Examining Korean political figures using co-word analysis in agreement with facial expressions in posted self-images*

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This study combines online image content analysis and text content analysis of the homepages of political figures, specifically South Korean National Assembly members. The study attempts to explore the relations between (1) the types of facial expressions present, using the official photographs on the members’ homepages, (2) the textual contents of self-posted public profiles, again using members’ homepages, (3) members’ socio-political-demographic attributes, and (4) their web visibility and link counts on popular websites.

In a previous study, we examined the emotional content contained in facial pictures of South Korean politicians. The results suggested significant patterns between facial expressions, web visibility and the socio-demographic attributes of politicians. In this paper, we further explore the textual contents of members’ homepages using co-word analysis techniques to ascertain to what extent textual contents are in agreement with facial expressions in posted self-images. In addition, having employed co-word analysis we attempt to derive a strategic diagram of the 18th National Assembly based on clusters of key phrases and words

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Examining Korean political figures using co-word analysis in agreement with facial expressions posted on the members’ homepages. This approach allows us to investigate central and peripheral clusters of keywords and their distribution considering members’ socio-political-demographic attributes.

**Keywords:** Visual Content Analysis; Emotional Content Analysis; Online Visibility; Web-based Campaigns; Facial Expressions; Candidate Web-sites; Co-word Analysis.

1. **Motivation**

In a previous study, we examined the emotional content contained in the facial pictures of South Korean politicians [14]. Data were collected from the official homepages of South Korean 18th National Assembly members. We classified facial expression types (smiling, frowning, no expression) using the official photographs on members’ homepages. Previous findings showed that (i) smiling is the most prevalent facial expression on the web pages of South Korean politicians, regardless of their socio-political-demographic attributes; (ii) the existence and strength of a smiling image has a statistically significant positive correlation with politicians’ web visibility count; (iii) opposition party members exhibit significantly more frowning faces and expressionless faces compared to those from the ruling party; (iv) more experienced politicians, contrary to their less experienced colleagues of similar generations, keep smiling regardless of party position. In the current study, we specifically address the following core research question:

To what extent are the online textual contents of politicians’ homepages in South Korea in alignment with the facial expressions in posted self-images?

In other words, by adopting a co-word analysis we identify the issues that appear within online political debates. Co-word analysis allows us to categorize those emerging issues as (i) peripheral, (ii) hot issues, (iii) emerging or (iv) fading. Adopting the extended method of conventional co-word analysis proposed by Ozel (2010), we also similarly categorize politicians based on their individual contributions to issues in the online political arena. This method enables us to test whether their choice of facial expressions is related to the type of issues on which they focus. In order to examine relevance of politicians web visibility and their received web link count in comparison with the above issue categorization, we further address following auxiliary research question:

To what extent is web visibility and web link count relevant to the choice of issues debated by South Korean politicians?

In this study, we enhance our discussion of these research questions using a set of descriptive analysis tools. We employ a meta-network analysis to examine the semantic relations between individual keywords as well as the cognitive attributes of politicians in relation to each other. The adoption of meta-network analysis for this research is not extensive; nevertheless it does suggest potential future research extensions.
2. Methods

2.1. Meta-Network Analysis

In this study, web data is used to extract network relations. Two primary relations are extracted: the semantic network (KxK), and the cognitive network (PxK). In short, if two keywords appear on the same web page of a politician, then semantic relations can be formed between frequent keywords or phrases. Similarly, when cognitive mapping each politician, their political agenda is derived from the set of keywords he/she has publicized on his/her web site. This meta-network perspective, allows us to observe and analyze cascaded influences across the interrelated semantic and cognitive networks [4].

2.1.1. Metrics

Below, the set of metrics used to conduct network analyses is reported.

- **Degree Centrality**: this is used to quantify the relative number of direct semantic relations an issue has with other issues discussed by politicians. This score relates the relative number of semantic relations a keyword in the set has so far. It was adopted from the regular degree diffusion measure of Wasserman and Faust [19].

- **Between Centrality**: betweenness measures connections to the parts of a network separate from direct connections [6]. It is another means of assessing the centrality of a debate keyword. The betweenness of a keyword is computed by measuring the number of times that connections to other keywords pass through it.

- **Eigenvector Centrality**: this reflects a keyword’s connections to other well-connected keywords [2]. Roughly, this metric measures the importance of the theme or concept represented by a keyword. Eigenvector centrality in this work mainly serves to generate combined tag clouds of concepts and politicians in order to reveal important figures and themes in Korean politics.

- **Cognitive Distinctiveness (CD)**: Cognitive Distinctiveness [4] measures how distinct a politician is, based on the number of distinct issues mentioned on his/her website, compared to other members.

- **Cognitive Similarity (CS)**: Cognitive Similarity [4] estimates the degree to which a politician debates on issues compared to his/her peers.

2.2. Co-word Analysis

Relations as established and observed by a Knowledge Network (KxK) consider keywords to be the atomic unit of analysis. However, this does not present or visualize abstracted semantic relations between groups of keywords. Co-word analysis provides this higher level abstraction.

Co-word analysis is a content analysis technique developed to study relationships between ideas within the subject areas presented in published documents [9]. Co-word analysis is based on the theory that research fields can be characterized and analyzed based
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on patterns of keyword usage in publications [12]. Analysis is based on the co-occurrence frequency of pairs of words or phrases. Either a single word or a set of words forming a phrase may denote a key subject, a main theme or a basic concept. Co-word analysis is then employed to discover linkages among subjects or concepts in a field. The overall structure of linkages is used, for instance, to trace the development of a field over time. This technique has proved to be a powerful knowledge discovery tool when deriving maps of a science from bibliographic databases [12; 9;11; 3].

Co-word analyses progress by a sequence of steps: data selection, data pruning and information coding processes followed by statistical and algorithmic analyses of retrieved information. Briefly, the first stage comprises extracting keywords from each document in a data set. Then a co-occurrence matrix of keywords is generated. Various features of resulting co-occurrence matrix are analyzed statistically or algorithmically, based on the research question involved.

As different questions can be raised about interactions and relations between key-words within a political debate the co-occurrence matrix, or matrices in some longitudinal studies, is subjected to additional operations. Most uses of the method employ and adopt multivariate statistical techniques to discover and examine clusters of keywords that co-occur in the literature [3; 12].

The keywords can be extracted from webpages. Keywords, which appear together in the same publication are used while forming a cluster. A cluster, formed by one or more words, is then treated as representing a concept or a specific political theme, i.e., a debate issue.

Almost all of the recent studies employing co-word analysis have generated a strategic diagram to visualize the overall structure of the specific social domain [1;5;15] or the scientific field under examination [10; 17]. In order to derive a strategic diagram, we determine the diffusion and cohesion values of each cluster.* Diffusion of a cluster shows how strongly each keyword or phrase within the cluster is linked to other cluster keywords or phrases, whereas cohesion shows how strongly each keyword within the cluster is linked to others within the same cluster. Each cluster is then mapped on a strategic diagram based on its normalized diffusion and cohesion values. The resulting strategic diagram is a two dimensional Cartesian map, wherein the horizontal axis usually denotes diffusion and vertical axis denotes the cohesion of the field under examination. The origin of the axis is the intersection of median or mean diffusion and cohesion values.

Thus, if a cluster has relatively high diffusion and cohesion it is assumed to be central hot topic. If a cluster has both very low cohesion and very low diffusion, it is assumed to be peripheral. Alternatively, a cluster with high diffusion but low cohesion implies that although the subject is central to the debate it is underdeveloped, while a cluster with low diffusion and high cohesion implies that although the subject is very well debated, it is

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*In Co-word Analysis literature, diffusion is referred to as Centrality and Cohesion is referred to as Density. Herein, so as not to confuse them with conventional Social Network Analysis measures of Centrality and Density, we opted to rename them Diffusion and Cohesion.
not central or has not become mainstream so has a marginal importance to the political
debate.

2.2.1. Clustering

The conceptual clustering of themes is derived from raw co-occurrence data; in other
terms, KxK relations are derived from webpages. In order to derive or form clusters of
themes, an equivalence index \( E_{ij} \) for each pair of themes is calculated [12;9;11]. The
equivalence index \( E_{ij} \) measures the strength and proximity of two themes \((i,j)\) in the po-
litical arena based on their co-appearance in a webpage. Equation 1 shows the computa-
tion of strength between two given themes (He, 1999):

\[
E_{ij} = \frac{CC^2}{C_i \times C_j},
\]

where,

\(C_i\) = frequency of \(i\) in the set,
\(C_j\) = frequency of \(j\) in the set
\(C_{ij}\) = co-occurrence frequency of \(i\) and \(j\) in the set

Having computed the equivalence of each pair of themes, all of themes are grouped
into clusters. There are various clustering algorithms that can be applied to generate con-
ceptual group of themes. Clustering methods, in general, attempt to find groups of themes,
wherein the sum of intra-cluster equivalence values of themes within the same cluster
are maximized and the sum of inter-cluster equivalence values between themes from dif-
f erent clusters are minimized. However, there are two distinct approaches to clustering:
top-down and bottom-up. The choice of one approach over the other may result in signifi-
cant differences and interpretations dependent on the research questions involved. In the
top-down approach, the number of ‘desired’ clusters is predetermined and algorithms are
forced to partition themes into this number. In the bottom-up approach, the number of
clusters emerges based on the distribution of proximity between items.

In this study, Ward’s clustering algorithm is used [7]. This clustering method measures
Euclidean distances between themes based on their mutual equivalence values. This choice
is based on the exploratory nature of the case of this study; Ward’s method was chosen so
as to be able to detect an initially unknown number of theme clusters. For the analysis, the
R Statistical Tool and a Software (R) implementation of Ward’s bottom-up agglomerative
clustering algorithm was run.

2.2.2. Positioning Clusters of Themes on a Strategic Diagram

The diffusion and cohesion of each theme cluster (issue) is computed using classical
co-word analysis. A theme cluster can be taken to be a political issue. It should be noted
that on one hand a cluster may consist of a single theme, phrase or keyword, dependent on
how its prominence within the data set emerges; on the other hand it may include a large number of themes which are conceptually not very related to each other within the field. In most cases wherein there is a large number of themes, such an ‘outliers’ cluster is present, usually positioned as peripheral.

Diffusion of a theme is a measure that indicates how much a cluster or an issue is discussed within the debate alongside other issues. It is computed as follows [12]:

\[
D_{\text{cluster}} = \frac{\sum_{i=1}^{E_{ij}} \sum_{j=1}^{E_{iw}}}{n(N-n)}
\]

where,
\[
D_{\text{cluster}} = \text{Diffusion of the cluster}
\]
\[E = \text{Equivalence index of word pair link}\]
\[i = \text{First word in the pairing, internal to the cluster}\]
\[w = \text{Word in dataset, but not in cluster}\]
\[N = \text{Total number of unique words used in titles within the data set}\]
\[n = \text{Number of unique words in the cluster}\]

Cohesion of a theme is a measure that indicates the extent to which a cluster or an issue is studied repeatedly within a cluster. It is computed by the metric given in Neff and Corley (2009: p. 666):

\[
C_{\text{cluster}} = \frac{\sum_{i=1}^{E_{ij}} \sum_{j=1}^{E_{ij}}}{n(n-1)/2}, \text{ when } n > 1;
\]
\[
C_{\text{cluster}} = \sum_{i=1}^{E_{ij}} \sum_{j=1}^{E_{ij}}, \text{ when } n = 1
\]

where,
\[
C_{\text{cluster}} = \text{Cohesion of the cluster}
\]
\[E = \text{Equivalence index of word pair link}\]
\[i = \text{First word in the pairing}\]
\[j = \text{Second word in the pairing}\]
\[n = \text{Number of unique words in the cluster}\]

Note that the measure in Equation 3 also accommodates a cluster with a single theme, which simply yields the overall frequency of the word within the set.
There are various other diffusion and cohesion measures used and applied in the literature. The choice of the diffusion equation above was chosen so as to have a correcting advantage for the significant variances of Web page contents. The equation neutralizes the distorting impact of sites with inflated number of keywords [12].

2.3. Mapping Politicians onto Strategic Diagram of Issues

Application of a conventional strategic diagram would be deficient in the sense that it would isolate issues from their spokesperson, and would thus not fully capture how a voice is enacted within the debate. In other words, it would not show how a politician’s effort is divided between mainstream and peripheral issues within a political agenda.

We adopt a new method to overcome the aforementioned deficiency [13], which combines meta-network analysis and conventional co-word analysis clusters. While it detects cluster of issues and maps them on a strategic diagram, it also employs a PxK matrix to compute the contribution of each politician to each identified cluster. The method is simply a re-generation of strategic mapping of a field that considers the authors within this field. That is, it develops a metric in order to find each author’s Diffusion and Cohesion. In that sense, it parallels conventional strategic diagrams. Equations 4 and 5 are respectively used to identify the diffusion and cohesion of each politician.

(Equation 4)

\[
P_{D_{\text{politician}}} = \sum_{p} \frac{1}{a_p} \left( \frac{\sum_{i=1, j=1}^{E_{ij}}(E_{iw}/C_{iw})}{n(n-1)/2} \right)
\]

where,

\( P_{D_{\text{politician}}} = \) Diffusion of the politician
\( P = \) Set of Web pages by the politician
\( E = \) Equivalence index of word pair link
\( C_{ij} = \) co-occurrence frequency of i and j appearing on the same Web page.
\( N = \) Total number of unique words used on the Web pages
\( p = \) current page in the set
\( a_p = 1 \)
\( i = \) First word in the pairing, internal to the cluster
\( w = \) Word in dataset, but not in the cluster
\( n = \) Number of unique words in the cluster

This equation sums the contribution of each politician’s webpage to each issue. It examines these pages and the distribution of keywords within them across the clusters in the field. Using this cluster assignment information for each keyword, each politician’s...
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contribution to a cluster is shown. The other way around, the metric can be interpreted as distributing back the portion of each politician’s contribution to theme clusters, where the share is represented by a tuple, the diffusion of the issue and cohesion of the issue.

(Equation 5)

\[
P_{C_{\text{politician}}} = \sum_{p} \frac{1}{a_p} \left( \frac{\sum_{i,j=1}^{E_{ij}} (E_{ij}/C_{ij})}{n(n-1)/2} \right) \text{ for } n > 1
\]

\[
P_{C_{\text{politician}}} = \sum_{p} \frac{1}{a_p} \sum_{i,j=1}^{E_{ij}} (E_{ij}/C_{ij}) \text{ for } n = 1
\]

where,

\( PC_{\text{politician}} = \text{Cohesion of the politician} \)

\( P = \text{Set of Web pages by the politician} \)

\( E = \text{Equivalence index of word pair link} \)

\( C_{ij} = \text{co-occurrence frequency of i and j appearing on the same Web page.} \)

\( N = \text{Total number of unique words used on the Web pages} \)

\( p = \text{current page in the set} \)

\( a_p = 1 \)

\( i = \text{First word in the pairing} \)

\( w = \text{Second word in the pairing} \)

\( n = \text{Number of unique words in the cluster} \)

Based on this new pair of metrics, the model finds politicians’ positions on the strategic map. The axis of the politician strategic map is recomputed based on the average diffusion (PD) and cohesion (PC) of politicians. It should be noted that the strategic map of politicians and the strategic map of knowledge in the field are not necessarily the same two dimensional space. They are rather parallel and dual maps.

3. Data

The data consists of socio-demographic information on members of South Korea’s 18th National Assembly, which was elected in April 2008. The images were drawn from members’ official homepages. Besides this, the occurrence frequencies of the most common political issue phrases were retrieved from their webpages. Additionally, the website size for each politician and their Naver and Yahoo link counts were retrieved and recorded. This study analyzed 272-77 out of a total of 292 members, as of 13 August 2009.

Facial expression classification is given in Table 1. The facial expressions of images were coded by 2 coders. The inter-rater reliability of coding was computed, showing an
acceptable reliability both by Krippendorff’s Alpha ($> 0.7$) and percent agreement ($> 0.9$) methods [8].

4. Results

4.1. Clouds of Key Issues and Politicians

Figure 1 displays frequent keyword clouds for Korean politicians’ websites. It should be noted that the names of the most central politicians associated with respective keywords are also displayed. The visualization is driven by semantic network (KxK) relations between keywords as well as the cognitive map (PxK) of politicians. Here a semantic relation is assumed when a keyword pair co-occurs on the same webpage. Similarly, the cognitive map of a politician is driven by a set of keywords and occurrence frequencies of those keywords observed on his/her Web site. In this respect, the cognitive map of an individual simply implies his/her political agenda as presented on his/her Web page.

Figure 1 is produced considering the degree centrality of keywords and politicians simultaneously using a (PxK) matrix. We have also produced similar clouds employing eigenvector and betweenness centralities. However, the results were not significantly different and therefore are not shown.

4.2. Cognitive Differences

We aim to observe the cognitive properties of politicians with respect to others in the assembly based on the issue categories mentioned on their Web sites. In terms of their cognitive distinctiveness, we were not able to observe any significant differences. That is, counter intuitively, cognitively distinct politicians are distributed evenly in terms of mainstream and peripheral issue division. However, politicians with higher cognitive similarity values mostly debate mainstream issues. Figure 2 displays the distribution of cognitive
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**Figure 1**
Clouds of key issues and politicians with total degree centralities

**Figure 2**
Distribution of cognitive distinctiveness of politicians in the assembly
Figure 3
Dendogram of webpage keywords in Korean politics

Dendogram of Concepts in Korean politics
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distinctiveness between Korean politicians. It should be noted that this figure holds only for the issues posted on their websites.

4.2. Issues

Using keyword co-occurrence frequencies, a dendogram of issues is derived. The result is given in Figure 3, with Ward’s bottom-up hierarchical algorithm used. This algorithm helps to detect emerging debates as reflected on politicians’ webpages. Issue clusters are identified, and results are tabulated in Tables 2 and 3.

Figures 4 and 5 further display the distribution of diffusion and cohesion values for each emerging clustered issue. The diffusion and cohesion values result from co-word analysis.

4.4. Strategic Diagram of Issues

It should be noted that Cohesion and Diffusion axes are placed by computing mean diffusion and mean cohesion in the field. These measures, along with visualizations of clusters on the strategic map, are accomplished by developing and coding a new co-word analysis package for R. Figure 6 indicates that a set of issues (5, 16, 9) dominates in Korean online politics. Clusters 5, 16, 9 together imply that most politicians online primarily pres-

<table>
<thead>
<tr>
<th>ID</th>
<th>Diffusion</th>
<th>Cohesion</th>
<th>Size</th>
<th>Issues</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8.59</td>
<td>42.87</td>
<td>18</td>
<td>South Korea; Promotion; President; Polity; Policy; North Korea; Local Government; Education; Diplomacy; Debate of Policy; Debate Forum; Citizen; Business; Budget; Bill; Anti-Government; 4-Rivers</td>
</tr>
<tr>
<td>2</td>
<td>5.61</td>
<td>152</td>
<td>2</td>
<td>Mayor; Administration</td>
</tr>
<tr>
<td>3</td>
<td>4.24</td>
<td>4.6</td>
<td>41</td>
<td>Woman; We; Union; Ulsan; The Whole Country; Local Tax Law; The Disabled; Special Local Tax; Special Law; Special Bill; Small And Medium Sized Business; Rice; Regulation; Public Institution; Prosecution; Problem; Prime Minister; Ordinary People; Ministry Of Unification; Ministry Of Labor; Ministry Of Environment; Major Company; Job; Japan; Internet; Gyeongbuk; Gwanju; Governor-General Of Gyeonggi Province; Floor Leader; Feeding For Free; Educational Expenses; Economy; Detention; Daegu; Congress Person; Civil Servant; Child; Chairperson; Busan; Attention; Announcement</td>
</tr>
<tr>
<td>4</td>
<td>3.24</td>
<td>26.33</td>
<td>4</td>
<td>Myung-Bak Lee; Munlwa Broadcasting Corporation; Blue House; Assembly</td>
</tr>
</tbody>
</table>
Table 3
Clusters of Issues (5-16): Clusters based on Ward’s agglomerative clustering

<table>
<thead>
<tr>
<th>ID</th>
<th>Diffusion</th>
<th>Cohesion</th>
<th>Size</th>
<th>Issues</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>22.93</td>
<td>343.17</td>
<td>4</td>
<td>Work; Party; Congress; Assembly Member</td>
</tr>
<tr>
<td>6</td>
<td>2.45</td>
<td>64</td>
<td>2</td>
<td>Kyeongbuk; Candidacy</td>
</tr>
<tr>
<td>7</td>
<td>5.81</td>
<td>34.48</td>
<td>7</td>
<td>The Governing Party And The Opposition Party; Se-Jong City; Public Recommendation; Local Election; Great Park; Election Candidate</td>
</tr>
<tr>
<td>8</td>
<td>3.74</td>
<td>83</td>
<td>2</td>
<td>Sinking; Cheonan Ship</td>
</tr>
<tr>
<td>9</td>
<td>9.8</td>
<td>238</td>
<td>2</td>
<td>Democratic Party; Democracy</td>
</tr>
<tr>
<td>10</td>
<td>1.9</td>
<td>52</td>
<td>2</td>
<td>Special Taxation; Establishment</td>
</tr>
<tr>
<td>11</td>
<td>1.49</td>
<td>40</td>
<td>2</td>
<td>KCC; H1N1</td>
</tr>
<tr>
<td>12</td>
<td>6.63</td>
<td>164</td>
<td>2</td>
<td>Legislative Bill; Law</td>
</tr>
<tr>
<td>13</td>
<td>8.43</td>
<td>87.67</td>
<td>4</td>
<td>Revision; Representative Proposal; Proposal; Leader</td>
</tr>
<tr>
<td>14</td>
<td>1.41</td>
<td>28</td>
<td>2</td>
<td>Retirement Annuity; Mayor Of Seoul</td>
</tr>
<tr>
<td>15</td>
<td>1.5</td>
<td>40</td>
<td>2</td>
<td>The National Assembly Law; Seoul</td>
</tr>
<tr>
<td>16</td>
<td>12.65</td>
<td>313</td>
<td>2</td>
<td>The Grand National Party-Hanara; The Grand Nation</td>
</tr>
</tbody>
</table>

Figure 4
Distribution of diffusion values for issue clusters
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ent themselves as assembly members and mention their party affiliation. It is further seen that there is relatively a large number of issues (i.e. 11, 14, 15) that are of relatively peripheral importance compared to others.

4.5. Politicians on the Strategic Diagram

After having mapped politicians to a strategic diagram based on their contributions to clusters, we test whether any combination of facial expressions expressed via online images and the types of issue posted on webpages is relevant. The distribution of facial expressions onto quadrants of the strategic diagram is displayed in Figure 7. This distribution mimics the distribution of issues to quadrants as seen in Figure 6. This implies that no significant relations exist, with test results supporting this.

However, the results in Figure 8 show that there is correlation between the number of links a politician’s page receives and the category of political issues he or she engages with online. Figure 9 further hints a similar correlation between the online visibility of a politician and the issues with which she/he engages online. Those who post on hot issues or of-
Figure 6
Strategic map of Korean politics

Figure 7
Distribution of the facial expressions of politicians on different quadrants
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**Figure 8**
The distribution of in-link counts for politicians’ webpages in different quadrants

**Figure 9**
Web visibility distribution of politicians in different quadrants
tend present themselves receive a high number of links to their webpages and receive more hits on major national web portals. On the other hand, those who publish on ‘peripheral’ issues may receive more or less links compared to others, dependent presumably on the specific issues in question.

5 Conclusion and Future Directions

This work demonstrates how politicians’ choices in online images and the issues engaged with can be examined concurrently. In this study, we were not able to observe any significant relation between facial expressions and strategic categories of issues selected within political debates. However, the devised method, which maps politicians to strategic diagrams, is promising and could be refined for more detailed future analysis.

The current case study, nevertheless, shows that in the Korean assembly, members who post on hot issues or frequently present themselves receive a higher number of links to their webpages and accrue more hits on Naver.com, the major national Web portal. On the other hand, those who publish on ‘peripheral’ issues may receive more or less links compared to others, dependent on the issues with which they engage.

This study can be extended and repeated in different settings. Its method could be employed to conduct micro-level analyses, such as examining relations between the cognitive properties of individual politicians and the prevailing facial expression types they post on their websites. Moreover, the cognitive properties of individuals, i.e. their political party membership or their demographic attributes can be studied. The study could be further extended by incorporating any relevant social interaction information between politicians, for example, via retrieving data from online social media related to politics [10, 18].

References


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