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Meta modelling of job satisfaction effective factors for improvement policy making in organizations

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Abstract

Purpose – The purpose of this paper is to propose a Meta modeling based on regression, neural network, and clustering to analyze the job satisfaction factors and improvement policy making.

Design/methodology/approach – Since any job satisfaction evaluation supposes to improve the status by prescribing specific strategies to be performed in the organization, proposing applicable strategies is decisively important. Task demand, social structure and leader-member exchange (LMX) are general applications easily conceptualized while proposing job satisfaction improvement strategies.

Findings – On the basis of these empirical findings, the authors first aim to identify relationships between LMX, task demand, social structure and individual factors, organizational factors, job properties, which are easier to be employed in strategy formulation for job satisfaction, and then determine the sub-factors and subsequently cluster them. The effectiveness of the proposed model is verified by a case study.

Originality/value – Here, a Meta modeling based on regression, neural network, and clustering is proposed to analyze the job satisfaction factors and improvement policy making.

Keywords Neural network, Clustering, Job satisfaction, Regression analysis

Paper type Research paper

1. Introduction

Job satisfaction research has sought to establish the mechanisms through which job characteristics affect employee outcomes such as performance and well-being. Employee learning has been proposed as one such mechanism (Parker and Wall, 1999). The basic premise of the job satisfaction-learning mechanism is that job characteristics stimulate the learning process. This leads to the acquisition of knowledge about the job and its context, enabling the employee to perform more effectively and to cope better with demand. An additional benefit of the employee being able to cope better with demand is an improvement in well-being (Frese and Zapf, 1994; Karasek and Theorell, 1990). Consistent with this view, studies have found support for a job satisfaction-learning mechanism in relation to two employee outcomes, task performance (Wall *et al.*, 1992), and well-being (Holman and Wall, 2002; Taris and Kompier, 2005).

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The factors influencing job satisfaction may be listed as professional status, pay, administrative style, work requirement and policies, and individual characteristics. Some studies suggest exploring factors affecting job satisfaction such as age, marital status, gender, organization or institution, level of responsibility, employment type, work duration, and payments (Asti and Pektekin, 1994; Aydin and Kutlu, 2001; Cimete *et al.*, 2003; Fung-Kam, 1998; Kacel *et al.*, 2005; Mrayyan, 2005; Siu, 2002).

Job satisfaction not only depends on the quality of employment, but also on employee's expectations with respect to the job. The key to job satisfaction is, in fact, the degree of the match between objective conditions of the job and worker's expectation. The more the fit between the expectation and the conditions, the greater is the satisfaction. This is in consistent with the principles raised by social psychologists for job satisfaction (see Locke, 1976; Lawler, 1973).

Previous studies (e.g. McNeese-Smith, 1996; Lee *et al.*, 1999; Tzeng *et al.*, 2002) reported that managerial factors affected employees' attitudes, job satisfaction, organizational commitment, and motivation to perform well, and these factors, in turn, influenced organizational outcomes.

Job satisfaction, self-efficacy, occupational commitment, and change in employees level of motivation are put forward as indicators of teachers' sense of their professional identity. They are the representation of the more tacit construct that professional identity appears to be. Therefore, it is important to understand how these constructs relate to one another. They have been investigated separately and in diverse combinations in various studies (e.g. Cooper-Hakim and Viswesvaran, 2005), but no research has been done which relates them all to one another nor to provide, as argued in this study, an impression of teachers' perceptions of their own professional identity.

The examination of job satisfaction has a long tradition, starting with Hoppock's (1935) study and continuing to the present day, as can be seen in recent studies (e.g. Schirmer and Lopez, 2001) and for meta-analyses (e.g. Judge and Bono, 2001). There are three main areas of research concerning job satisfaction: first, job satisfaction is regarded as an antecedent of organizational outcomes such as performance (see meta-analyses by Iffaldano and Muchinski, 1985; Six and Eckes, 1991), turnover (Griffeth *et al.*, 2000; Mobley, 1977; Williams and Hazer, 1986), and organizational citizenship behavior (Organ and Ryan, 1995). Second, job satisfaction is regarded as an outcome of organizational conditions such as leadership (Podsakoff *et al.*, 1996; Schriesheim *et al.*, 1992; Sparks and Schenk, 2001), sex of leader (Trempe *et al.*, 1985), social support (Frone, 2000; Liden *et al.*, 2000; Sargent and Terry, 2000; Schirmer and Lopez, 2001; Stepina *et al.*, 1991), and task characteristics (Dodd and Ganster, 1996; Seers and Graen, 1984; Stepina *et al.*, 1991). Third, job satisfaction is regarded as a disposition influenced by personality traits (Dormann and Zapf, 2001; Judge and Bono, 2001; Judge *et al.*, 1998, 2000).

Job satisfaction and task demands

Several studies have shown the existence of positive relationships between different task characteristics and job satisfaction. More specifically, the following characteristics have been found to relate positively to job satisfaction: autonomy and variety (Dodd and Ganster, 1996), (positive) task characteristics in general (Stepina *et al.*, 1991), task variety (Zaffane, 1994), task clarity and significance (Ting, 1997), and task responsibilities (Blau, 1999). In the following section, some results of these studies are reported with respect to the relationship between task demands and job satisfaction.

Job satisfaction and leader-member exchange (LMX)

Several studies have focussed on leadership and job satisfaction (e.g. Podsakoff *et al.*, 1996; Schriesheim *et al.*, 1992; Sparks and Schenk, 2001) or on superior and/or coworker support and job satisfaction (e.g. Bradley and Cartwright, 2002; Ducharme and Martin, 2000; Sargent and Terry, 2000; Schirmer and Lopez, 2001).

Job satisfaction and social structure

In addition to leader behavior and quality of leader-member relationship, the relationships with colleagues are part of the social structure at the work place and assumed to influence job satisfaction.

This research aims at categorizing effective factors of job satisfaction in organizations. Since, job satisfaction is vital for productivity improvement in organizations. Therefore, determining and analyzing effective job satisfaction factors is significant. The previous works of job satisfaction tried to determine the factors and evaluated them in a questionnaire study to only imply the most effective ones or rank the factors. So, the phase of improvement policy making which crucial after evaluation was neglected. The main contribution of this work is to first categorize the job satisfaction factors systematically and then develop improvement policy making via clustering. The remainder of our work is organized as follows. Next, we review the job satisfaction factors. In Section 3, our research methods and materials are presented. Section 4 presents the case study. We conclude in Section 5.

2. Job satisfaction effective factors

Having concentrated so far on the single relationships between predictors and job satisfaction, we will now review research that has combined several variables in predicting job satisfaction. Seers and Graen (1984) established a model combining task characteristics and LMX in their relationship to job satisfaction. LMX was positively related to the overall job satisfaction and facets of job satisfaction. In addition, both LMX and task characteristics were found to add to job satisfaction in a complementary way. In general, Stepina *et al.* (1991) replicated these findings. A similar but more complex model was established by De Jonge *et al.* (2001). In a sample of nurses, in controlling gender, age was negatively affected and a negative relationship between task demands (time pressure, hard work, complexity) at Time 1 and job satisfaction at Time 2, as well as a positive relationship between work-place social support (by supervisor and by colleagues) at Time 1 and job satisfaction at Time 2 were found. Job autonomy 1 did not have an impact on job satisfaction.

Since any job satisfaction evaluation supposes to improve the status by prescribing specific strategies to be performed in the organization, proposing applicable strategies is decisively important. Task demand, social structure, and LMX are general applications easily conceptualized while proposing job satisfaction improvement strategies. On the basis of these empirical findings, we aim to establish relationships between LMX, task demand, social structure and individual factors, organizational factors, job properties, which are easier to be employed in strategy formulation for job satisfaction, and then determine the sub-factors and cluster them.

First, two categories for job satisfaction is considered namely, concept and application. Concepts are easier to be asked for job satisfaction evaluation and as shown by the past research, applications are simpler for strategy formulation. Then, a relationship between the category of concept and application is determined. After that, we formulate job satisfaction improvement strategies based on the concept of category factor.

3. Methods and materials

Several studies have shown that task demands, social structure, and LMX are positively related to job satisfaction. In the dual attachment model (Seers and Graen, 1984), two factors, task characteristics, and LMX, were combined in order to evaluate their complementary influence on job satisfaction. In the present study, the aim is to extend the model to be more general by addition of social structure to the prediction of job satisfaction. In different organizational contexts, these factors might enhance job satisfaction to differing degrees depending on, for example, the task that employees have to fulfill or the strength of the organizational structure. Thus, the results obtained by Seers and Graen (1984) and, in part, those obtained by De Jonge *et al.* (2001) should be replicated and extended in a heterogeneous sample rather than in a one-organization sample.

Therefore, to establish a relationship between concept category and application, a multiple linear regression model is developed. One way to analyze the effect of independent variables on a dependent one is regression modeling. The aim is to find which concept factor is effective on any application factor and to what extent. A configuration of such a method is shown in Figure 1.

After forming three regressions for the concept factors, another analysis is performed to determine the effectiveness of the concept sub-factors on the regressed application factors. The concept sub-factors are the ones related to each concept factor being asked from the participants via a questionnaire. The aim here is to prepare sub-factors for clustering. Therefore, a comprehensive data analysis technique is required to relate the concept sub-factors to the regressed application factors. A neural network is proposed to perform this function. The neural network helps to relate some input parameters (concept sub-factors) to some outputs (regressed application factors) via a training process using the past data.

Then, using the values of sub-factors and the obtained values of the regressed application factors, clustering is performed to classify the sub-factors into groups in simplifying and organizing the improvement policy-making process. This process is shown in the following flowchart (Figure 2).

The methods used in our work are fully explained below.

Multiple linear regression

As stated before, some rules affect the cost of the system. We should investigate whether an application factor is effective on a concept factor or not. One way to survey

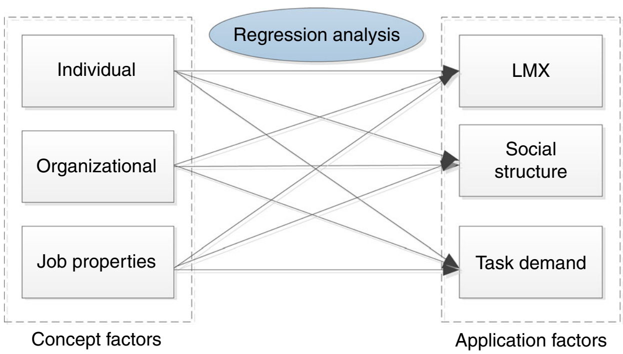

Figure 1. Regression model to establish a relationship between concepts and application factors

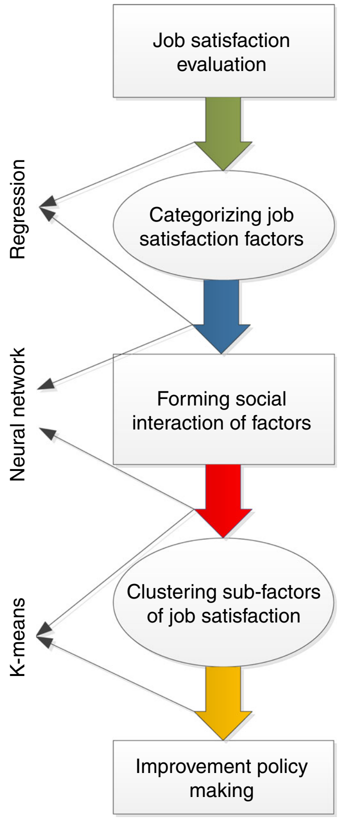

Figure 2.
A flowchart of the research

the effect of independent variables on dependent variable is to use a multiple linear regression model. Therefore, we consider the following equation:

$$u_i = \beta_0 + \beta_1 r_1 + \ldots + \beta_j r_j + \varepsilon_j, \quad i = 1, \ldots, n, j = 1, \ldots, m, \tag{1}$$

where with respect to each i, β_0 is the intercept, β_j the coefficients of the r_j factor and the ε_j the error terms. The aim is to identify the β_j not being important on application factor. Here, we employ the two-sided hypothesis testing as follows:

$$\begin{aligned} H_0&: \beta_j = 0, \\ H_1&: \beta_j \neq 0. \end{aligned} \tag{2}$$

The null hypothesis indicates whether a factor coefficient is zero or not. If the hypothesis is accepted (a certain coefficient factor is zero), then we can omit the corresponding factor from the regression model. The test of the null hypothesis H_0 against the two-sided alternative proceeds in three steps. The first is to compute the standard error of β_j,$SE(\beta_j)$. The standard error of β_j is an estimator of σ_{β_j}, the standard deviation of the sampling distribution of β_j:

$$\sigma^2_{\beta_j} = \frac{1}{m} \times \frac{\frac{1}{m-2} \times \sum_{j=1}^{m} (r_j - \overline{r})^2 \varepsilon_j^2}{\left[\frac{1}{m}\sum_{j=1}^{m} (r_j - \overline{r})^2\right]^2}, \quad (3)$$

$$SE(\beta_j) = \sqrt{\sigma^2_{\beta_j}}. \quad (4)$$

Although the formula for $\sigma^2_{\beta_j}$ is complicated, but, in practice, the standard error is computed by a regression software. The second step is to compute the t-statistic:

$$t = \frac{\beta_j - 0}{SE(\beta_j)}. \quad (5)$$

The third step is to compute the p-value, the probability of observing a value of β_j at least as different from zero as the estimate actually computed $\left(\beta_j^{act}\right)$, assuming that the null hypothesis is correct. Stated mathematically:

$$p\text{-value} = \Pr_{H_0}\left[\left|\beta_j - 0\right| > \left|\beta_j^{act} - 0\right|\right] \Rightarrow \Pr_{H_0}\left[\left|\frac{\beta_j - 0}{SE(\beta_j)}\right| > \left|\frac{\beta_j^{act} - 0}{SE(\beta_j)}\right|\right]$$
$$\Rightarrow \Pr_{H_0}\left(|t| > \left|t^{act}\right|\right), \quad (6)$$

where $\Pr_{H_0}$ denotes the probability computed under the null hypothesis, the second equality follows by dividing into $SE(\beta_j)$, and t^{act} is the value of the t-statistic actually computed. Because β_j is approximately normally distributed in large samples, under the null hypothesis the t-statistic is approximately distributed as a standard normal random variable, and so for large samples:

$$p\text{-value} = \Pr\left(|Z| > \left|t^{act}\right|\right) = 2\Phi\left(-\left|t^{act}\right|\right). \quad (7)$$

A small value of the p-value, say less than 5 percent, provides evidence against the null hypothesis in the sense that the chance of obtaining a value of β_j by pure random variation from one sample to the next is less than 5 percent, if, in fact, the null hypothesis is correct. If so, the null hypothesis is rejected at the 5 percent significance level. Simply, we can reject the null hypothesis at the 5 percent significance level if $|t^{act}| > 1.96$. Therefore, if the hypothesis is accepted, then we ensue that the corresponding factor is not important and is not effective on application factor. The estimation of the coefficients is performed using a regression software.

The backpropagation neural network

The backpropagation algorithm trains a given feed-forward multilayer neural network for a given set of input patterns with known classifications. When each entry of the sample set is presented to the network, the network examines its output response to the sample input pattern. The output response is then compared to the known and desired output and the error value is calculated. Based on the error, the connection weights are adjusted. The backpropagation algorithm is based on Widrow-Hoff δ learning rule in which the weight adjustment is done through mean square error of the output response to the sample input (Abdi *et al.*, 1996).

We are now in a position to state the backpropagation algorithm formally.

Algorithm 1. Formal statement of stochastic backpropagation.
(Training examples, η, n_i, n_h, n_o)

Each training example is of the form $\langle \vec{x}, \vec{t} \rangle$, where $\vec{x}$ is the input vector and $\vec{t}$ is the target vector, η is the learning rate (e.g. 0.05), n_i, n_h and n_o are the number of input, hidden and output nodes, respectively. Input from unit i to unit j is denoted by x_{ji} and its weight is denoted by w_{ji}. Create a feed-forward network with n_i inputs, n_h hidden units, and n_o output units.

Initialize all the weights to small random values (e.g. between −0.05 and 0.05).

While termination condition is not met Do

For each training example $\langle \vec{x}, \vec{t} \rangle$:

(1) input the instance $\vec{x}$ and compute the output o_u of every unit;

(2) for each output unit k, calculate:

$$\delta_k = o_k(1-o_k)(t_k-o_k). \tag{8}$$

(3) For each hidden unit h, calculate:

$$\delta_h = o_h(1-o_h) \sum_{k \in Downstream(h)} \delta_k.w_{kh}. \tag{9}$$

(4) Update each network weight w_{ji} as follows:

$$w_{ji} \leftarrow w_{ji} + \Delta w_{ji}. \tag{10}$$

where:

$$\Delta w_{ji} = \eta \delta_j x_{ji}. \tag{11}$$

K-means clustering technique

K-means (MacQueen, 1967) is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because different locations produce different results. So, a good choice is to place them far from each other as much as possible. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early grouping is at hand. At this point, we need to re-calculate k new centroids as centers of the clusters obtained from the previous step. After we have these k new centroids, a new binding has to be performed between the same data set points and the nearest new centroid. A loop is generated. As a result of this loop, we may notice that the k centroids change their locations step by step until no more change is possible. In other words, centroids cannot move any more.

Finally, the algorithm aims at minimizing an objective function; in this case, a squared error function. The objective function is:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|_2^2, \tag{12}$$

where $\left\| x_i^{(j)} - c_j \right\|_2^2$ is a chosen distance measure between a data point $x_i^{(j)}$, and the cluster center c_j is an indicator of the distance of the n data points from their respective cluster centers.

The steps of the algorithm are given next.

Algorithm 2. Statement of K-means clustering.

Step1: place k points into the space represented by the objects that are being clustered. These points represent initial group centroids.

Step 2: assign each object to the group that has the closest centroid.

Step 3: when all objects have been assigned, re-calculate the positions of the k centroids.

Step 4: repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

Although it can be proved that the procedure will always terminate, the k-means algorithm does not necessarily find the global optimal configuration when the model has several local optimal solutions. The algorithm is also significantly sensitive to the initial randomly selected cluster centers. The k-means algorithm can be run a number of times to reduce this effect.

4. A case study

The case study developed here was performed at Mazandaran Gas Company in Iran. Mazandaran Gas Company is an organization with more than 700 employees. A methodology for job satisfaction evaluation given by Mahdavi *et al.* (2010) was implemented to determine the job satisfaction status in the organization. Mahdavi *et al.* (2010) first analyzed the employees considering categorized factors as given in Figure 3.

Then, for each category a separate questionnaire was designed. Here, sampling was performed using the STRATA technique. A sample size of 70 was required extracting from different categories. Three categories of individual, job properties, and organizational factors, as concept factors in our work, were considered to compose separate questionnaires (see Table AI). In the questionnaire, employees were asked to indicate their opinions about different factors corresponding to job satisfaction, in triangular fuzzy linguistic terms (high, fair, low). The mean of the results for each question was used to decide the fuzzy rules. Then, the appropriate number of questionnaires to each category were disseminated, randomly. After the questionnaires were filled in by the employees, they were analyzed using the proposed fuzzy rules. Since each category contains some factors taking low, fair, or high-linguistic values, all the existing rules describing different statuses of the satisfaction in the organization were incorporated. Analyzing all the rules and deffuzifying them using the MATLAB function, FNTool, the numerical values were computed and inserted into the proposed job satisfaction matrix. The concept factor results are summarized in Tables I-III.

In Tables I-III, the gaps show the dissatisfaction values for the corresponding factors. The gaps with values more than 40 are critical and should be treated to shorten the gap. Next, we propose strategies to reduce the gaps to provide a productive organization.

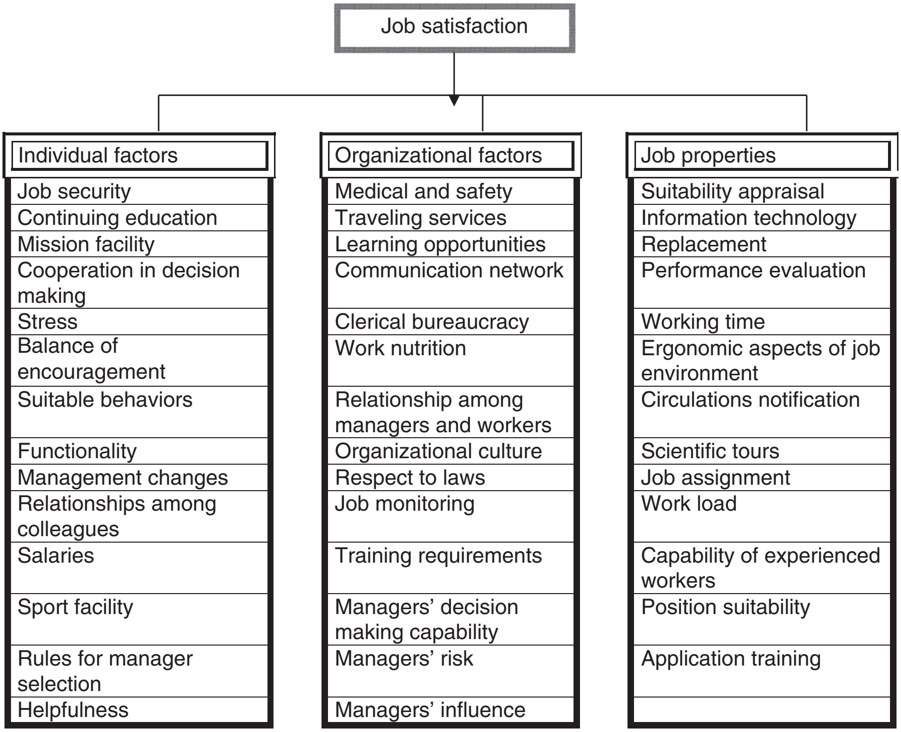

Figure 3.
Job satisfaction concept factors with their sub-factors

Table I.
Results for individual factors

Factor status	Job security	Continuing education	Mission facility	Cooperation in decision making	Stress	Balance of encouragement	Suitable behaviors
A_C^0	73	82	77	63	51	41	52
A_I^0	100	100	100	100	100	100	100
G_{I-C}^0	27	18	23	37	49	59	48
Factor status	Functionality	Management changes	Relationships among colleagues	Salaries	Sport facility	Rules for manager selection	Helpfulness
A_C^0	41	32	57	85	61	32	51
A_I^0	100	100	100	100	100	100	100
G_{I-C}^0	59	68	43	15	39	68	49

Since the current status of the organization is obtained based on a job satisfaction view, while being critical, it is required to compose strategies to draw an improvement path. We consider strength, weakness, opportunity, and threat factors of the organization in proposing strategies. Therefore, we have four positions such as strength-threat, threat-weakness (critical), weakness-opportunity, and strength-opportunity. The last position is the optimal one and the goal of strategies is to reach this position. The improvement strategies are proposed for employing experts via brain storming as shown in Table IV.

Implementing these strategies should result in an improvement in the early periods. Reconsidering and reevaluating job satisfaction in the next periods, we eventually get

Table II. Results for organizational factors

Factor status	Medical and safety	Traveling services	Learning opportunities	Communication network	Work nutrition	Relationship among managers and workers	Organizational culture
A_C^0	41	45	48	61	65	39	26
A_I^0	100	100	100	100	100	100	100
G_{I-C}^0	59	55	52	39	35	61	74
Factor status	Respect to laws	Job monitoring	Training requirements	Managers' decision making capability	Managers' risk	Managers' influence	
A_C^0	53	67	68	59	56	68	
A_I^0	100	100	100	100	100	100	
G_{I-C}^0	47	33	32	41	44	32	

Table III. Results for job properties factors

Factor status	Suitability appraisal	Information technology	replacement	Performance evaluation	Working time	Ergonomic aspects of job environment	Circulations notification
A_C^0	54	61	17	29	36	48	65
A_I^0	100	100	100	100	100	100	100
G_{I-C}^0	46	39	83	71	64	52	35
Factor status	Scientific tours	Job assignment	Work load	Capability of experienced workers	Position suitability		
A_C^0	68	13	56	38	54		
A_I^0	100	100	100	100	100		
G_{I-C}^0	32	87	44	62	46		

to the best position. The current position and the improvement path using the proposed strategies for the periods are shown in Figure 4.

For better and more efficient implementation of the job satisfaction improvement strategies, our Meta modeling helps to turn the job satisfaction factors from concept to application. As explained in Section 3, the first three regression models are proposed to relate the concept factors with the application ones. The regressions for the three concept factors based on the three application factors (r_1, r_2, r_3) are given below:

$$u_1 = 3.2 + 0.75r_1 + 0.35r_2 + 1.2r_3,$$

$$u_2 = 2.12 + 0.85r_1 + 0.38r_2 + 3.2r_3,$$

$$u_3 = 0.72 + 2.5r_1 + 1.45r_2 + 0.62r_3.$$

Also, note that the model fitting is based on the past data obtained from the organization. Therefore, several regression models can be obtained for different time periods.

Table IV.
Some of the improvement strategies

Sub-factors	Gap
1. Job assignment Improvement policy: test, interview, score, evaluation scientific committee, experiences, satisfaction for the assigned job, relationship between the academic certificate and the new job, balancing jobs with the new study fields, helping employees to continue their studies	87
2. Replacement Improvement policy: candidates, score table, priority vector, training candidates, authorize the potential candidates in a job position	83
3. Organizational culture Improvement policy: behavioral and oral education, research, new working groups, new communications, hierarchical respects	74
4. Performance evaluation Improvement policy: scientific committee for performance evaluation, score table, clear and measurable evaluation system, efficiency analysis, evaluating employees' creativity, designing employees' evaluation database	71
5. Rules for manager selection Improvement policy: management functions, popularity score, performance score, attractiveness score, patience and support of supreme authorities in crisis	68
6. Working time Improvement policy: alternatives, recommendations for maximizing output, decision making, study and research time	64
7. Relationship among managers and workers Improvement policy: education, promoting culture, creating horizontal relationship	61
8. Balance of encouragement Improvement policy: rules, periodic reforms, designing encouragement packages, surveying employees' performance	59
9. Functionality Improvement policy: education, research, evaluation, system attitude, benchmarking	59
10. Medical and safety Improvement policy: education, research, evaluation, system attitude,	59
11. Welfare and traveling Improvement policy: knowing the services, kinds of services, measuring the services, proposing services to all levels of the organization	55
12. Study opportunity Improvement policy: rules, facilities, creating opportunities based on the organization requirements	52
13. Ergonomic aspects of job environment Improvement policy: education, engineering pattern, professional health pattern	52
14. Helpfulness Improvement policy: education, behavioral pattern, social wealth and cases, clarification in relations and communications	49
15. Stress Improvement policy: education, research, psychological consultants for analysis, creating medical forms for employees	49

Then, using the regressed application factors we ran the neural network to analyze the relationship between the concept sub-factors and the regressed application factors.

A feed-forward backpropagation network can be used to approximate a function to relate the sub-factors to the application factors. To facilitate the computations of backpropagation neural network, MATLAB 7 user interface, NNtool, was applied. A feed-forward network was programed with sub-factor inputs, ten hidden units with logistics activation function, and the outputs. A configuration of the feed-forward neural network is shown in Figure 5.

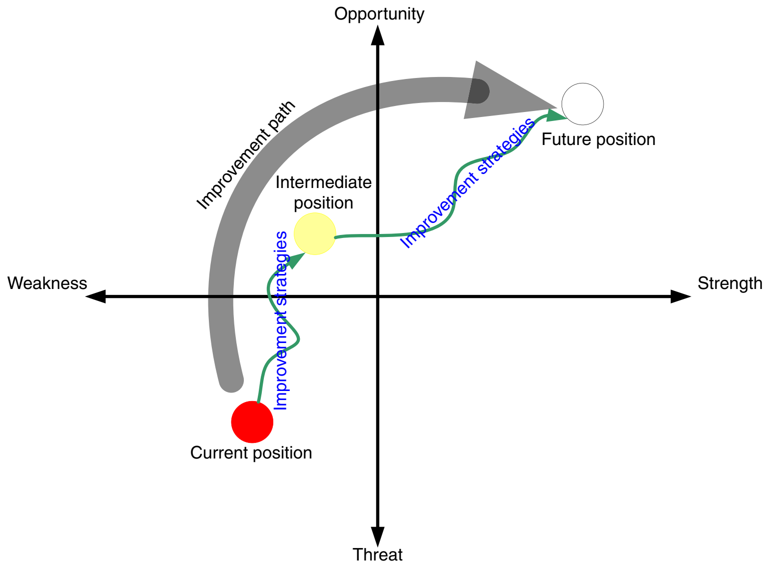

Figure 4.
The current status and the improvement path

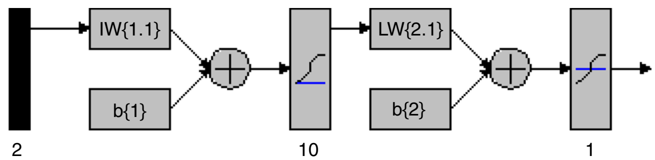

Figure 5.
A configuration of the feed-forward neural network

Using NNtool, the data were inserted and the required settings were made to train the data to obtain an appropriate pattern.

Next, using the output of the neural network, we clustered the sub-factors into application factors being fulfilled in strategy implementation via k-means.

We had 39 sample feature vectors $x_1, x_2, \ldots, x_{39}$ all from the same class, and we know that they fall into three compact clusters. Let m_i be the mean of the vectors in cluster i. If the clusters are well separated, we can use a minimum-distance classifier to separate them. That is, we can say that x is in cluster i if $\| x - m_i \|$ is the minimum of all the k distances. This suggested the following procedure for finding the k-means:

Make initial guesses for the means m_1, m_2, m_3
Repeat
Use the estimated means to classify the samples into clusters
  For i from 1 to 3
  Replace m_i with the mean of all of the samples for cluster i
  End for.
Until there are no changes in any mean.

Using the above procedure and the data we obtained from the neural network, we proposed the following clusters. These clusters were presented to the managerial team to implement and monitor the status changes toward job satisfaction improvement and the number of clusters are set to be 3. Also, it should be noted that, the criteria of selecting clustering method includes build time and smallest cluster.

Cluster 1: task demands:

- Job security
- Medical and safety
- Information technology
- Replacement
- Performance evaluation
- Working time
- Ergonomic aspects of job environment
- Circulations notification
- Work load
- Training requirements
- Capability of experienced workers
- Position Suitability
- Application training

Cluster 2: social structures:

- Continuing education
- Traveling services
- Learning opportunities
- Communication network
- Work nutrition
- Functionality
- Scientific tours
- Management changes
- Sport facility
- Managers' risk
- Managers' influence
- Helpfulness

Cluster 3: LMX:

- Mission facility
- Cooperation in decision making
- Stress

- Suitability appraisal
- Clerical bureaucracy
- Balance of encouragement
- Relationship among managers and workers
- Suitable behaviors
- Organizational culture
- Respect to laws
- Job assignment
- Relationships among colleagues
- Job monitoring
- Managers' decision making capability
- Rules for manager selection
- Salaries

As a result, task demand, social structure, and LMX are general applications easily conceptualized while proposing job satisfaction improvement strategies. Therefore, we established relationships between LMX, task demand, social structure and individual factors, organizational factors, and job properties, to be easily employed in strategy formulation for job satisfaction. Each cluster is planned to be implemented under the supervision of the corresponding management team

5. Conclusions

First, two categories for job satisfaction were considered namely, concept and application. Concepts were easier to be asked for job satisfaction evaluation and as shown by the existing research, applications were simpler for strategy formulation. Then, a relationship between the category of concept and application was established. After that, we formulated job satisfaction improvement strategies based on the concept factor. To hold a relationship between concept and application, a multiple linear regression model was developed. The aim was to find which concept factor is effective on any application factor and to what extent. After performing three regressions for the concept factors, a second analysis was performed to determine the effectiveness of the concept sub-factors on the regressed application factors. The concept sub-factors were the ones corresponding to each concept factor being asked from the participants via a questionnaire. The aim was to prepare the sub-factors for clustering. Therefore, a comprehensive data analysis technique was required to relate the concept sub-factors to the regressed application factors. A neural network was proposed to perform this task. Neural network helped to relate some input parameters (concept sub-factors) to some outputs (regressed application factors) via a training process using the past data. Then, using the values of sub-factors and the obtained values of regressed application factors, clustering was performed to classify the sub-factors into groups to simplify and organize the improvement policy-making process. The process was fully verified and shown to be effective in a case study conducted in Mazandaran Gas Company in Iran.

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Appendix

No.	Scores Questions	High	Fair	Low
1	Job security			
2	Continuing education			
3	Mission facility			
4	Cooperation in decision making			
5	Stress			
6	Balance of encouragement			
7	Suitable behaviors			
8	Functionality			
9	Management changes			
10	Relationships among colleagues			
11	Salaries			
12	Sport facility			
13	Rules for manager selection			
14	Helpfulness			

Table AI. A proposed questionnaire