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Analysis of Employee Competencies and Identification of High-Performance Employees Based on Individual Competency Using Self-Organizing Maps

Majid Ayyoobi
Department of Management,Birjand Branch,Islamic Azad University, Birjand, Iran

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ABSTRACT

This study examines employee competencies and identifies high-performance employees by analyzing individual competency metrics. Using a self-organizing map (SOM) with 2000 nodes, network training and evaluation were conducted through the Viscovery Profiler software. The assessment incorporated both an evaluation center and a 360-degree performance evaluation, ensuring a comprehensive analysis of employee competencies. Hierarchical clustering (SOM Ward Clusters) determined segmentation, with clusters evaluated for key performance indicators such as personality fit, teamwork, creativity, decision-making, and leadership. Statistical tests, including the Kappa correlation coefficient and Pearson correlation, assessed the alignment between the two evaluation methods. While the Kappa test revealed no direct relationship between clusters from both methods, the Pearson correlation coefficient (0.481) indicated a significant positive relationship between competency scores and performance evaluation. These findings highlight the reliability of assessment center evaluations in predicting real-world performance, aiding organizations in talent management and employee development.

Introduction

Although the focus on competency-based selection may not seem like a new approach, it has long been a topic of interest alongside issues such as personality, individual differences, and organizational behavior. However, the methodology governing competency studies in its current form emerged in the early 1970s, and since then, researchers have conducted extensive studies to identify and introduce the key factors influencing competency[1].

One of the earliest and most important studies in this field was conducted in the early 1970s, aiming to identify various aspects of employees' job performance. This research led to the introduction of the competency concept. Competency is considered a defining characteristic that enables an individual to perform at a high level in a specific job role or position.

In the early 1990s, competency was defined as a combination of motivation, personal attributes, knowledge, skills, self-concept, and social roles. This perspective opened new discussions on competency. Later, further studies expanded on previous research, suggesting that competency consists of motivation, habits, self-perception, attitudes or values, cognitive-behavioral skills, and any personal characteristics that can be reliably measured and distinguish high-performing individuals from those with average performance.

Further research emphasized that competency is the ability to integrate and apply knowledge and skills for the optimal use of resources and the enhancement of both individual and organizational performance. A review of competency-related research in recent years, focusing on either the job or the employee, highlights two major schools of thought. One school of thought considers competency as the level of skill required to perform an assigned task. In contrast, the opposing school argues that competency encompasses individual characteristics that influence job performance and, unlike the first approach, focuses on the employee rather than solely on the job itself[2].

As emphasized in theoretical foundations, competency is a predictive construct, and competency-based selection in organizations requires identifying the factors shaping employees' competencies. However, the multiplicity of competency predictors and computational challenges arising from high-dimensional data have led to the widespread use of dimensionality reduction techniques.

In dimensional analysis, researchers either eliminate some variables or aggregate and categorize those that are deemed less significant. Over the years, dimensionality reduction techniques have progressively evolved. One of the most significant methods involves feature extraction, which maps a high-dimensional space to a lower-dimensional space. This approach reduces the number of features by combining existing feature values while retaining all (or most) of the original information.

These methods are categorized into two types: linear and nonlinear. Linear methods seek a general flat subspace, whereas nonlinear methods, which are more complex and challenging to analyze, aim to find intricate underlying patterns in competency modeling.

1.2 Competency-Based Assessment

Organizations always need to enhance efficiency and create value in all transactions. One of the key sources of value creation stems from the skills and attitudes of employees. Moreover, in the effective execution of a job, employees' skills and attitudes play a fundamental role. To understand how employees work effectively, it is best to use a scientific approach. One such scientific approach is competency-based performance assessment. Competency-based assessment refers to evaluating employees' performance based on predefined competencies and individual behavioral indicators. A fundamental requirement for competency-based performance assessment is the organization's adoption of a specific competency framework. This competency framework must align with the organization's long-term goals, vision, and mission[3].

These competencies should then be interpreted based on the tasks employees perform at different levels. Therefore, the competency framework defined for senior managers differs from that of lower-level managers. Competencies serve as a guiding star for organizations, especially for senior managers. Competency-based assessment is an effective tool for organizations to achieve their desired outcomes. Since competencies are measurable and analyzable, employees' performance can be evaluated based on them.

Unlike personal traits, competencies are developable and learnable. If organizations identify and define key success criteria in the form of core competencies, they can extend them throughout the entire organization[4].

1.3 Competency-Based Employee Performance Assessment Approach

Having a competency-based employee performance assessment framework provides a comprehensive picture of the organization's skill map, developmental needs, and potential managers. Additionally, it defines an effective approach to talent management. As a result, employees gain a better understanding of potential career advancements, leading to greater engagement with the organization.

An organization can use a structured competency-based model to integrate its management practices. This structured and systematic approach helps the organization define and determine its priorities, thereby aligning its human resource strategies with key organizational behaviors. Moreover, it ensures that employees take responsibility for their performance, learning, and development. This behavior fosters a culture of transparency within the organization. Most importantly, competency-based performance assessment enables organizations to gain better insight into hiring decisions, helping them recruit the right individuals as the starting point of the employee lifecycle within the organization[5].

2- Research Methodology

In general, research designs are divided into two categories: exploratory and inferential. The primary purpose of conducting exploratory research is to identify the problem or decision situation and to acquire the necessary insight and understanding regarding the issue. In fact, we carry out exploratory studies to better understand the nature of the problems when there may have been little previous research on the related phenomena. Inferential research, on the other hand, is conducted under the assumption that the researcher has a proper understanding of the problem, so that the information needed for solving the managerial decision problem is clearly defined. The goal of this type of research is to test hypotheses and examine specific relationships. Therefore, exploratory research is question-driven, while inferential research is hypothesis-driven. Given that this study is exploratory, it seeks to find answers to specific questions[6].

Since this research emphasizes discovering the relationship between two groups of information and examines the data on a case-by-case basis, it is a correlational study. In terms of its objective, the study is applied and was conducted in the field.

To collect the necessary data, documents and records were used. The information contained in an individual's records consists of two types. The first section pertains to the individual's performance, which is obtained from their personnel file, and the second section consists of the scores that the individual achieved by participating in the assessment center. In other words, individuals who have participated in the assessment center, after being selected and promoted to their new positions, are later re-evaluated through a 360-degree performance evaluation to assess their performance level in the new position. For data analysis, individuals are first clustered using the self-organizing maps method, which is one of the neural network techniques, and then, based on correlation tests, the relationships among the clusters as well as between competence and performance are examined[7].

The statistical population of this study consists of those who have participated in the assessment center in a petrochemical company over the past 5 years. The sampling method is purposive sampling based on specific criteria. Since not all members of the population possess the desired characteristics, the population is filtered based on these criteria to achieve an appropriate sample. The criteria include the participation of employees in the assessment center and the presence of a performance evaluation score in their personnel file. Using this method, the sample size was determined to be 75 individuals. The demographic information of the sample is presented in Table 2. As the table data indicate, most participants are men, hold a bachelor's degree, are in the 41–49 age range, have 10–20 years of work experience, and are official employees as well as non-local.

Table 1: Demographic Information of the Statistical Sample

Variable	Component	Frequency	Percentage (%)
Gender	Female	5	6.7
	Male	68	93.3
Education Level	Bachelor's	48	64.0
	Master's	18	24.0
	PhD	9	12.0
Age	30 - 40 years	23	30.7
	41 - 49 years	36	48.0
	50 and above	14	18.7
Work Experience	10 years and below	18	24.0
	11 - 20 years	50	66.7
	21 years and above	7	9.3
Employment Type	Permanent	48	64.0
	Contractual	18	24.0
	Temporary	9	12.0
Native Status	Native	73	97.3
	Non-native	2	2.7

For data analysis, statistics and data mining were used. Data mining is an exploratory and complex process that involves several stages. In the first stage, the main recovered datasets are selected. In the second step, the chosen data are preprocessed to remove incomplete records and those with significant inconsistencies, thereby improving quality. In the third step, the datasets are examined using various algorithms—such as decision trees, clustering, and others—to identify patterns that reveal relationships among the data[8].

Clustering is one of the most important data mining algorithms and has extensive applications in knowledge discovery. It involves dividing a large population of individuals into different groups so that individuals within each group are similar to one another, while those in different groups are distinct. Consequently, this study focuses on the clustering algorithm as a key tool in data mining.

Self-organizing maps (SOMs) are effective tools used for visualizing high-dimensional data. In their initial phase, a map similar to the input data is created. Essentially, SOMs transform nonlinear relationships among high-dimensional data into a simple geometric relationship, typically represented as a two-dimensional grid of nodes or neurons.

The original self-organizing map algorithm was developed by Kohonen, which is why SOMs are also known as Kohonen maps. They can convert multidimensional data into a two-dimensional image plane and visualize the clusters that emerge. In this algorithm, a special recurrent regression process is defined where, at each step, only a part of the model is adjusted. SOMs consist of two layers of neurons: the first is the input layer, comprising n neurons—each corresponding to one input variable—that transfer the input data to the neurons of the second layer. All computations occur in the second layer, referred to as the map, which serves as the output layer. The map is composed of networks of neurons arranged in a hexagonal pattern and operates in parallel. Each neuron in the input space is connected to a neuron in the output layer through a weight, meaning the map can be considered as a two-dimensional array of identical elements, each storing a weight vector[9,10].

3- Research Findings: Network Training and Evaluation

For training the network, a total of 2000 nodes were employed. The self-organizing map structure used in this study consists of 1956 nodes in the evaluation cluster and 1930 nodes in the output layer during the 360-degree evaluation—both figures being close to 2000.

The training speed was configured so that the software automatically achieves maximum accuracy during network training, and the network's tension parameter was set to 0.5. The Viscovery Profiler software automatically selects the optimal dimensions for the network during training by considering the number of neurons in the output layer. After testing and training, the software chose dimensions of 43×46 for the evaluation cluster and 50×39 for performance evaluation.

To assess the accuracy and fidelity of the self-organizing maps, a metric known as the progressive error is used. This error, which ranges between 0 and 1, indicates how well the output maps are able to represent the input data in a two-dimensional space. The closer the progressive error is to zero, the higher the accuracy of the network (Wendel & Batnfeld, 2010). In this research, the final progressive error for the network was 0 in both methods.

3-1 Analysis of Output Maps and Final Segmentation

Viscovery Profiler software uses a hierarchical clustering method called "SOM Ward Clusters" to determine the boundaries of each segment and to establish the optimal number of clusters.

Table2: Frequencies of Individuals in the Two Segmentation Methods

Cluster	Evaluation Cluster (%)	360-Degree Evaluation (%)
First Cluster	36	44
Second Cluster	20	18.67
Third Cluster	33.33	20

Cluster	Evaluation Cluster (%)	360-Degree Evaluation (%)
Fourth Cluster	10.67	17.33

Table 3. A. Average of Examined Dimensions in the Evaluation Cluster

Indicator	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Personality Fit	5.36	7.07	8.67	7.56
Schema Fit	5.70	7.39	8.65	7.56
Teamwork	5.26	7.16	7.99	6.58
Creativity	5.03	6.98	8.29	7.03
Analytical Thinking	6.15	7.25	8.84	7.85
Communications	5.23	7.21	8.49	7.47
Leadership	5.19	7.14	7.96	6.96
Planning	5.61	7.23	8.66	7.61
Decision-Making	5.62	7.36	8.46	7.09
Emotional Intelligence	4.72	5.49	5.73	5.59

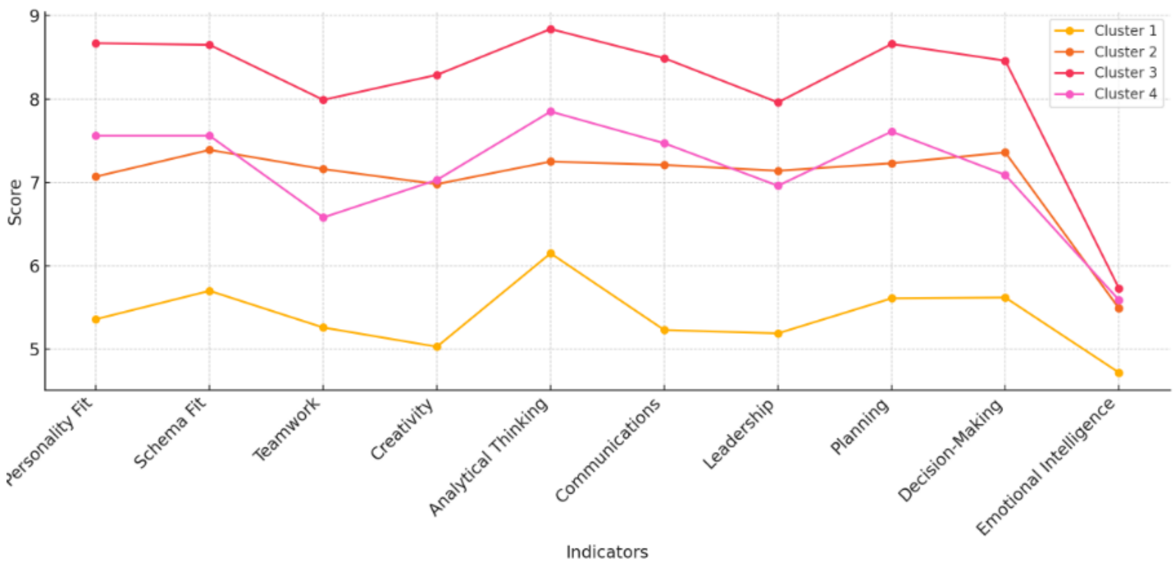

Figure 1 Average of Examined Dimensions in the Evaluation Cluster

B. Average of Examined Dimensions in the 360-Degree Evaluation

Indicator	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Monitoring	8.31	9.00	3.29	9.03
Delegation	6.30	6.40	6.14	5.81
Team Building	4.91	6.21	6.25	6.23
Creativity	5.68	7.15	6.61	6.57
Coordination	3.27	5.09	3.44	3.41
Goal Setting	4.74	6.47	5.34	5.16
Leadership	3.48	5.80	4.49	4.52
Planning	4.07	6.15	5.72	5.79
Decision-Making	4.73	5.92	5.84	5.48

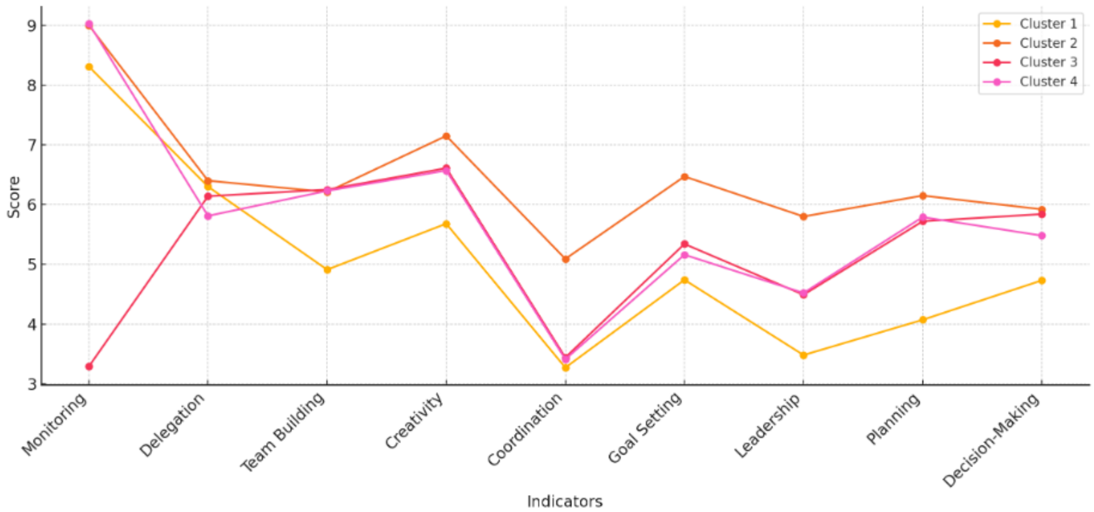

Figure 2. Average of Examined Dimensions in the 360-Degree Evaluation

The software, for a better description of each section, presents a diagram of the variables under investigation in the evaluation center, as shown in Figure 1. Using this diagram, the above results can also be achieved. In the diagram, the status of the examined variables in each section is displayed relative to other sections, as well as relative to the status of the other variables within that section. In this diagram, each level of the examined variables is designated by a specific color. The column charts with different colors indicate the level status of the variable in each section.

To examine the relationship between the ratings obtained from the evaluation center and those from the 360-degree evaluation, two tests are conducted:

A. Kappa Correlation Coefficient: This coefficient is calculated based on the frequency of clusters from the evaluation center and the 360-degree evaluation. The frequency of cluster agreement by both methods is presented in Table 4.

Table 4: Frequency of Clusters in Assessment Center and 360-Degree Evaluation

360-Degree Evaluation	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Total
Cluster 1	33	4	10	7	54
Cluster 2	12	0	4	3	19
Cluster 3	17	0	7	5	29
Cluster 4	13	4	4	0	21
Total	75	8	25	15	123

By using the **Kappa correlation coefficient significance level**, we can evaluate the relationship between clusters in the two performance assessment methods: **360-degree evaluation and the assessment center**. When the significance level is **less than the 5% error threshold**, the hypothesis of dependency between the two variables is confirmed.

Based on this test, since the **significance level is 0.204**, which is **greater than 5%**, we conclude that the clusters obtained from the two methods do not show a relationship with each other. The results of the **Chi-square test** are presented in **Table 5**.

Table 5: Results of the Chi-Square Agreement Test

Value	Asymp. Std. Error	Approx. T	Approx. Sig.
Measure of Agreement Kappa	0.087	0.076	1.271
N of Valid Cases	75	-	-

Based on the clustering results from the two methods, we can also determine their **overlap**. According to **Table 7**, only **12 individuals from Cluster 1, 5 individuals from Cluster 2, 6 individuals from Cluster 3, and 4 individuals from Cluster 4** are **shared between the two**

clustering methods.

Table 6: Overlap of Clusters in the Two Methods

Clusters 1	Clusters 2	Clusters 3	Clusters 4
Individuals shared between the two methods	12	5	6
Overlap percentage (%)	16%	6.6%	8%

3-2 Pearson Correlation Test:

Regardless of the relationship between clusters, the correlation between the Assessment Center's prediction and performance evaluation has been measured using the Pearson correlation test. In other words, each individual has a competency score obtained through the Assessment Center, and the same individual has a 360-degree performance evaluation score recorded annually in their personnel file. These two sets of scores were tested using the Pearson correlation coefficient. The Pearson correlation coefficient for these two scores is **0.481**. Given the obtained significance level (close to zero as shown in Table 7), the correlation between the Assessment Center score and the performance evaluation score can be considered significant. The positive coefficient indicates that individuals who scored higher in competency also received higher performance evaluation scores, and vice versa. In other words, individuals who appeared more competent in the Assessment Center also demonstrated better real-world performance. The results of this test are presented in Table 7.

Table 7: Pearson Correlation Test for Examining the Relationship Between Core Competency and Performance

Description	Assessment Center	360-Degree Performance Evaluation
Pearson Correlation Coefficient	0.481	-
Significance Level	0.000	-

Conclusion

This research provides a data-driven approach to analyzing employee competencies and identifying high-performance employees using self-organizing maps and clustering techniques. By integrating competency assessment through an evaluation center and 360-degree performance evaluation, we demonstrated the strengths and limitations of these methods in predicting job performance. The Pearson correlation results confirm a significant relationship between competency assessments and real-world performance, reinforcing the importance of structured evaluation processes. While the Kappa test did not establish a direct correspondence between segmentation methods, the overlap analysis and competency-performance correlation underscore the value of assessment centers in talent identification. These findings contribute to the ongoing development of competency-based evaluation frameworks, helping organizations enhance workforce efficiency and employee development strategies. Future research may explore alternative machine learning models to refine competency segmentation further.

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