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Turnover Prediction using Machine Learning: Empirical Study

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Abstract

In this work we attempt to study the turnover aspect in an organization located in a country in the Middle East, namely, Jordan. This organization consists of 1000 employees and it works in the service sector. A questionnairee was harvested from 280 employees in this organization throughout an entire year. Afterwards, a statistical study has been conducted. In addition, a soft clustering (SC) algorithm has been leveraged to construct a turnover prediction model. The model divides the employees into three clusters depending on the survey results. At the end of the year, the predicted clusters and the actual results from the company's records have been compared. 84% of the employees clustered in the mobile cluster voluntarily turned over. Moreover, our results showed that public sector and abroad contracts are the main criteria of turnover. This statistical study, also, indicated that the HR department should take serious steps to improve the quality of the work environment in order to reduce the turnover rate in this company. These steps vary from small management gratitude to employees to financial incentives.

Keywords: *Turnover rate, Statistical Study, HR, Career Stability, Soft-Clustering (SC)*

1 Introduction

Employee turnover is defined as the total number of employees are replaced by new workers in a fixed period of time. This replacement occurs due to the employees' resignation or termination. Turnover rate, however, is a percentage of this calculated number. Turnover rate is a measurement tool that is utilized to measure career security and stability in an enterprise [1]. This number impacts both employees and enterprises equally [2]. A higher turnover rate is a bad impression since it means that pursuing a career path is difficult in such enterprises. Moreover, career seekers attempt to move away from such organizations since no job stability could be found. At this point, it is worth mentioning that the difference between career and job opportunities is that a job is just working in multiple fields to earn a living such as part time jobs while as a career emerges from years of working and advancing in the same field. Employees always attempt to seek career paths to gain experience, financial security, and life stability. This is hard to apply in organizations with high turnover rates.

Turnover is classified into two classes: voluntary and involuntary. These classes affect companies and employees in different ways. In voluntary turnover, employees leave their positions to work in other companies. This class is also referred to as labor mobility. In this class, employees may leave for different reasons like higher pay, job satisfaction, poor working environment, bad management, or even because of issues between employees. This class of turnover harms organizations for two reasons. First, an expertise migration situation will occur. In this scenario, some of the turnover employees who are very well trained and expert in their fields leave to competitors. These competitor companies will infuse their staff with new skills while the original one loses them. Second, the organization lose all the training costs they paid to prepare and tailor these employees. Moreover, the organization will lose more on training new workers and staff.

The second class of turnover is involuntary turnover. In this class, the company terminates career employees for different reasons. First an employee's bad performance or attitude such as absenteeism and tardiness. Second, violating an organization's policy in a way that could impact the performance of a department or the whole company. Third, the company may require different skills that the employee cannot obtain or learn. In all cases, the company tries to replace the employee with talented ones, preferably, to increase its performance. Unfortunately, sometimes companies attempt to reduce the number of their staff to increase revenues by attracting expert worker to replace multiple ones. This is the worst example of involuntary turnover.

There are two other categories of career mobility that are not a part of turnover: job rotation and attrition. Job rotation is the process of moving employees from one section in an organization to another section or from one branch to another branch to refresh those departments or branches. In job rotation, the company does not lose or gain new employees. However, it enhances some sectors with new skills proliferated in other sections. On the other hand, attrition refers to the situation when employees leave their job for retirement, health issues or death. In attrition, the employee is not replaced for bad performance as in involuntary turnover. Further, the employee does not leave seeking another job or career with competitors as in voluntary turnover. In both cases, the company search for new employees for the new empty positions.

In this work, we attempt to study turnover reasons in a private organization located in Middle East, Jordan. The company has approximately 1000 employees. This work is a case study that seeks to answer the following questions:

- Does organization management impact employees' turnover decision?
- Do employees prefer public sector for its stability?
- How organization polices impact the turnover rate?
- What are the main criteria of turnover in the Middle East?
- Is it possible to predict the probability of turnover in an organization?

To facilitate our study, a questionnaire has been distributed on 280 employees from all departments in this company throughout an entire year. We kept the name of the company undisclosed and we will refer to it as company X. Subsequently, a statistical analysis has been utilized. Also, soft-clustering unsupervised machine learning algorithm with maximum likelihood (MLH) has been leveraged to generate a model to divide the employees into three main clusters: stable, take-experience and mobile clusters. To test the model accuracy, we compared the models with the names of voluntary turnover employees at the end of the year.

The rest of this paper is organized as following: In section 2, some of the related works that have been conducted in this area is discussed. In section 3, problem formulation, questionnaire and the statistical methods and tools is demonstrated. Finally, we conclude this work in section 4.

2 Related Work

Studying turnover rates have attracted researchers for years now with many studies found in the literature [1-3]. Two main methods have been utilized to study the turnover: theoretical and empirical. Many empirical studies have been conducted in different areas, such as, industries and sectors like oil and gas [4], healthcare [5], public sectors [6-7], and even the casino industry [8]. Turnover has been studied from different point of views. In additions, its types have been heavily studied to gain more insights of their causes. Psychologically, social aspects and wages dominated in the causes of voluntary turnover [9]. For instance, job satisfaction, which is defined as the feeling of enjoyment that is resulted from the employee's job experience, is one of the psychological factors that affect turnover intention. One study showed that there are several categories that influence job satisfaction like job stability, flexibility, and the friendliness of the workplace which, in turn, impacts turnover [10]. Further, intricate relationships with coworkers and supervisors may cause job dissatisfaction [11]. In contrast, other studies concluded that appreciation and proper training may reduce turnover rates [12]. In [13], the author attempted to study working conditions in workplaces and their relation to turnover. The author claims that there is a massive relation between work condition and voluntary turnover. Social aspects, on the other hand, appear when an employee is emotionally exhausted [14] or his or her personal life affect or interfere with the job [15-16]. In [13], the author studied the impact of gender and risk on turnover in Japan. The author found that these characteristics increase turnover rate. The last critical factor in employee voluntary turnover is wages. Lower salaries are often linked with higher turnover rates [14] with employees looking elsewhere for better pay. A previous study concluded that wages is a statistically significant predictor in turnover [17]. Another empirical investigation concluded that living wage workers have more commitment to their jobs, higher organizational citizenship behavior, and lower turnover compared to minimum wage workers [18].

In [19], the author studied the relation between involuntary turnovers with long time sick leaves. Data has been collected for 16 years from Sweden hospitals. The study showed that long time sick leaves not only increase the involuntary sick leaves but also reduces the opportunities of finding new careers in the future. From an economical point of view, organizational turnover rate shows the financial impact on enterprises, governments, and the public sector in general [20-21]. It has been claimed that voluntary turnover may enhance countries resources since that experts are propagated in different society sectors [22].

Different methods have been utilized to study turnover rates over the past decade. These studies have utilized data from cross-nation. In [23], the authors studied turnover utilizing time series over data collected from 6 different countries. The author claimed that mobility or turnover rate correlate with employment rate. Moreover, they demonstrated that no structural differences between turnover rates among these countries. Nevertheless, they claimed that mobility is lower in Japan than other countries. In [24], the authors studied aggregated data of ten different countries. The authors found that employment protection legislation (EPL) and the trainability of the workforce have a great impact on mobility and turnover in all these countries. Finally, the authors in [25] claimed that the collected data in other studies are limited. This data has been gathered and obtained from different resources. In their work, the authors collected data from 25 countries utilizing one survey. The authors concluded that turnover rate is lower in Japan than other countries. The authors claimed that customs and traditions play an important role in turnovers especially in Europe and USA. In the Middle East for instance, which is the region at which is study was conducted; a study in Egypt conducted the first Arabic language survey to measure wage satisfaction and relate it to turnover. The results showed that there is a strong correlation between pay and turnover intention [26]. Another study in the UAE highlighted on the importance of trust and job satisfaction on turnover intention in the public and private sectors in the country [27]. In Jordan, a case study was conducted on turnover intention in the healthcare sector. The study showed that, among nurses, there is a significant impact of wages and leadership on turnover. The same study did not find a strong relation between turnover intention and new job opportunities [28]. There is still, however, some ambiguity about turnover rates and intention in the Middle East region in many public and private sectors. The investigation presented in this paper discusses the factors affecting turnover in the aviation sector in Jordan. In addition, machine learning has been utilized in this work to construct a model to predict the probability of employees' mobility 'voluntary turnover'. Finally, the impact of new factors also has been investigated.

3 Soft-Clustering Algorithm

Soft clustering is an unsupervised machine learning algorithm. Two main forms of clustering algorithms are presented: soft and hard clustering. In hard clustering, the boundaries between the clusters are obvious. However, in soft-clustering cluster participation probability is shown, which mean that there are data points that can be clusters in more than one class according to their probabilities. This technique has been utilized in many research areas [29-30].

Soft clustering consists mainly of two layers: the estimation and maximization layers. In the estimation layer, the data points are divided into m clusters according to their probabilities for each cluster. To calculate this probability, a probability distribution model should be adopted. Since the features extracted from the data in this work follow normal distribution model, Gaussian distribution (GD) is leveraged. GD with multivariate version has been adopted since the number of features in this work is more than one since each feature is an independent random variable. Eqn.3 shows the multivariate GD (MGD) distribution.

$$P(x_n|\mu,\varepsilon) = \frac{1}{(2\pi)^{\frac{1}{2}}|\varepsilon|^{\frac{n}{2}}} e^{\left(-\frac{1}{2}(x-\mu)^T \varepsilon^{-1}(x-\mu)\right)} \qquad (1)$$

Where μ is the distribution mean and ε is the covariance matrix.

Eqn.1. is used in the first layer to calculate the probability of each data points. In order for this formula to be used, the two variables have to be calculated. The maximization layer is responsible of the probability distribution variables calculations. Maximum likelihood (MLH) has been utilized to estimate these variables. Eqn.3 and 4 shows the estimated values of μ and variance after applying MLH to GD. Subsequently, the estimated σ^2 is used to construct ε as in matrix 5. This process iterates until no changes occurs in the probabilities.

$$\{\mu,\sigma^2\}_{MLH} = \max\{l(\mu,\sigma^2; x_1, x_2, \ldots \ldots x_n)\} = \max\{f(x_1, x_2, \ldots \ldots x_n;\ \mu,\sigma^2)\}$$
$$= \max\{P(x_1|\mu,\sigma^2) * P(x_2|\mu,\sigma^2) \ldots \ldots .. P(x_n|\mu,\sigma^2)\}$$
$$= \max\{\prod_{i=1}^{n} P(x_i|\mu,\sigma^2)\} \qquad (2)$$

$$\mu = \frac{1}{n}\sum_{i=1}^{n} X_i \qquad (3)$$

$$\sigma^2 = \frac{\sum(X_i - \mu)^2}{n} \qquad (4)$$

$$\begin{bmatrix} \sigma_{12}^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_{1n}^2 \end{bmatrix} \qquad (5)$$

4 The Conducted Study

This section consists of two main subsections. In the first subsection, the statistic results of the study are shown and discussed. In the second subsection, the machine learning unsupervised soft-clustering algorithm will be shown.

4.1 The statistical Study

A questionnaire has been written with 14 different questions. Five options for answering each question have been provided with 5 for strongly agreed and 1 for extremely disagree. These questions are divided into two main groups. The first three questions emphases on the involuntary turnover. They can be used to defend the fairing judgment of the organization. The second group of questions is used to predict the voluntary turnover. This group consists of eleven questions divided into three classes. The first class consists of four questions attempt to measure the management process of the company. The second class, which consists of five questions, measures the quality of the environment. Finally, the last class measures career stability and salary. The question can be found in the appendix. The correlation of these questions in each class and the same size has been studied utilizing Cronbach's Alpha. Table 1 shows the obtained values. We can observe from the table the high correlation value since all questions gain more than 60% value.

Table 1: Cronbach's Alpah

Question Number	Value	Question Number	Value
1	0.73	8	0.69
2	0.69	9	0.70
3	0.78	10	0.71
4	0.72	11	0.701
5	0.73	12	0.75
6	0.74	13	0.83
7	0.71	14	0.8

280 questionnaires have been distributed among the employees. The sample size (n) has been calculated using the formula in Eqn.6 with confidence level of 95% and error rate of 5%.

$$n = N * \frac{x}{x + N - 1} \qquad (6)$$

Where,

$$x = Z_{\frac{\partial}{2}} * p * \frac{1 - p}{MOE^2} \qquad (7)$$

$Z_{\frac{\partial}{2}}$ is the critical value of the Normal distribution at α/2 and MOE is the margin of error, p is the sample proportion, and N is the population size.

Figure 1 shows a box diagram of answers' distributions. We can observe from the figure that the average value of extremely disagree answer is approximately 100. Moreover, we can observe that agree and extremely agree values obtained an average less than 30. This figure reflects a general idea of collected data, which shows that the collected data in all categories tends to extremely dis-agree result. Figure 2 shows the CDF of extremely agree and dis-agree results. We can observe from this figure how that 100% of the questions harvested an agree answer of less than 100. In the other hand we can observe how the dis-agree answer obtained this value for 50% of its answers and exceeded 110 for 40% of the answers (110 Answers is the approximately average since the survey has been distributed for 280 people).

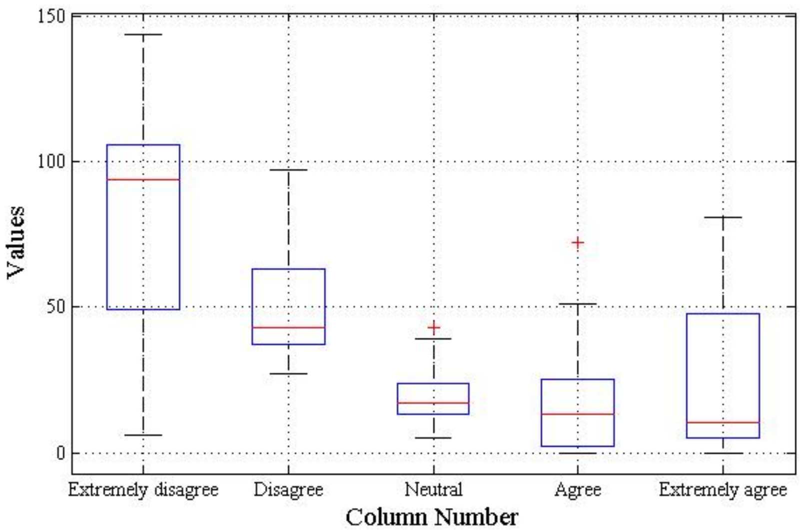

Figure 1: Answers' Distributions

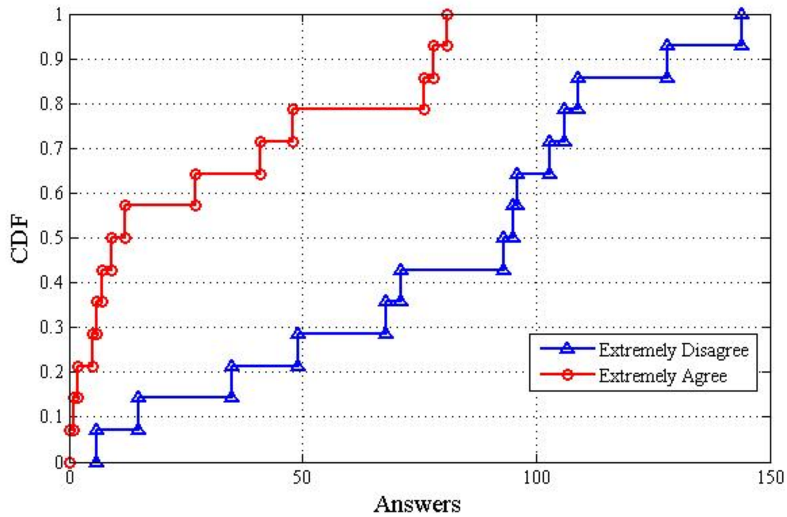

Figure 2: Answers' CDF plot of the first and last options

Figure 3 shows the box plot for the first three questions, which measures the involuntary turnover. We can observe that the employees gain an average positive impression when answering these questions. More than 60% of the questionnaires agreed. This gives a good impression that the involuntary turnover rate will be low for his company.

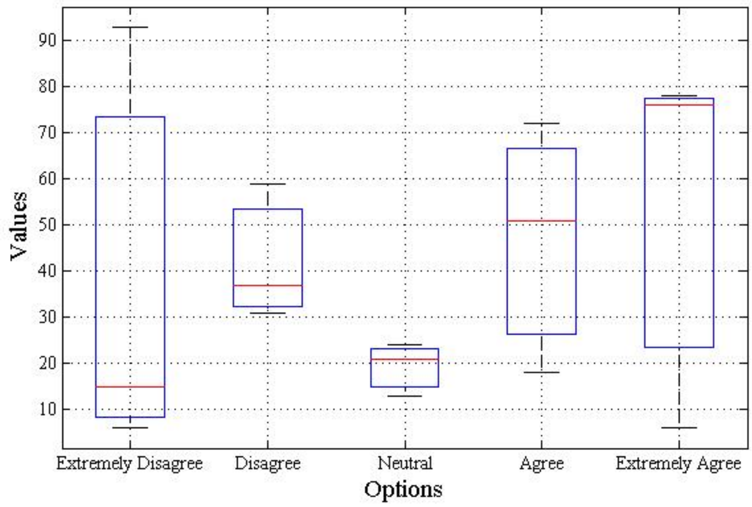

Figure 3: Involuntary Turnover Questions

Figure 4 and 5 study the voluntary turnover questions. Figure 4 study the management behavior of the company. We can observe that most of the works agreed that management sector of the company has issues in encouraging workers to do their jobs. More than 86% of the works answered with extremely disagree or disagree according to encouraging process of the management.

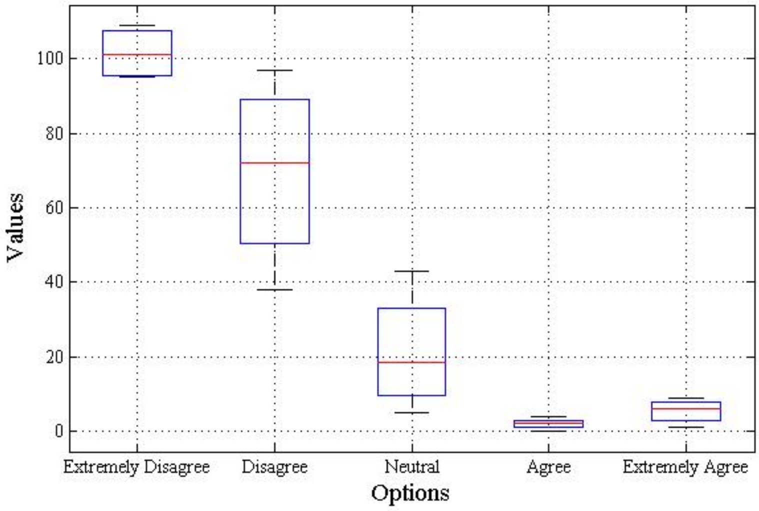

Figure 4: Management Sector Questions

Moreover, figure 5 shows the quality of the working environment questions. We also can observe that the questionnaires agreed that the environment is not intimate. We can predict from the last two figures predict that the voluntary turnover rate value will be massive. The impact of these criteria has been shown in the related works. However, figure 5 and figure 6 shows the impact of new criteria on the voluntary turnover rate, the public sector, and the abroad jobs. Questions 13 and 14 in the question measure these criteria. We have divided the answers into two classes '+' and '-' where agree and extremely agree in the '+' class and the other levels in the '-' class. Figure 5 shows the answers of public sector jobs. We can observe that 80% of the employees agreed that they will voluntary turnover if they have a career in the public sector. Finally, figure 6 measured the employees' mobility in the present of abroad career opportunities. We can observe that more than 85% of the employees have no opportunities outside the country. This is one of the factors to stay in company.

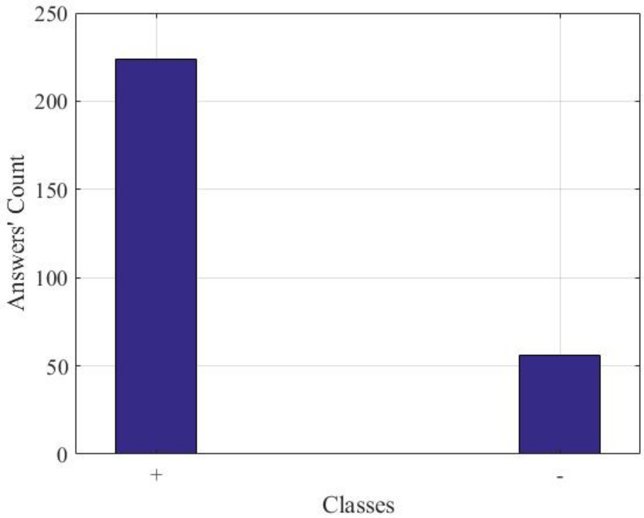

Figure 5: Public Sectors Careers

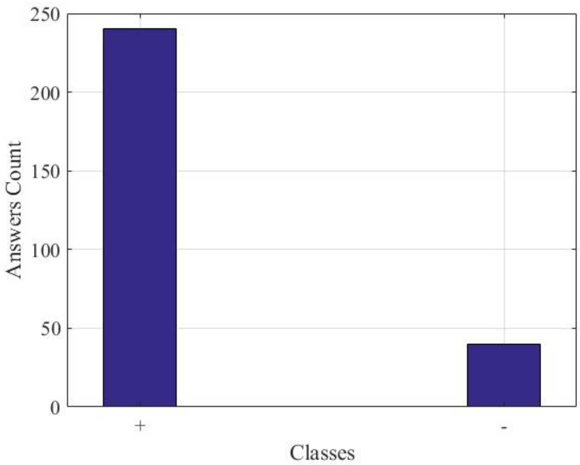

Figure 6: Working Abroad Opportunities

Table 2 shows the recorded values from the company's records of the turnover rates. We can observe how the predicted results are reflected in this table. This shows how the HR department should take serious procedures to enhance the management and working environment to reduce the value of turnover rate.

Table 2: Turnover Rate

Year	Resigning (%)	Termination (%)	Death (%)	Retirement (%)	Total (%)
2015	16.2	13.4	0.6	1.4	31.6
2016	20	15.6	0.2	0.4	36
2017	31.8	0.4	0	1.2	33.4
2018	30	0	0	0.4	30.4
2019	25	0	0	1	25.8

Finally, the last two questions measure the career stability. We observed from the answers that 80% of the questionnaires prefers public sector work “with the government” over private sector even if the salary is lower. The reason behind this is life stability.

4.1 Soft –Clustering Model

To cluster the questionnaire data, the first three questions have been deleted since they do not measure the voluntary turnover. The last 11 questions have been utilized as features for the clustering algorithm. These means we have a matrix of 11 columns ‘features’ and 280 rows ‘data points’. The data should be divided into two main clusters: mobile and stable. However, as mentioned this unsupervised clustering technique calculates a probability value. If the probability of any data point in a cluster is less than 60%, the data point is categories in a third cluster. We call it ‘stay for experience’ cluster. However, if the probability is higher than 60% it belongs to that cluster. The algorithm has been implemented in MATLAB. To measure the accuracy of this algorithm, the turnover data in table2 for 2019 has been utilized. We kept the name of each employee when the questionnaire has been distributed. We categories these employees in the three clusters we have. Finally, we compared their names with the turnover data harvested at the end of 2019. If the turned-over employee is not in the last ‘did not take the questionnaire’, his name is deleted from the list. However, if the employee took the questionnaire, his name is compared against the list constructed from the model. 84% of the names in each clustered matched the real data from the company. However, the algorithm should be evaluated over more data. Unfortunately, this evaluation requires the waiting of other one or two years to collect these data.

5 Conclusion

In this work, we attempted to study turnover environment in an organization that located in Middle East. A questionnaire has been collected from 280 employees in this organization. A statistical study has been implemented. A soft-clustering machine learning model has been constructed to predict the turnover probability of an employee. Two new turnover factors have been investigated; public sector career opportunity and seeking careers abroad. Our results show that the new two factors have massive impact on turnover rate in the country. Moreover, after evaluating the soft-clustering model, 84% accuracy has been reported after comparing its predicted values and real recorded values. We believe that the HR department has to take serious steps to improve the quality of the environment to reduce turnover rate. These steps vary from financial incentives to small management gratitude to employees.

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