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TEXTUAL ANALYSIS FOR DEVELOPING FUZZY COGNITIVE MAPS – THE CASE OF STRATEGY MAPS

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ABSTRACT

Expert opinions have been applied to construct fuzzy cognitive maps (FCMs) to support the process of strategic planning. FCMs are beneficial tool to represent strategy maps due to their capacity to model causal-effect relationships among the key strategy concepts. To overcome the problem of rather subjective expert evaluation of the relationships, automatic knowledge acquisition is preferable. Moreover, the causal-effect relationships evolve dynamically and are context-specific. Here, the knowledge acquisition is performed to obtain knowledge on causal strategic concepts. This knowledge is extracted from strategic documents. This approach has two major steps. First, latent semantic analysis is employed to obtain an interpretable semantic model. Second, collocated causal concepts are used to model relationships among strategic concepts. This approach also requires theoretical background literature/domain experts to determine the direction of the causalities. The generated FCMs can subsequently be used to simulate the effects of strategic management and, thus, provide an effective decision support tool. Several innovation strategies of regions for two periods are used as a case study. To verify the proposed approach, it is demonstrated that the generated FCMs are consistent with expert opinions and fuzzy ANP method. The analysis of the dynamic evolution of the FCMs also shows how strategic priorities change over time.

Keywords: *Fuzzy cognitive map, Business strategy, Textual analysis, Innovation strategy*

1. INTRODUCTION

Researchers and practitioners have witnessed rapidly growing interest in fuzzy cognitive maps (FCMs). This has been largely triggered by the ability to utilize expert knowledge in causal cognition models, which makes the FCM particularly effective for knowledge representation and decision support [1]. In fact, the FCM [2] is a version of the cognitive map generalized for situations where knowledge representation is uncertain and imprecise. More specifically, it is used when the causality between concepts cannot be described precisely owing to high complexity or data unavailability. This holds true for many fields of application, ranging from traditional ecology and environmental management to engineering and information systems [3], [4]. In business domain, the applications include, among others, the design of balanced scorecards [5], performance management [6], knowledge management modeling [7], supplier selection [8], customer relationship management [9], project management [10] or production management [11].

Despite this interest, far too little attention has been paid to the utilization of FCMs in strategic planning. Indeed, both the concepts and strength of causalities remain unclear and context-sensitive in business strategies. Moreover, rapidly changing environment requires from management to continuously adapt their objectives and revise strategic plans. The introduction of strategy maps

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was reported as a great progress for the organizational performance measurement systems [12]. Strategy maps are used to represent causal-effect relationships among the key components of an organization's strategy [13]. They can be used for describing strategy, thus promoting its communication and understanding. The causal-effect relationships are crucial because strategy balances contradictory priorities and it consists of simultaneous complementary concepts. However, traditional strategy maps suffer from several shortcomings [12]. First, static strategy maps do not correspond to dynamically changing environment. Second, tools with simulation capabilities are necessary to calculate the effects of intended strategic measures. Finally, predictions of future impacts always addresses the issue of uncertainty. Moreover, the cause and effect relationships themselves are strongly associated with uncertainty as more causes can lead to the same effect with different levels of influence. FCMs have therefore been used to accommodate this fuzziness in the causal relationships of strategy maps [12]. Hence, FCM was chosen also in this study because it is one of the most practical ways to model this uncertainty in causal relationships.

The main issue to be addressed when designing a FCM for strategic planning is the choice of concepts in the FCM and the quantification of causal relationships between these concepts. Previous efforts to develop FCMs for strategic planning was limited to expert opinions [12]. Causal relationships in business and economics evolve dynamically; moreover, they are context-specific. This makes automatic knowledge acquisition preferable. To the best of the knowledge available, no automatic (or semi-automatic) knowledge acquisition has been developed for strategic FCMs in previous literature. Here, the research approach was based upon a contextual analysis of innovation strategy priorities. The advantage of this approach is a semi-automatic generation of FCMs from the text of innovation strategic documents. In the proposed approach, content and collocation analyses are used to create the structure of FCM and expert knowledge is utilized to determine the directions of causal relationships between regional innovation strategic priorities. It is demonstrated that both strategic priorities and causal relationships between them can be extracted from strategic documents. In addition, FCMs can be utilized to simulate the effects of strategic priorities achievement and, thus, support strategic decision-making processes. Furthermore, it is also showed that the generated FCMs are in strong agreement with the knowledge acquired from experts. This is an extended version of the conference paper [14]. Compared to the previous version, here we study the dynamics of strategy maps in more detail by exploring strategy maps for two periods in the case study. We also provide some more insight by performing additional sensitivity analyses of the FCMs.

The paper is structured as follows. The next section presents research methodology, including theoretical background on FCMs as a tool for supporting strategic planning. It also shows how an FCM can be constructed using textual analysis of strategic documents. Further, empirical research on strategic programming for regional innovation strategy is presented based on a case study of Polish regions. The paper ends with conclusions and implications.

2. RESEARCH METHODOLOGY

The research methodology of this study is depicted in Figure 1.

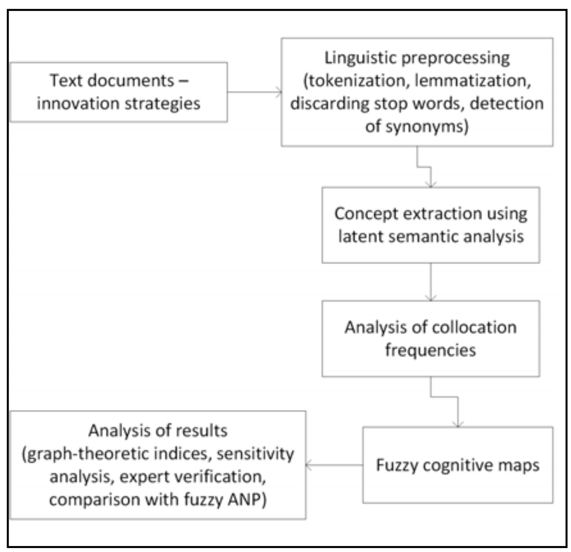

Figure 1: Research Methodology

For the purpose of this study, text documents containing innovation strategies were collected for Polish regions (all documents were in English). Linguistic preprocessing was carried out first in order to perform the LSA (latent semantic analysis). This step included tokenization, lemmatization, and discarding the stop words and the least frequent words in the corpus of documents, see [15] for details. Thus, a set of potential term candidates was obtained. This analysis was performed in the RapidMiner 5 programming environment. The detection of

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synonyms represented another issue to be addressed. The WordNet ontology [16] was also used for this task. This ontology also enabled finding the correct sense of the terms for the domain, where the terms with the highest score for the "economy" domain were chosen. The tf.idf term weighting scheme [17] was used to extract the weights of terms w_{ij} in the corpus of documents:

$$w_{ij} = \begin{cases} (1+\log(tf_{ij}))\log\dfrac{N}{df_i} & \text{if } tf_{ij} \geq 1 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where N is the total number of documents, tf_{ij} is the frequency of the i-th word in the j-th document, and df_i is the number of documents with at least one occurrence of the i-th term. Top 1000 terms with the highest weights w_{ij} were chosen using this term weighting scheme. This number is considered sufficient in related text mining applications [18].

Next, singular value decomposition (SVD) was performed as a standard method to extract the concepts in LSA. SVD was selected for several reasons. First, this method combines the original terms in order to capture the meaning of the underlying concepts. Second, the structures and links between the concepts can be detected. Third, SVD deals effectively with the heterogeneity in the data. The resulting concepts can be interpreted by means of the keywords with the highest contributions. Moreover, the frequency of concept-related terms in the innovation strategies were used to estimate the degrees of strategic priorities.

In the next step, the collocations of the relative frequency of the keywords that represent the causality between concepts were obtained. The analysis of collocation frequencies was performed with Voyant Tools [19]. The directions of the causalities were determined based upon the theoretical background literature.

In an FCM, fuzzy weights with positive/negative signs represent causal relationships between concepts. The activation degree A_i of concept C_i is the sum of all incoming edges multiplied by the values of the preceding concepts:

$$A_i^{t+1} = f\Big(A_i^t + \sum_{\substack{j=1 \\ j\neq i}}^{n} A_j^t \times E_{ji}\Big) \quad (2)$$

where A_i and A_j stand for the degrees of activation of the concepts C_i and C_j, respectively; t denotes time; and f is a threshold function. A directed edge, E_{ij}, determines how much C_i causes C_j and lies in the fuzzy causal interval [-1, 1], where $E_{ij} > 0$ denotes a positive causality, $E_{ij} < 0$ refers to a negative causality, and $E_{ij} = 0$ indicates no causality. For n concepts C_j, i = 1,2, …, n, an $n \times n$ weighted (adjacency) matrix **E** can be constructed.

In general, FCMs can be constructed using three broad methods [20]: (1) acquiring knowledge from experts via questionnaires or interviews, (2) designing FCMs using text analysis, or (3) constructing them from data. However, there are also several difficulties associated with these approaches. Text analysis requires an understanding of natural language semantics. Moreover, causal relationships may be stated implicitly in the text. Constructing FCMs from data, on the other hand, has been extensively investigated recently (see [21] for a review study). In particular, population-based optimization algorithms such as genetic algorithms and particle swarm optimization have attracted considerable attention [22]. However, this approach requires data that reliably approximate the investigated concepts [23]. This is increasingly difficult in business strategy domain because, for example, knowledge is an essential strategic factor that is difficult to measure.

To address these issues, a novel approach is developed that employs text analysis to obtain data depicting the causal concepts. This is based on the assumption that causally connected concepts are collocated in the text [24]. More specifically, this approach calculates the difference between the relative frequency of the collocates near the keywords and the relative frequency of the collocates in the entire document. Thus, higher values indicate that the concepts are more closely associated. The keywords representing the concepts were extracted from text documents using LSA [25].

After the FCM was drawn from textual documents, it was encoded into the adjacency matrix **E**. Then the structure of the FCM was analyzed using graph-theoretic indices. Finally, various policy options were simulated using an autoassociative neural network computation for the FCM using the FCMapper software tool [20]. The goal of this step is to determine whether the system is in a steady state. In the neural network, the initial concepts' states are multiplied by the adjacency matrix **E** according to Eq. (2). The total input of each neuron is calculated in this way. The total output is then a function f of the total input. A logistic function 1/(1+exp(-1×x)) was used to transform the values into the interval [0,1]. The resulting vector was then repeatedly multiplied by the adjacency matrix **E** and transformed until the system entered a stable state. To verify the design of the FCM based on text analysis, local domain experts were asked to assign directions and weights to the causal relations.

3. CASE STUDY

In a case study, innovation strategies in Polish regions are examined. Innovation strategies at the regional level is one of the key factors involved in socioeconomic development, especially in the context of the European Union. Previous research has indicated that innovation strategies are the result of complex interactions between various regional actors and institutions. At the same time, issues of an effective and efficient regional innovation strategy have become strategically important in Central and Eastern Europe [26].

A regional innovation strategy is usually developed in three stages [27]: (1) building up consensus, (2) analyzing the region's innovation potential, and (3) defining priorities and an action plan. The analysis was based on the content of the innovation strategies for two periods, in the years 2005 and 2013, in the following Polish regions (NUTS II level): the Śląskie Region, the Podkarpackie Region, the Małopolskie Region, and the Dolnośląskie Region. Thus, the corpus included four strategic documents, ranging from 7705 (Dolnośląskie) to 48988 words (Małopolskie) in the year 2013. The most frequently used terms were "regions", "innov", "develop", "project", "technolog" and "implement", respectively. Using LSA, the following concepts were identified: (1) material infrastructure, (2) entrepreneurship, (3) R&D, (4) networks/clusters, (5) learning/education, and (6) a culture of innovation. Those concepts were chosen with singular values greater than 1. Table I shows the concepts represented by the keywords with the highest word coefficients. Finally, the concepts were labelled based on the keywords.

The relationships between the extracted concepts were further determined. The strengths of the relationships were defined on a scale of [-1, 1] using collocation frequencies in Voyant Tools [19]. Specifically, a collocation analysis was performed with keywords for each concept (as presented in Table I) to detect keywords for the remaining concepts. Only those were included occurring within five words coming before/after the respective keyword. The sum of collocation frequencies for the whole corpus was scaled to [0, 1] and rescaled to [-1, 1] depending on the positive/negative directions of the relationships.

Table 1: The Concepts Identified by LSA.

Concept	Keywords
Culture of Innovation (CI)	innov, pro-innov, high-technolog, knowledge, creativ
Entrepreneurship (EN)	business, compani, commerci, industri, SME, entrepreneuri
Networks / Clusters (N/C)	network, co-use, diffus, neighbour, cooperat, partner, cluster, transfer
Strategic Priority (SP)	strateg, action, support, council, committe, polici, prioriti, object
Research and Development (R&D)	research, scienc, scientif
Learning / Education (L/E)	educ, univers, train, student, school, learn, academi, skill, teach

As mentioned above, the directions of the relationships were based upon the conceptual studies. Specifically, the following sets of edge directions were used: (1) MI->N/C, EN, CI, R&D, L/E; (2) N/C->EN, CI; (3) CI->EN; (4) L/E->EN, N/C, CI, R&D; (5) R&D->CI, EN. Note that those relationships were not included for which no theoretical justification was available.

First, regarding the effect of material infrastructure, innovation centers/industrial parks provide an appropriate material infrastructure and resource network for the creation of spin-offs and high-technology start-up firms [28]. Moreover, innovation centers also serve as a source of local networks of collective learning [29]. It was also demonstrated that ICT infrastructure both operates as efficiency-enhancing technologies and has the potential to create competitive advantage through product innovation [30].

Second, it was found that clusters do have a significant impact on entrepreneurship at the regional level [31]. Moreover, networks/clusters represent a natural environment to (open) innovation generation. For example, locating in the industry cluster enhances firm innovation [32]. Third, recent studies suggest that knowledge and innovation play a key role in shaping the creation of innovative start-ups [33]. In fact, new knowledge and ideas represent an important source of entrepreneurial opportunities in the knowledge spillover theory of entrepreneurship [34].

Fourth, learning and education (human capital) is an important driver of entrepreneurship [33], knowledge networks in clusters [35], regional innovation activity [36], as well as R&D activities [37]. Fifth, R&D activity (usually measured as R&D investment) has been recognised as a significant determinant of innovation performance in previous studies because it estimates the level of knowledge creation, dissemination and exploitation in a region [38], [39]. In addition, university R&D activity (codified in academic patents), for example, also represents an important source of the creation of new knowledge-intensive firms in a region [40]. Indeed, this positive effect is reported to rapidly diminish with geographic distance.

Finally, the effect of regional strategic priorities was also included because regional innovation policy supports all the above-mentioned concepts and, thus, it is a base for operational activities in a region. Note that the strategic priorities are region-specific and strongly depend on regional innovation patterns [41], [42].

The collocation frequencies were transformed into FCM edges and completed the adjacency matrices for each region in this way. Table 2 and Table 3 show the average values of the edges over the four strategic documents in the year 2005 and 2013, respectively.

Table 2: Adjacency Matrix from Textual Analysis – Year 2005.

	Concepts						
	CI	EN	N/C	SP	R&D	L/E	MI
CI	0.00	0.22	0.00	0.00	0.00	0.00	0.00
EN	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N/C	0.07	0.19	0.00	0.00	0.06	0.00	0.00
SP	0.34	0.13	0.08	0.00	0.06	0.04	0.07
R&D	0.03	0.11	0.00	0.00	0.00	0.00	0.00
L/E	0.10	0.00	0.08	0.00	0.10	0.00	0.00
MI	0.13	0.06	0.07	0.00	0.30	0.00	0.00

Legend: MI – material infrastructure, EN – entrepreneurship, R&D – research and development, N/C – networks/clusters, L/E – learning/education, CI – a culture of innovation, SP – strategic priority.

Note that positive causalities denote high collocation frequencies while zero edges indicate no causality. The strongest causalities were observed from SP to CI and from CI to EN, indicating that SP affects EN indirectly, this is via the CI concept. Also note that positive causalities are in agreement with the above-mentioned theoretical background. It is also interesting that some concepts, such as MI, promoted the other concepts without being affected by these concepts. In contrast, EN was driven by all remaining concepts without affecting them.

Table 3: Adjacency Matrix from Textual Analysis – Year 2013.

	Concepts						
	CI	EN	N/C	SP	R&D	L/E	MI
CI	0.00	0.22	0.00	0.00	0.00	0.00	0.00
EN	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N/C	0.05	0.06	0.00	0.00	0.03	0.00	0.00
SP	0.39	0.12	0.06	0.00	0.05	0.06	0.04
R&D	0.04	0.02	0.00	0.00	0.00	0.00	0.00
L/E	0.06	0.10	0.00	0.00	0.06	0.00	0.00
MI	0.04	0.06	0.06	0.00	0.13	0.08	0.00

Legend: MI – material infrastructure, EN – entrepreneurship, R&D – research and development, N/C – networks/clusters, L/E – learning/education, CI – a culture of innovation, SP – strategic priority.

Strategy maps corresponding to Table 2 and Table 3 are depicted in Figure 2 and Figure 3, respectively.

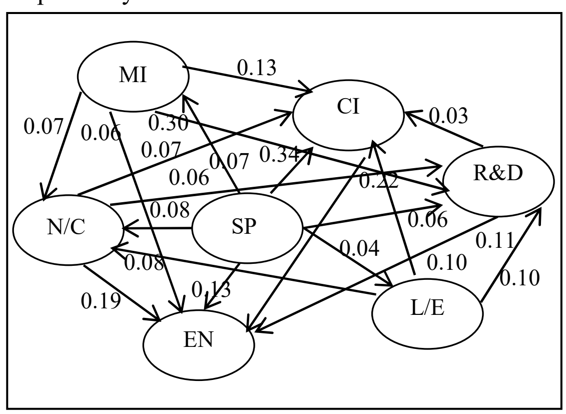

Figure 2: Strategy Map for Year 2005

Apart from direct effects, indirect effects can be identified in the FCMs. Indirect-effect operator I (as minimum) and total-effect operator T (as maximum) can be defined [2]. For example, SP affects EN in one direct way (with E=0.13) and five indirect ways in the year 2005. These indirect-effect operators are defined as I1=min{0.07,0.06}, I2=min{0.08,0.19}, I3=min{0.34,0.22}, I4=min {0.06,0.11}, I5=min{0.06,0.03,0.22}, I6=min{0.04, 0.08,0.19}, I7=min{0.07,0.13,0.22}, I8=min{0.07, 0.07,0.19}, I9=min{0.08,0.07,0.22}, I10=min{0.08, 0.06,0.11}. Then, the total-effect operator is defined as T=max{0.13,0.06,0.08,0.22,0.06,0.03,

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0.04,0.07,0.07,0.07,0.07,0.06}=0.22. In this case, the indirect effect is greater than the direct effect and, thereby, represents the total effect. However, direct effects can be stronger than indirect effects. This holds true for the relationship SP->CI in both years.

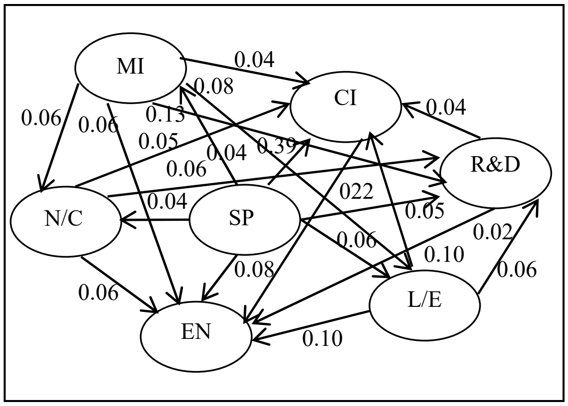

Figure 3: Strategy Map for Year 2013

We performed a more detailed analysis due to the fact that each strategy was developed for two periods, 2005 and 2013, respectively. In fact, we could observe an evolution consisting in transition from strategic priorities related to "Entrepreneurship" and "R&D" to those related to "Learning / education" and "Culture of innovation". Thus, we could observe a phenomenon that we call "cognitive turn" in regional policy and regional programming theory and practice.

However, the regions differed in their priorities. Figure 4 and Figure 5 provide some more insight.

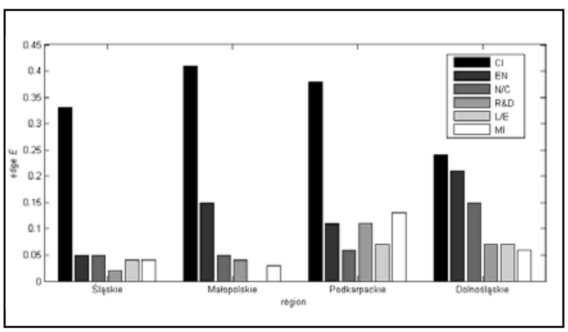

Figure 4: Strategic Priorities in 2005

The values of all concepts and strategic priorities were calculated for each region's innovation strategy using the *tf.idf* weights. In other words, a higher frequency of concept-related terms in the innovation strategy automatically determined the degrees of strategic priorities for each region.

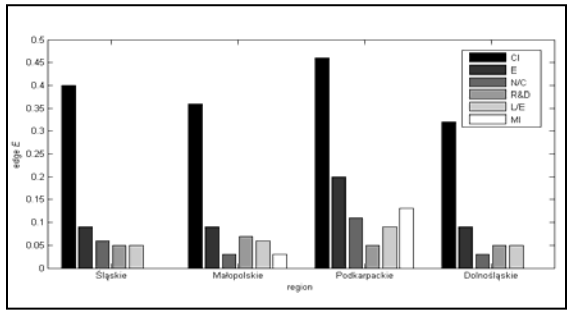

Figure 5: Strategic Priorities in 2013

To further examine the behavior of the FCM, graph-theoretic indices introduced for FCMs were used [20]. The indices facilitate an understanding of the FCMs' structures. Figure 6 and Figure 7 show the average graph-theoretic indices for the year 2005 and 2013, respectively. Specifically, outdegree and indegree denote the cumulative strengths of the connections exiting and entering the node (innovation strategic concept), respectively. In this way, it was possible to identify transmitter, receiver, and ordinary nodes. The SP node is a transmitter, with a positive outdegree and zero indegree. EN, by contrast, is a receiver, having a positive indegree and a zero outdegree. The remaining nodes are ordinary nodes, being more or less receivers or transmitters. Centrality equals the sum of the outdegree and the indegree, showing the concept's total contribution to the FCM.

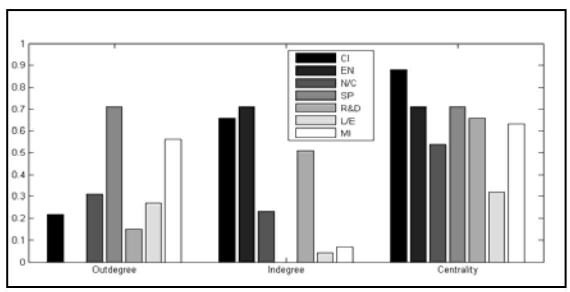

Figure 6: Graph-theoretic Indices for Innovation Strategic Concepts in 2005

We observed a considerable decrease of several concepts (EN, N/C R&D and MI) between 2005 and 2013. Furthermore, the role of some nodes may change over time. The L/E was considered a more outdegree than indegree node in 2005 than in 2013.

The effects of the regions' strategic priorities were also tested to simulate the effect of specific innovation policies. The effect of SP achievement was examined on the remaining concepts for all regions. First, the initial value of SP was set to a medium achievement of 0.5. This setting led (after no more than five iterations) to stable concept values, as shown in Figure 8.

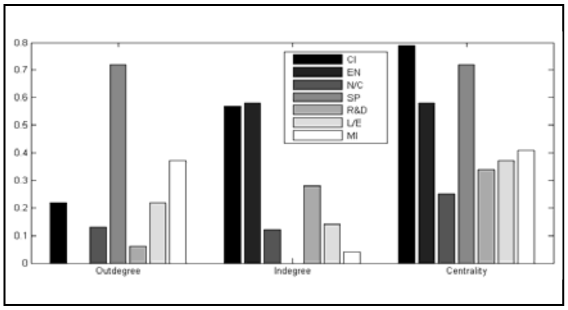

Figure 7: Graph-theoretic Indices for Innovation Strategic Concepts in 2013

The main difference between the two periods is the increase in the level of the L/E concept in 2013.

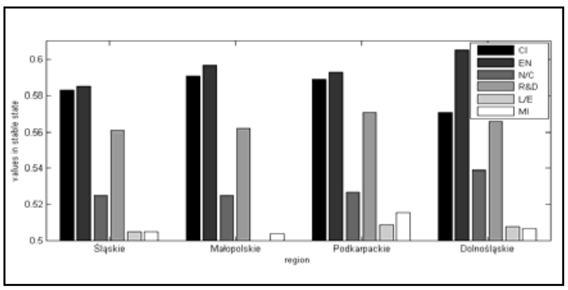

Figure 8: The stable values of the innovation strategy concepts for SP=0.5 in 2005

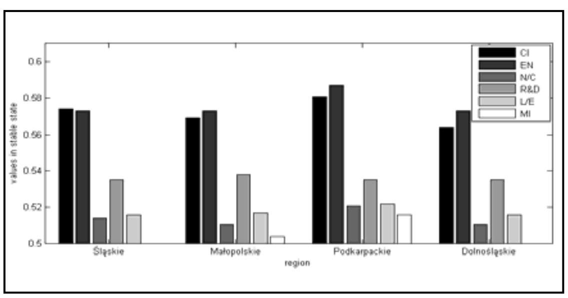

Figure 9: The stable values of the innovation strategy concepts for SP=0.5 in 2013

Furthermore, the evolution of the concepts was examined for when SPs were achieved only at the low degree of 0.2 (Table 4). This change led to a decrease in CI and EN in particular. Of the regions observed, the Podkarpackie region seems to be highly sensitive to the SP concept. Note that a similar change in percentage (though positive) would be obtained if the high degree of SP=0.8 were used. Similarly, sensitivity analyses of the levels of the remaining concepts can be performed.

Table 4: Change in Concept Values [%] for SP=0.2.

	Concepts					
	CI	EN	N/C	R&D	L/E	MI
Śląskie	-2.99	-0.85	-0.43	-0.35	-0.35	0.00
Małopol.	-2.66	-0.84	-0.26	-0.53	-0.44	-0.26
Podkarp.	-3.42	-1.66	-0.87	-0.39	-0.71	-0.95
Dolnośl.	-2.40	-0.82	-0.26	-0.35	-0.35	0.00

Legend: MI – material infrastructure, EN – entrepreneurship, R&D – research and development, N/C – networks/clusters, L/E – learning/education, CI – a culture of innovation, SP – strategic priority.

To verify the design of the FCM based on text analysis, three local experts on regional innovation strategies were asked to assign directions and weights to the causal relations for the strategy maps in the year 2013. Seven values of linguistic variables (very low, low, medium low, moderate, medium high, high, very high) were used to express the weights, and the final weights were determined using the center of gravity defuzzification method. The pooled expert opinions are presented in Table 5.

Table 5: Adjacency Matrix from Expert Opinions.

	Concepts						
	CI	EN	N/C	SP	R&D	L/E	MI
CI	0.00	0.15	0.00	0.00	0.00	0.00	0.00
EN	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N/C	0.05	0.05	0.00	0.00	0.05	0.00	0.00
SP	0.15	0.10	0.05	0.00	0.05	0.05	0.05
R&D	0.10	0.05	0.00	0.00	0.00	0.00	0.00
L/E	0.05	0.10	0.00	0.00	0.10	0.00	0.00
MI	0.05	0.05	0.05	0.00	0.05	0.00	0.00

Legend: MI – material infrastructure, EN – entrepreneurship, R&D – research and development, N/C – networks/clusters, L/E – learning/education, CI – a culture of innovation, SP – strategic priority.

To compare this adjacency matrix with that constructed from text documents, the Pearson's correlation coefficient R=0.835 was obtained. This results suggest that the two adjacency matrixes are in strong agreement with each other. Finally, to compare the results obtained by the FCM based on text analysis with an alternative method, we used fuzzy ANP (analytic network process) [43]. The adjacency matrix in Table 3 was used as the supermatrix of a network. Similarly, initial concept values were used as fuzzy numbers and simple weighted sum was used to calculate the final scores. To maintain comparability, equal local weights were defined for all the concepts. The interdependent weights of the concepts were calculated by multiplying the supermatrix and equal local weights. The scores for each regional strategy in Table 6 suggest that the results of the FCM inference process are consistent with the results of fuzzy ANP.

Table 6: Results of Fuzzy ANP.

	Concepts							Score
	CI	EN	N/C	SP	R&D	L/E	MI	*S*
Śląskie	0.051	0.000	0.005	0.208	0.002	0.006	0.000	0.271
Małopol	0.045	0.000	0.003	0.208	0.002	0.007	0.007	0.273
Podkarp	0.058	0.000	0.009	0.208	0.002	0.012	0.027	0.316
Dolnośl	0.041	0.000	0.003	0.208	0.002	0.006	0.000	0.259

Legend: MI – material infrastructure, EN – entrepreneurship, R&D – research and development, N/C – networks/clusters, L/E – learning/education, CI – a culture of innovation, SP – strategic priority.

4. CONCLUSION

Currently, a type of "cognitive turn" can be observed in business strategies towards terms related to, e.g., learning processes (learning organization), ways of perception (an intercultural environment), intelligence (intelligent or smart organizations), and so on [44]. However, it is difficult to accurately quantify these concepts, as well as causal relationships among them. In this paper, the innovation strategies of selected Polish regions were mapped using FCMs. This mapping was based upon collocation analysis of text documents and provides several interesting practical implications. Within the regional innovation strategies, a trend toward the areas of a culture of innovation and entrepreneurship was observed. This finding suggests that the existing material infrastructure is sufficient and enterprises do cooperate in innovation networks. However, this infrastructure and these networks should be used more effectively by developing learning and a culture of innovation. The mutual relationships identified in the FCMs support the idea that the individual areas of regional innovation systems are interdependent. Thus, reinforcing one area may result in the improvement of other subsystems as well.

Regarding the objectives and assumptions of this research, it can be concluded that the study confirms that strategic documents can be transformed into FCMs using text analysis. From the point of view of testing the methodological approach, it seems possible to consider that the scientific methods applied generate interesting outcomes. However, it should be noted that this approach requires further development of both its conceptual and methodological aspects in order to be implemented in practice as a useful tool for analyzing strategic documents. Therefore, in future research, it is planned to expand this approach to make it operate more effectively, for example using the collocations containing +/- effect words and uncertainty words. Thus, the process of FCM generation would be fully automatic. Notwithstanding, this paper may contribute to scientific discussion in this interdisciplinary field.

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