technology	0	Science and Technology	0	Science and Technology	3.72×10^{-15}

[1] Cd: degree centrality. [2] Cb: betweenness centrality. [3] Cc: closeness centrality. [4] Ce: eigenvector centrality.

4.3. CONCOR Analysis and Visualization

A CONCOR analysis was conducted based on structural equivalence by analyzing the Pearson correlation from the keyword COM, resulting in clusters. Figure 2 presents the outcome of the CONCOR analysis performed on the digital transformation network generated from online news, identifying a total of seven clusters. The clusters are represented as [Word1, Word2, . . .]. The cluster [Operation, Data, Bio, Development, Contents, Plan, Smart, Construction] can be interpreted as embodying the theme of technological advancement and strategic growth. The cluster [Support, Government, Corporation, Field, Project, Promotion] suggests that the government and various corporations collaborate to support innovative projects aimed at advancing key industrial sectors. The cluster [Training, Infrastructure, Cloud, Leading, Competence, Institution, Personal Information, Finance, Professor] represents the context of education, technology, and expertise development within an institutional framework. The [Software, Tech, Study, School, Student] cluster indicates an education or learning environment focused on technology and software. The cluster [Information, Innovation, Artificial Intelligence, Education, Future] encompasses future-oriented and technology-driven themes. The [Citizens, New, Human Resources, Investment, Region, Cooperation, Service, Metaverse] cluster can be seen as focusing on community and technological development within geographic or digital spaces. Lastly, the [Strategy, Platform, Society, Policy, Center, Global, Economy, Nation, Era] cluster can be interpreted as countries developing policies centered around digital platforms to drive economic growth or societal development in the global era.

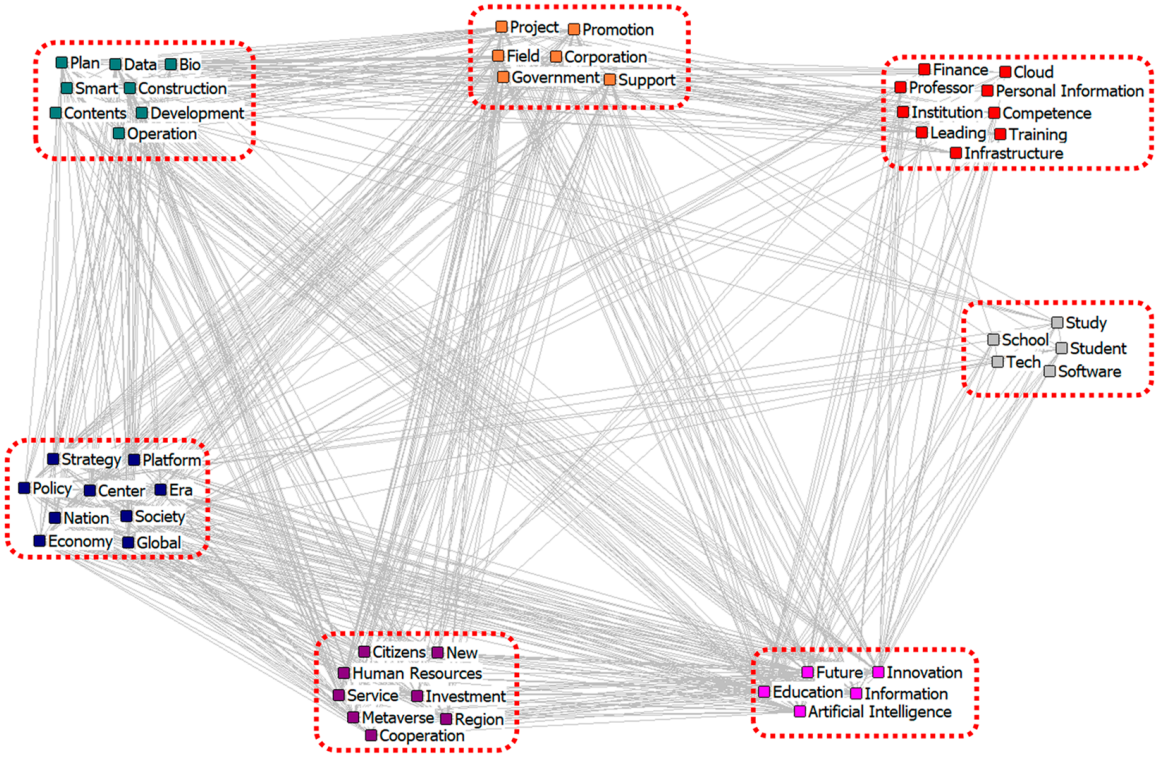

Figure 2. CONCOR analysis of news network of the digital transformation.

Figure 3 depicts the results of a CONCOR analysis on the digital transformation network generated from blogs, identifying a total of seven clusters. The cluster [Finance, Corona, Study, Space, Big Data, Change, Economy] can be interpreted as showing that the coronavirus pandemic has accelerated the digital transformation of finance and the economy, with research highlighting the importance of Big Data and digital spaces in driving change. The cluster [Personal Information, Citizens, Strategy, Information, Plan] suggests that themes of personal information, public engagement, and strategy are crucial regarding information. The cluster [Nation, Government, Era, Society, Policy, Future, Global] presents themes related to national and global governance, societal adaptation, and future-oriented policies in a digitally evolving world. The cluster [Development, Center, Education, System, Platform, Field] indicates that digital transformation is central to the development of the educational sector, platforms, and systems. The cluster [Region, Leading, Cloud, Infrastructure, Online, Market] points to a focus on regional development through cutting-edge cloud infrastructure and online marketplaces. The cluster [Project, Construction, Metaverse, Promotion, Corporation, Smart, Support, Service, Data, Innovation, Artificial Intelligence] represents a comprehensive approach to integrating advanced technologies into corporate projects and services. This can be interpreted as innovative projects initiated by corporations to focus on building smart services like the metaverse, supported by artificial intelligence and data analytics, to facilitate a new era of digital transformation and customer engagement. The cluster [New, Professor, Industrial Revolution, Human Resource, Software, Research, Science and Technology, Business] expresses the narrative of education and industrial evolution towards a technologically advanced future, emphasizing the collaborative role of academia and industry in pioneering R&D efforts using cutting-edge software and human resource innovation to underpin the digital transformation of businesses and society.

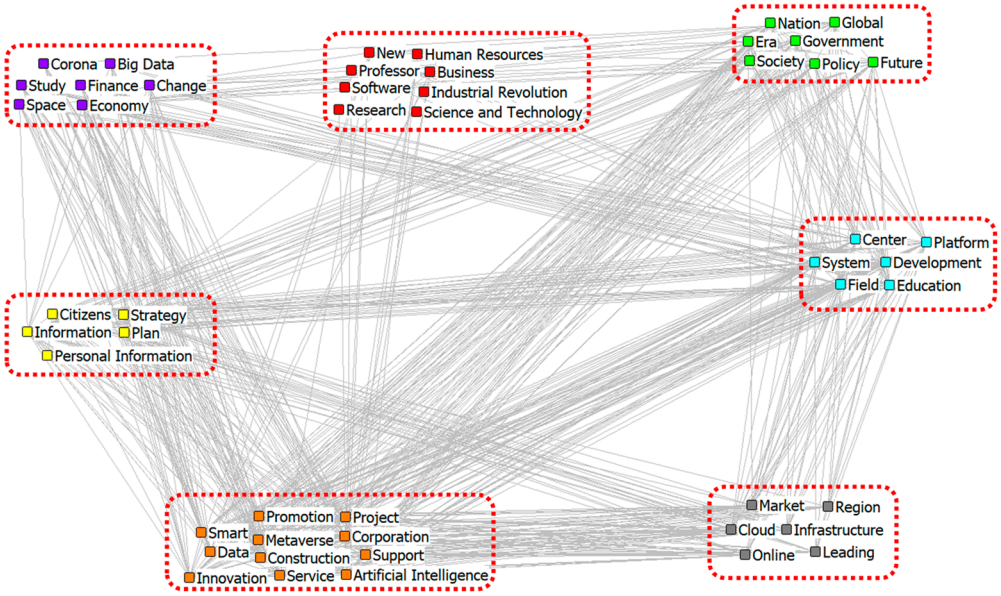

Figure 3. CONCOR analysis of blog network of digital transformation.

5. Discussion

The arrival of the digital transformation era brings technological advancements and consequential changes, fundamentally restructuring educational, occupational, and everyday life practices. The integration of digital technologies presents new opportunities and challenges across all age groups. This research utilizes text mining techniques to analyze social media data generated online on a large scale, aiming to understand the phenomena of digital transformation and its impacts. It delves into the effects of digital technology on various sectors such as society, economy, and education, seeking adaptation strategies and policy responses necessary for navigating the digital age. Also, this study has been conducted to elucidate the distinct patterns observed in both formal (articles) and informal (blogs) discourse on digital transformation within the Korean context. By analyzing these diverse sources of content, our intent is to provide a comprehensive view that enables readers from various countries to gain a nuanced understanding of how digital transformation is perceived and discussed in Korea.

Text mining related to digital transformation revealed the top five words with the highest frequency in online news articles as “Education”, “Innovation”, “Corporation”, “Information”, and “Artificial Intelligence” and in blogs as “Artificial Intelligence”, “Corporation”, “Education”, “Data”, and “Innovation”. These results indicate the significant impact of technological advancement in various fields such as education, innovation, corporations, and artificial intelligence [50,51]. Additionally, artificial intelligence has been confirmed as one of the key elements in the era of digital transformation [52,53].

To refine our analysis, we employed the TF-IDF methodology, which assists in distinguishing significant keywords from those frequently appearing across different texts without substantial informational value.

An analysis of online news articles showed high centrality for “Innovation”, “Education”, “Artificial Intelligence”, “Support”, and “Data”. These words are strongly interconnected as the main themes of digital transformation, highlighting the interaction between these themes in the context of technological progress in modern society, the evolution of education, data-driven decision-making processes, the expansion of artificial intelligence applications, and the importance of supporting systems in all these areas. A blog centrality analysis highlighted “Artificial Intelligence”, “Data”, “Corporation”, “Innovation’”, and “Service” as highly central. While “Education” and “Support” were emphasized as important themes in news articles, “Corporation” and “Service” showed greater centrality in blogs, suggesting that interests may vary depending on the community or platform dis-

cussing digital transformation. Blogs tend to focus more on in-depth analysis or opinions on personal or corporate experiences, products, and services, particularly highlighting corporate activities and service provision. In contrast, online news pays attention to broader topics like education and social support, dealing with the impact of digital transformation across society. The high centrality of "Innovation", "Data", and "Artificial Intelligence" in both mediums suggests that the advancement of digital technology is interconnected in areas such as innovation, data analysis, and artificial intelligence. The technological innovation enhances data-based decision-making processes, and the advancement of artificial intelligence enables new innovative solutions, driving change across various fields, as emphasized in other studies [54–56].

The CONCOR analysis identified seven clusters each in online news and blogs related to digital transformation, confirming the importance of technology and education in both mediums. The emphasis on technological advancements, particularly digital technologies like artificial intelligence, cloud computing, and Big Data, alongside education, is recognized as a leading force in driving the digital transformation. It suggests a focus on innovating educational systems to introduce new learning methods and competency development, potentially causing significant changes across the economy and society [57,58]. The acceleration of digitalization in economic activities due to the pandemic is a phenomenon already reported in various studies [59–61].

Online news tends to focus more on digital transformation support and the promotion of industry development through collaboration between governments and corporations. Words such as "Government", "Corporation", "Support", "Field", "Project", and "Promotion" highlight the strategic partnerships' vital role in supporting digital transformation and fostering innovative projects in specific industrial sectors. For small-scale service businesses, the digital transformation aims to expand competitive advantage, improve business outcomes, and achieve growth. The government's role in this context is identified as supporting the construction of digital platforms for small-scale service businesses, enabling mobile/digital payments, providing digital education, and building a digital collaboration ecosystem [62]. In contrast, blogs, with terms like "Personal Information", "Citizens", "Strategy", "Information", "Plan", and "Metaverse", reflect how individuals and small communities integrate and use digital technologies, especially innovative services like artificial intelligence and the metaverse, in daily life and business, indicating experiences and impacts on these practices.

Thus, online news tends to view digital transformation from the perspective of policy, economy, and national strategy, while blogs explore it from a standpoint closer to everyday life. This difference stems from each medium's purpose and target audience [63]. Online news aims to provide information to a broad readership, offering insights useful to policymakers and businesspeople, whereas blogs cater to personal interests, in-depth analysis, and detailed exploration of specific topics, providing customized content for the general public, particularly users and small communities interested in digital technologies [63].

Our analysis identifies several features unique to the Korean context, which significantly influence the discourse on digital transformation on Korean social media platforms. For instance, Korea's collectivist cultural norms shape the adoption of technologies that emphasize communal benefits and organizational harmony [64]. Additionally, the country's leading position in digital transformation fosters a progressive environment for discussing advanced digital infrastructure [65]. Economically, the interplay between large conglomerates and dynamic SMEs creates diverse viewpoints on how digital transformation can drive business growth and innovation [66]. These unique cultural, technological, and economic contexts provide a distinctive backdrop to Korea's digital transformation discourse, offering insights into the challenges and opportunities specific to this setting.

We found that global opinion polls often focus on general technological adaptation and digital readiness, whereas our analysis dives deeper into the specific themes and concerns prevalent in Korea. For example, global surveys like those conducted by the IFRC [67] highlight varied regional responses to digital transformation, with Korea em-

phasizing advanced analytics and system interoperability compared to other regions. Our findings, which underscore the high centrality of innovation and artificial intelligence in Korean discourse, align with these global trends but also reveal unique local priorities and cultural influences.

In conclusion, the findings illuminate the multifaceted impacts of digital transformation, offering diverse perspectives on technological changes, social, and economic transitions as manifested through online news and blogs. The real-time feedback and variety of user content on social media are valuable for policymakers, entrepreneurs, educators, and the general public to understand the advancements in digital technology and how these can be applied to their fields and lives. The insights and user engagement provided by social media data can lead to the development of innovative approaches and strategies that guide the digital transformation era, contributing to socially meaningful conversations about upcoming technological changes.

6. Conclusions

This study leveraged text mining techniques and a semantic network analysis to extract keywords and their associations from social media data, online news, and blog content related to digital transformation. Focusing on Korean language data, it intensively collected data from major Korean portal sites using "digital transformation" and related search terms, ensuring the selection of keywords and consistency of data by exclusively targeting content in Korean.

Despite some limitations, the analysis of Korean data collected from Korean portal sites offers insights into digital transformation, contributing to a comprehensive understanding of various aspects related to the advancement of digital technologies, social changes, and economic impacts. The insights derived from this study provide essential foundational data for in-depth analysis of the continuous development of digital technologies and their impacts on individuals, corporations, and society.

Furthermore, the results can serve as an important reference for strategic planning and policy development related to digital transformation. The data and analysis will offer valuable information to policymakers, entrepreneurs, and academic researchers in integrating digital technologies, seeking social adaptation strategies, and exploring economic sustainability.

To enhance the practical relevance of these findings, we plan to incorporate feedback from industry experts through structured interviews and align our results with documented case studies. It will bridge the gap between theoretical research and practical applications, ensuring that our insights are grounded in real-world experiences and contribute to the development of actionable and effective strategies in digital transformation.

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