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PROVIDING A COMPREHENSIVE MODEL TO MEASURE THE PERFORMANCE DIMENSIONS OF INDUSTRIAL CLUSTERS USING THE HYBRID APPROACH OF Q-FACTOR ANALYSIS AND CLUSTER ANALYSIS

Abstract: *One of the most important development strategies with the emphasis on small and medium industries is the geographical concentration of production units and the formation of cluster. The industrial cluster is a globally economic phenomenon that has been proposed as a modern model for economic development. Theoretically, an industrial cluster can strengthen specialized sectors and facilitate industrial cooperation. The aim of this study was to provide a comprehensive model for measuring the performance dimensions of industrial clusters in Markazi province using a hybrid approach of Q-factor analysis and cluster analysis. For this purpose, at first and in the first phase of the research, 41 effective factors in the clustering of the performance dimensions of the statistical population were identified with the study of previous research and the use of Q-factor analysis, and in the second phase, a model for comprehensive performance measurement of industrial clusters was presented using cluster analysis in R software. The results of the study indicated that industrial clusters in Markazi province have four financial, competitive, economic and environmental performance dimensions.*

Keywords: *Performance Dimensions, Industrial Clusters, Q-factor Analysis, Cluster Analysis*

1. Introduction

From the second half of the twentieth century to now, various patterns of industrial growth and development models have been experienced in the world. Industry growth and development without designing and implementing a suitable strategy is not feasible. One of the most important development strategies with the emphasis on small and medium industries is the geographical concentration of production units and cluster formation. Today, industrial clusters have been raised as a key strategy for national and international competition. The industrial cluster is a globally economic phenomenon that has been proposed as a modern model for economic development. Theoretically, an industrial cluster can strengthen specialized sectors and facilitate industrial cooperation. The history of scientific discussion and investigation about industrial clusters goes back to around 1920, when Alfred Marshall showed in his book

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entitled “The Principles of Economics”. The focus of specialized activities in industrial areas increases the company's external economies. According to view of Marshall, external economies occur with the presence of three factors including local availability of inputs, presence of a pool of skilled workforce and knowledge overflow. These three factors are known as Marshall External Economies. With the presence of these three factors in the business environment, an industrial cluster is created (Mansouri & Aziz Mohammadlou, 2009). To achieve the above advantages, industrial cluster performance should be evaluated so that its results can be used to improve the performance of clusters. In order to conduct a valid and reliable evaluation, awareness of industrial cluster performance dimensions and the availability of an appropriate model is essential. This research seeks to understand the performance dimensions of the cluster so that the views of the experts in this field are summarized, and the performance of industrial clusters in the form of a model of dimensions and indices is explained.

2. Thematic literature of the research

2.1. Industrial clusters

Different definitions of industrial clusters have been provided, each of which emphasizes one or more specific aspects of this phenomenon. The United Nations Industrial Development Organization (UNIDO) (2000) defines the industrial cluster as "the geographical concentration and part of the manufacturing activities of companies that produce and sell a range of related and complementary products and have common problems and opportunities". Based on this definition, the industrial cluster has four characteristics of geographical concentration, common industrial tendency, cooperation, and challenges and opportunities. In the most general sense, the cluster refers to the spatial concentration of economic activities in a particular context. What makes clusters so attractive to policymakers is the opportunities for collective performance that derive from external economic costs, low transaction costs, and collective action. The mere space accumulation of companies that do not communicate with one another cannot increase collective performance. These interactions and external effects are of interest. Thus, the cluster is a relatively large set of economic enterprises, which are within a specific location, have a specialist background, and in that (the cluster) of inter-firm trade and firm specialization is significant (Altenberg & Stamer, 1999). In the first edition of his book entitled the Competitive Advantage of Nations, Michael Porter (1990), as one of the experts in the field of clusters, considers the national clusters including of companies and industries that link together through public relations (buyer/supplier) or horizontal relationships (technology and customers) and located in a country or province. In other words, the cluster is the geographic concentration of institutions and related companies in a particular domain (Porter, 1998).

2.2 Performance dimensions and measures of industrial clusters

Despite numerous studies on performance indicators of organizations, systematic studies on the performance measures of industrial clusters have not been conducted, but models related to the performance of industrial clusters have been developed. These models are generally a combination of dimensions, measurements and performance determinants of industrial clusters, each presenting a different look.

Stimson et al. (2006) used the fifteen measures of economic performance to analyze clusters: employment, employment changes, average annual wages, annual average wage change rates, establishing new companies, rates of change in the number of newly established companies, level of wages relative to the level of national industry wages, rate of change in relative wages, inter-industry dependence, productivity, rate of change in productivity, contributing to GDP of the state, rate of change in the contribution to GDP of the state, place interest, and changes in the place interest (Stimson, Stough & Robert, 2006). Ionescu (2005) states that social capital can directly affect cluster performance in two ways: supporting innovation and reducing the transaction costs. This study implicitly proposes innovation and costs as two measures of industrial cluster performance (Ionescu, 2005). Sölvell et al. (2003) designed a model to evaluate organized actions for increasing cluster performance within a region. In this model, three indicators of competitiveness, growth, and achievement of objectives have been defined in order to show the effect of improvement programs on promoting the performance of the industrial cluster (Sölvell, Lindqvist, & Ketels, 2003). Then, the results of evaluating and studying various models in terms of the dimensions and performance measures of industrial clusters are presented in Table 1.

Table 1: Summary of research related to the performance dimensions and measures of clusters

Row	Year	Researcher	Performance dimensions and measures
1	1990	Porter	Demand situation, strategy, structure and corporate competitiveness, status of (input) factor, related and supporting industries
2	1997	Padmore and Gibson	Resources, infrastructure, suppliers/related firms, firm structure and strategy, local markets and external markets
3	2003	Sölvell et al.	Business environment, policy environment, cluster strengths, competitiveness, growth, achievement of goals, setting up and planning, management and financing, size of membership, resources and facilitators, creation of a framework and consensus, achievement of acceleration of movement
4	2005	Kuchiki	Location-based market, exports, domestic market, export processing zone, industrial zone, infrastructure, institutions, human resources, living conditions, firm anchor, related enterprises, regional economic growth
5	2005	Ionescu	Social capital, innovation, interaction costs, cluster performance
6	2007	Ketels	Industrial policies of government, innovation and entrepreneurship policies, micro-economic environment, regional specialization
7	2007	Karaev et.al	Geographical proximity, entrepreneurship culture, critical mass of firms, confidence-building, productivity, specialization, innovation, costs, trust, competitiveness
8	2007	Chiffoleau et al	The size and expertise of cooperatives, the amount of production, turnover, innovation, the number of new products, new processing technology, organizational changes, marketing innovations, economic performance, turnover growth, average income of each firm, average sales price per unit of product
9	2007	McDonald et al.	Cluster depth, cluster development phase, industrial sector, employment dynamics, international importance
10	2008	Aziz & Norhashim	Innovation, commercialization, new companies, creation and storage of knowledge, knowledge circulation, cluster role players, cluster dynamics, cluster location, focus, proximity, links and interactions between role players, social capital, savings resulting from the accumulation, critical mass

Table 1: Summary of research related to the performance dimensions and measures of clusters (continued)

Row	Year	Researcher	Performance dimensions and measures
11	2008	Beckett	Cooperation, maturity, relative heterogeneity of participants, economic benefits, enhancing the capabilities of members, knowledge circulations, established cooperation of created jobs, overflow benefits, government policies, business environment, competitive pressures, cluster resources management, cluster members resources
12	2008	Carpinetti et al.	The average selling price of value added per person employed in the company, the total cost, profit, total workforce, the total trained personnel, the total amount of the raw materials owned collectively, the percentage of participating companies in the collaborations
13	2009	Soren et al	Factors status, structure and strategy and the rivalry of companies
14	2010	Lin & Sun	Local demand, skilled labor, capital, information infrastructure
15	2010	Malakauskaite & Navickas	Level of cauterization (cluster life cycle), competitiveness, entrepreneurship (new companies), productivity, innovation, competitiveness determinants (factors), competitiveness indicators
16	2010	Eisingerich et al.	The frequency of interactions, the intensity of interactions, the durability of interactions, the confidence level, the diversity of membership in the network, the willing to accept the new member, the degree of solidarity with organizations outside the cluster, the number of new companies, the number of jobs, the (financial) output of cluster compared to the growth rate of these criteria in related industries, market volatility including the rate of change in the composition of customers and their preferences, the intensity of competition, technological turbulence
17	2010	Jimenez & Junquera	Trust, access to infrastructure and incentives, quantification of performance, cost of access to information and specialized resources, human capital improvements, flexibility, creation of new businesses, innovation
18	2010	Cagnazzo et al.	Development of new product, business model, investments, development of new service, infrastructure, collaboration, network model, technical knowledge of production-related methods, knowledge related to the development of new goods/services, investment attraction capability, sales generated by network, the cost of goods/service commercialization, the cost of manufacturing processes, the costs of internal processes
19	2010	Gagné et al.	Skilled workforce, innovative technology and technology transfer, government-sponsored of risk capital, business support service, networking, external knowledge resource, leadership, cluster dynamics, cluster trademark, specialized skill learning and training infrastructure
20	2011	Dos & Dos	Rural poverty, rural income and regional economic development, innovation and new business enterprises
21	2011	Villa & Taurino	Annual sales, percentage of exports to total production, percentage of market coverage (market share), number of patents registered (to measure innovation power), network size, long-term training programs

Table 1: Summary of research related to the performance dimensions and measures of clusters (continued)

Row	Year	Researcher	Performance dimensions and measures
22	2010	Wang et al.	The input dimension of production (including engineering and technical personnel relative to the entire cluster, per capita equipment, investment in fixed capital, environmental endowment, average cluster size), competitive performance dimension (cluster internal market share, the degree of cluster industry extraversion, average cluster output value) , the efficiency of competition dimension (total productivity of the cluster human resources, interest rate of funds, rate of tax on profits, current capital turnover rate, value added rate, ratio of profit to intrinsic value of assets), competitiveness potentiality dimension (fixed assets value, technological progress , intensity of energy consumption, scale development)
23	2013	Casanova et al.	Product innovation, process innovation
24	2013	Yu et al.	Industrial financial development (including the balance of deposits of urban and rural residents, the balance of foreign currency deposits of urban and rural residents, available sales revenue, the number of local firms, the percentage of the financial value of the industrial production to GDP, the number of financial lawyers of industry to lawyers in the city), the economic basis (including per capita GDP, total amount of investment in fixed assets), financial market (including index of financial market orientation), infrastructure (rail and air traffic, number of people with Internet access), human capital (number of graduates of diploma)

2.3 Q-factor analysis

Using Q method, the required information can be obtained from authorities and elites of the community. In other words, the researcher, using this method, wants to explain to the factors the meaning and interpretation that identifies the mentality of individuals and reveals the vague and hidden information that lies behind this apparent information. While having features of qualitative method, Qi method also has a quantitative approach and greatly benefit of Statistics, because it helps with statistical methods such as factor analysis method and principle components analysis for classifying people. Therefore, the Q method is a technique that enables the researcher first to identify and classify individual perceptions and opinions, secondly, to classify groups of individuals based on their perceptions (Khoshgouyanfard, 2007). The capabilities of the Q method are that the typical Q sample (phrases) is chosen from concourse space, which is compiled based on the feelings, beliefs and attitudes of the participants. The contents of concourse space not only include facts that may be in thematic literature, but also include personal views and perceptions that are completely self-reference and may not have any scientific acceptance. Thus, the identification of mentalities is formed regardless of the theoretical frameworks, and it is possible to discover the mentalities that have not been discovered until now. Enjoying an analytical facility is another feature of Q approach. Among these features, factor arrays are very important and the thought of the factor array is one of the most valuable successes of the Q method (Kerlinger, 1997).

2.4 Cluster analysis

A cluster analysis is a classification technique for the formation of homogeneous groups in a complex set of data that does not rely on any presupposition about the number or structure of groups. In cluster analysis, membership in groups is unknown for all observations, and even the number of groups is uncertain. The goal of this technique is to identify homogeneous groups. The groups are determined in such a way that the degree of consistency between the members of a group is strong and the degree of consistency among the members of the different groups is weak. Therefore, cluster analysis is a tool for the exploration that can reveal the consistency and structure of the data (Hooman, 2011). In examining the theoretical literature, various types of clustering methods have been suggested in theoretical literature. In one of these methods, clustering is an agreement that is also referred to as integration of clustering. In this method, it is assumed that m clustering of C1, C2..., Cm are made from existing information and the goal is aggregation of these clustering and creation of a clustering C (Kamber & Pei, 2012). This method can be used to aggregate the views of experts on the clustering of a number of variables. Many clustering algorithms have been proposed by researchers, such as k-mean, hierarchical, CLARA, DIANA and.... (Jin, kim, Han, Cao & Yin, 2011). Each of these algorithms is based on rules for placing objects in a group and may provide different clustering for a set of data that requires clustering obtained by each algorithm to be validated. In cluster analysis, the assessment of the validity of the obtained clusters is the best method for data clustering. The validity of clustering requires the measurement of three concepts of connectivity, compactness and separation of cluster components. Connectivity refers to the range of observations located in a cluster. This concept is measured by the link index. The numerical value of the link index is between zero and positive infinity and should be minimized. The concept of compactness evaluates cluster homogeneity by examining the variance of intra-cluster data. Separation states the degree of separation between the clusters by measuring the distance between the centers of the clusters. Because compactness and separation show opposite trends, compactness increases with increasing number of clusters, but the separation decreases. The common indicators are the result of the combination of these two concepts.

3. Research Methodology

This is a descriptive-survey research in terms of methodology. In other words, the research is descriptive as it tries to investigate the factors creating industrial clusters and provide a comprehensive model for measuring the performance dimensions of industrial clusters with the cluster analysis approach in Markazi province and is a survey research, because it examines the amount of impact of designing and implementing a comprehensive model for measuring the performance dimensions of industrial clusters by surveying and referring to the views of people, then using field studies, collects data and information in order to identify the variables of research and measure the performance dimensions of industrial clusters among the experts in the statistical population. The statistical population of this study is all managers and experts of the industrial estates corporation in Markazi province. Existing experts are employed in organizations or associated companies or in the management of clusters, such as the organization of industries and mines, the governor's office, industrial estates Corporation, and the small industries organization and Iran's industrial estates. In this study, 41 clusters in which the defined development plan is introduced as a statistical population. In each cluster, there is a development factor (one person) trained in cluster areas and master the clusters and cognitive studies have been carried out about it. To collect data from the research, the researcher utilizes the contributions of these individuals in the research. In cases where a survey of experts is required, academic and executive specialists will be surveyed in addition to cluster development agents. The field method is used to collect information on the topic of the research. The necessary tools for this subject are interviews and questionnaires. In fact, the data collection tool for this research includes an interview questionnaire, a review of documents by reference to the statistics and information available in the industrial estates corporation. In qualitative stage of research, methods such as interviews, reviews of documents to identify the variables involved in determining the dimensions and determinants of cluster performance and the questionnaire. In this study, in the first phase, the criteria and variables affecting the creation and development of industrial clusters have been identified with the study of the subject literature of the research and reviewing previous research, and then, using a Q confirmatory factor analysis, the data collected related to these criteria and detected dimensions are analyzed to eventually identify the variables involved in determining the dimensions and determinants of cluster performance in the studied population (Markazi province). In the second phase of the research, in order to develop an industrial cluster performance evaluation model, we first group the indices of industrial cluster performance evaluation using cluster analysis method and consequently, to extract the performance dimensions of industrial clusters.

4. Analysis of data

In this part of the research, the effective and determinant variables of industrial cluster performance in the statistical population are initially identified using Q factor analysis. For this purpose, at first 10 experts and academic professors were interviewed. After careful review and data organization, 41 statements were selected as sample Q. In the next step, for the formation of class Q, 41 Q cards were designed in such a way that a statement of sample Q was written on each card. After reading the cards, the participants sorted them according to the given Q charts.

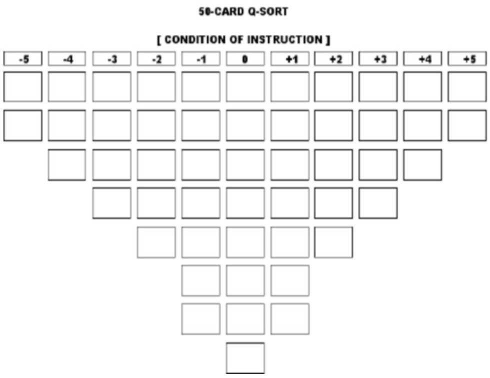

Figure 1. Q Sorting Matrix

The reliability coefficient conducted in this study was 85% using the test-retest method; in other words, the repetition of sorting was 85% consistent with previous sorting. Validity is also obtained through the fit between the content of propositions that are either on the same level of the range or on the vertices of adjacent degrees, as well as the degree of consent of the participants. To identify the mental models, the ranking and sorting of Q conducted by experts was entered into SPSS software and Q-factor analysis was performed. Correlation matrix was used for conducting factor analysis. The factors were extracted by principle component method and rotated five rounds by the Varimax method. The method of factor analysis is the main statistical method for analyzing Q data matrix. The factor loads extracted are shown in Tables 2 and 3. Given that the principle component method for extracting factors is used, the term COMPONENT was used instead of the factor. According to the results of Table 3, the existing factor loads show that three factors (mental model) have been correctly identified (factor load greater than 0.5). Thus, according to the results of this table, the first, third, eighth and tenths as the joint first mental model, the second, the sixth, the ninth as the joint second factor, and the fourth, fifth, and seventh, jointly constitute the third mental model.

Table 2. Identified Factor Matrix

3	2	1	COMPONENT
0.181	0.469	0.867	1
0.511	0.709	-0.486	2
0.841	-0.531	0.108	3

Table 3. Rotational matrix of factors

COMPONENT			
3	2	1	
0.102	0.175	0.941	P8
0.163	0.271	0.918	P1
0.180	0.822	0.888	P10
-0.148	-0.142	0.601	P3
0.233	0.654	0.413	P6
0.031	0.938	0.173	P9
0.115	0.915	0.197	P2
0.692	-0.304	0.072	P7
0.869	0.032	-0.145	P5
0.838	-0.059	0.177	P4

The specific value of each factor (TOTAL column) and the proportion of the variance are explained by each factor, and finally their accumulation, are presented in Table 4.

Table 4. Total explained variance values

Cumulative	Variance	Total	Component
31.733	31.733	3.173	1
52.599	20.866	2.087	2
69.136	16.537	1.645	3

As can be seen, the total variance explained is equal to 69.136 percent. The above tables show that, according to the experts' opinion, three factors (mental models) are identified (factors that have eigenvalues above 1) and three mental models explain in total about 69.316% of the total variance. According to this table, the first mental model explains 31.733% of the total variance and the subsequent mental models of 21.733% and 16.538% of the total variance.

In general, the results of the first phase of the study represented that, based on Q-factor analysis method, 41 indicators were identified and introduced as performance measures of industrial clusters. These measures are presented in Table 5.

Table 5. Performance measures of industrial clusters

Measures	Measure Code
Product innovation	M01
Jobs created	M02
Process innovation	M03
Number of cluster enterprises	M04
New companies formed in clusters	M05
Sales created by network	M06
Total desire of investment in fixed assets	M07
Profit	M08
Costs of production processes	M09
Costs of internal process	M10
Cluster financial output	M11
New technology and processing	M12
Number of new products	M13
Market share of existing products	M14
Production rate	M15
Export volume	M16
Earnings	M17
Costs of goods/services commercialization	M18
Cost of purchasing goods/services	M19
ROI/EDIBTA/ROS/ROE	M20
Turnover	M21
Turnover rate of current capital	M22
Ratio of profit to intrinsic value of assets	M23
Growth in turnover	M24
Average sales price per unit of product	M25
Marketing innovations	M26
Success rate in the commercialization of produced goods	M27
Number of patents registered	M28
Market share of new products	M29
Market share of new brands	M30
Market share of improved products	M31
Product quality	M32
Average size of firms	M33
Percentage of the financial value of the industrial production to GDP	M34
Local poverty reduction	M35
Local revenue generation	M36
Contributing to GDP	M37
VAT rate	M38
Fair distribution of wealth in the region	M39
Changing the natural ecosystem of the region	M40
Industrial pollution	M41

Variables presented in Table 5 are a combination of performance determinants, performance dimensions, macro components, and micro measures. Performance determinants, as enablers, have a direct impact on performance. Variables such as economic performance, operational performance, socio-economic outcomes, and other very large macro variables represent a performance dimension of industrial clusters, while variables such as productivity are a macro component of the performance measurement system and include several micro measures. Micro measures are clear and measurable variables that are referred to as the basic components of a performance evaluation system. In this study, each measure measures a limited scope of multi-dimensional cluster performance. In order to design a performance measurement system, these micro measures should be set in the form of a model.

In the following, after identifying the dimensions and measures affecting the industrial clustering in the studied population (Markazi province) using Q-factor technique, at this stage, we group the indicators of industrial cluster performance evaluation and thus present the model of performance dimensions of industrial clusters with the help of adaptive cluster analysis.

To evaluate the measures and their classification, the relevant list was given to 41 experts of industrial clusters, including those involved in the development of industrial clusters, specialists of the small-scale industries organization and academic specialists and their views on classification of measures were received in form. In this step, each of the experts was asked to perform their own classification from the measurements and determine which measures together constitute one dimension. After collecting opinions, a cluster analysis method was used to extract the unit classification. The results of cluster analysis led to the creation of a classification of performance measures, and each class of measures was named according to the nature of the measures within the class.

Cluster analysis input is usually raw data. In the next step, the dissimilarity matrix is built by calculating the distance of each data from other data, and then, by reversing the data or using the concept of the opportunity cost lost, the dissimilarity matrix is created. A cluster analysis requiring a numerical matrix represents a similarity between two measures. To convert these classifications into similarity matrices, an innovative method was used, so that whenever an expert opinion points out that the measures A and B are in a group, in a similarity matrix, one unit is added to the intersection box of measure A with measure B.

To analyze the data, R-Open Source Statistical Software was used. The software provides a language and environment for computations and statistical charts, and enjoying many modules, is capable of performing a wide range of computations and drawing complex charts. Using the hclust module and command in R software, cluster analysis of the similarity matrix was performed using complete link method. Figure 2 shows the dendrogram of clustering. With the changes in graphics of Figure 2, Figure (chart) 3 was created, which more clearly shows groups and subgroups.

In the following, seven hierarchical clustering algorithms including K-Means, DIANA, FUNNY, PAM, CLARA, and MODEL were used for data analysis. The software respectively examined 4 to 10 clusters in the data using seven algorithms from the perspective of three indicators. To carry out this test, the added package clValid was used in R software, the output of which is provided in Figure 3. The resulting values show that the lowest connectivity index is related to the hierarchical, K-Means and DIANA methods in the four-cluster pattern, and the Dunn and Silhouette index have the highest values in the ten-cluster model of all methods. The four-cluster and ten cluster models are presented in Figure 4.

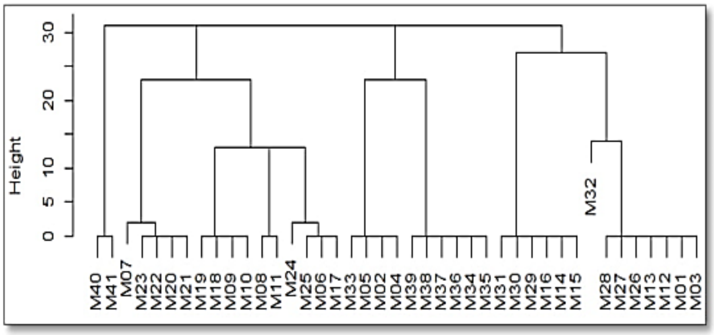

Figure 2. Clustering of measures and performance dimensions

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Clustering Methods:
 hierarchical kmeans diana fanny pam clara model

Cluster sizes:
 4 5 6 7 8 9 10

Validation Measures:
                                  4       5       6       7       8       9      10

hierarchical Connectivity    5.0940 11.4206 18.6770 23.9052 27.4980 34.7544 39.1210
             Dunn            0.8426  0.9724  0.9807  1.5102  1.1296  1.0241  5.2738
             Silhouette      0.5262  0.6766  0.7900  0.8843  0.8858  0.8964  0.9640
kmeans       Connectivity    5.0940 11.4206 18.6770 23.9052 27.4980 34.7544 39.1210
             Dunn            0.8426  0.9724  0.9807  1.5102  1.1296  1.0241  5.2738
             Silhouette      0.5262  0.6766  0.7900  0.8843  0.8858  0.8964  0.9640
diana        Connectivity    5.0940 11.4206 18.6770 23.9052 27.4980 36.2298 39.1210
             Dunn            0.8426  0.9724  0.9807  1.5102  1.1296  0.9296  5.2738
             Silhouette      0.5262  0.6766  0.7900  0.8843  0.8858  0.8897  0.9640
fanny        Connectivity   10.4627 16.1131 21.6052 28.8615 31.1615 37.8849 39.1210
             Dunn            0.7892  0.6875  0.7855  0.4092  0.7868  0.4218  5.2738
             Silhouette      0.6626  0.7049  0.8071  0.8177  0.8949  0.9317  0.9640
pam          Connectivity   10.4627 16.2266 21.6052 23.9052 31.1615 35.5282 39.1210
             Dunn            0.7892  0.7201  0.7855  1.5102  0.7868  0.7313  5.2738
             Silhouette      0.6626  0.7042  0.8071  0.8843  0.8949  0.9625  0.9640
clara        Connectivity   10.4627 16.2266 21.6052 23.9052 31.1615 34.7544 39.1210
             Dunn            0.7892  0.7201  0.7855  1.5102  0.7868  1.0241  5.2738
             Silhouette      0.6626  0.7042  0.8071  0.8843  0.8949  0.8964  0.9640
model        Connectivity    8.5206 13.7488 21.6052 23.9052 31.1615 34.7544 39.1210
             Dunn            0.7935  0.6912  0.7855  1.5102  0.7868  1.0241  5.2738
             Silhouette      0.6635  0.7285  0.8071  0.8843  0.8949  0.8964  0.9640

Optimal Scores:
             Score  Method       Clusters
Connectivity 5.0940 hierarchical  4
Dunn         5.2738 hierarchical  10
Silhouette   0.9640 hierarchical  10
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Figure 3. The result of internal validity calculations

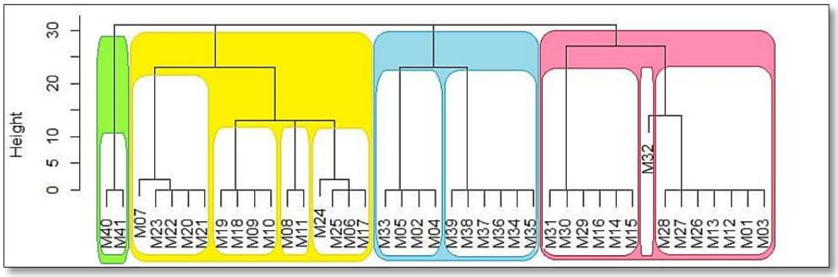

Figure 4. Grouping the measures in the dendrogram chart

5. Discussion & Conclusion

To clarify the concept of industrial cluster performance, the dimensions of this concept should be clearly defined and the components of each dimension should be specified. The results of cluster analysis carried out in this study represented that performance measures can be classified into four general (dimensions) groups. By carefully evaluating the results in the clustering section, it became clear that three components of quality, growth and innovation can be identified in the first dimension, and this performance dimension can be called "competitive performance". Other components and dimensions were also extracted and named with the similar analysis. The results of this extraction are provided in Figure 5.

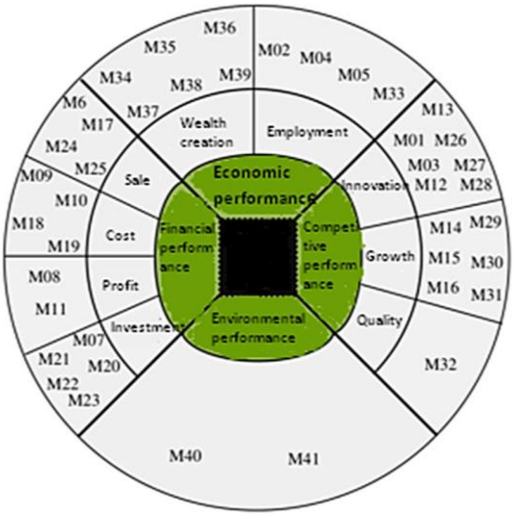

Figure 5. Performance dimension model of industrial clusters

Based on the results of this study, industrial clusters have four financial, competitive, economic and environmental performance dimensions. Financial performance dimension refers to cluster effects on firm's financial indicators, and is divided into four components of sales, cost, profit and investment. Competitive performance dimension refers to the success of the cluster in innovation, market development, and quality, and includes these three components. Innovation in the area of production, product and market processes can be revealed, and the growth of market share in the field of new or old or improved products can be evaluated and product quality determines the current competitive ability of the cluster. Economic performance dimension refers to the effects of industrial clusters on the region's economy, which, on the one hand, increases employment in the region, and on the other hand, by transforming raw materials into goods, deals with value creation and wealth creation, and affects the economy of the region. Another performance dimension is environmental, which refers to the destructive effects of industrial clusters on the natural environment. Because the activity of a large number of industrial or semi-industrial units usually leads to the production of industrial wastewater or manipulation into the nature of the region, it is therefore necessary to pay attention to this unsatisfactory performance dimension of clusters in order to control damage to nature and sustainable development of the region.

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