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Addressing Voluntary Turnover in Manufacturing Sectors: An Empirical Study

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ABSTRACT

Main objectives: Voluntary turnover of employees are increasingly becoming serious problems in manufacturing sectors. Turnover creates a hindrance to practical access to ensure a continuous production process. That is why, turnover prediction model was proposed to address such problem in manufacturing organizations. **Background problems:** Despite the introduction of automation in manufacturing-based organizations across the world, Human resources are still one of the key determinants of production and Voluntary employee turnover still remain the barrier to remove such problem. **Novelty:** The study took broad aspects resulting in voluntary turnover firstly and applied the multinomial regression and multilayer perceptron model for analyzing categorical data. **Research method:** Along with the descriptive analysis, the research applied multinomial regression and multilayer perceptron model to analyze data. Besides, Secondary data of manufacturing-based organization was collected from kaggle.com archive for the study purpose. **Findings:** Table 2 to 8 display the empirical findings of the study. Table 5 explained correlation and table 6 showed regression results of the study. Correlations showed that performance score and complaints directly contribute to the turnover decision, while multinomial regression proved that error, performance score, pay, complaints, abutments lead to the voluntary turnover decision. **Contribution:** The findings contribute to the literature by identifying different causes of voluntary turnover in manufacturing organizations. The study will help the manufacturing organizations to address the voluntary turnover. **Conclusions:** The different independent variables (the reason for termination, performance score, pay, error, and _90_days, etc.) are identified to suggest the possible action to be taken by the organization to minimize the influence of voluntary turnover. Manufacturing organizations may be able to take necessary actions to recruit or retain the existing workers with the identification of workers who may leave the organizations.

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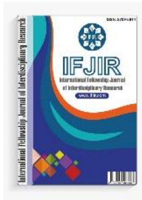

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INTRODUCTION:

Employee turnover is a serious problem for all types of organizations. A certain degree of turnover may be desirable and unavoidable, but which is sometimes considered beneficial to the organization. Acquiring, developing, and keeping a talented workforce has become one of the important goals of human resource management (HRM) practices (Luis et al., 2001) for most of the organization. Organizations cannot remain competitive (Rappaport et al., 2003) if they fail to retain a high-performing workforce which is the result of voluntary turnover. Voluntary turnover happens when permanent workers of the organization leave the organization willingly. The Manufacturing industry is the pillar of the national economy for some country like China. Chinese journal of human resource management started in 2010 could be the evidence of HRM practice importance. Western countries and Asian countries researchers are trying to compare human resource management practice among manufacturing companies (Cooke, 2013).

High-performance work practices (HPWPs) plays a significant role in minimizing the voluntary turnover rate. For long term competitive advantage, attracting and retaining qualified employees for the development of value-generating activities are crucial factors (Sieger et al. 2011). Lack of balance between work and personal life, isolation, relatively low pay in comparison to what is expected, long work hours, low promotional options, professional responsibility, illness, and death daily, a sense of failure, and more (Burbeck et al., 2002) results in turnover in the organization.

In a labour-intensive organization, manpower plays an important role in the running of the organization. So, voluntary turnover is one of the elements to be avoided to ensure the smooth performance of the organization. (Aharon et al., 2015) found negative relationships between satisfaction and burnout intentions of workers. Pay and pay-related variables have a modest effect on employee turnover (Griffeth et al. 2000) where (Goodman & Boss, 2002) presented a significant relationship between stress and turnover of employees.

The goal of this study is to assess how voluntary turnover prediction models predict voluntary turnover in manufacturing organizations. This study develops a complex turnover analysis system by practically applying MRA and MLP – for identifying each of the elements contributing to turnover- for applying those methods based on the particular variables.

The main findings. In this paper, there are presented general recommendations for the organizations on how to assess the voluntary turnover of the workers that are applying in production organization for turnover management. The turnover complex prediction system is based on MRA and MLP.

Research limitations. This research includes voluntary turnover prediction only for steel production firm, but methods' can be adapted and accordingly modified to any other industry.

Study background:

In today's competitive world, switching cost is very low for the employees to leave from one organization to another organization with the help of intense facilities of information technology. But this turnover results in financial and non-financial losses associated with operational break down which can be controlled by sound turnover prediction method. Employees' turnover causes common problems to most business enterprises recently, as it has unavoidable consequences to the operations of the organizations (Shamsuzzoha & Shumon, 2010). An organization often fails to ensure on-time delivery of the order due to employee turnover which results in losing the reputation of that organization. That is why employee turnover must be addressed seriously to remain competitive in the market. Though it cannot be eliminated from the organization for different reasons it can be predicted and reduced at the minimum level. Some previous works find that there is no interaction between work-related and mentality–related aspects, for instance, cultural differences, demographics, and personal characteristics are related to voluntary individual level turnover (Peter et al., 2019). This may not be right as some prediction has proved some interactive effect among different aspects of employee turnover. For example, the lack of crucial facilities could promote employees' turnover (Shamsuzzoha & Shumon, 2010). Besides remuneration, the interrelationship between employees and management and lack of career progression (Shukla & Sinha, 2013) are the key variables studied in the employee turnover area. As a result, the likelihood of the factors that may result in employee turnover becomes the aspect of research. But the major issues like how many workers may leave the organization and work-related causes of such departure are lacking in the literature.

RELATED WORK

Voluntarily turnover can be described as the willing departure of workers (intellectual capital) from an organization. (Bontis & Stova, 2002). That is when employees voluntarily end their relationship or job commitment to an organization. Voluntary turnover means when employees' decision to end their relationship with organizations on their own, whereas involuntary turnover occurs when employers fire or lay off workers (Hausknecht and Trevor, 2011). Firing a poorly performing employee and hiring a new worker of average or above-average skill level can positively affect organizational performance, which suggests a positive effect of involuntary turnover on performance (Boyne, & Dahya, 2002), whereas voluntary turnover indicates firm-specific skills, knowledge, and abilities that have been acquired over time and possessed by the person who left the organization (Lee & Whitford, 2013). The cost associated with such loss includes finding the replacement and training of new employees (Boyne et al., 2010; Messersmith et al., 2014; and Watlington et al., 2010).

Human resource requirement forecasting has been a key part of today's human resource management. It has created an immense impact on today's' business organization. Human resource requirements can be forecasted in many ways. One way is to predict how many workers will voluntarily terminate from the organization during a specific period. Different skills and HR profiles are needed at different stages for organizations' growth. Moreover, efficiency improvement during the consolidation process or layoffs might be related to hiring mistakes or recruitment of marginal employees (Baron et al., 2001) and (Coad et al., 2014). Predictably, all types of the firm with better growth prospects often choose a high growth strategy. None of the studies covers employee turnover specific to voluntary turnover to accelerate growth. This paper develops two models to assess the voluntary turnover and the factors contributing to such turnover in the organization. Peter et al., (2019) applied descriptive statistics and ANOVA tests to focus on human resource management practice of manufacturing companies in china.

Different researchers have conducted much research regarding employee turnover. (Gogia, 2010) considers work compensation relationships among workers using equity theory and finds that workers leave the organization with a view to seek better opportunities and minimizing unfairness among workers. (Sincero, 2008) uses hygiene factors to understand the relationship between wages, job security, administration, and working conditions among workers. The results show the experiences and feelings of workers at work. (Boundless, 2015) examines job satisfaction and dissatisfaction of workers using two types of factors and finds no linear relationship between job satisfaction and dissatisfaction in the working environment. (Nikolaos et al., 2018) focuses on pay, promotion, supervisor, sectors, and the work itself with turnover applying correlation and identifies intense relationships among the variables. (Demier et al., 2017) considers growth and turnover as research variables using the correlation method and finds higher growth with higher turnover in the organization. While the voluntary turnover literature has primarily focused on an individual's choice to stay or leave his/her organization, recent studies have proposed the importance of studying voluntary turnover rates at the collective level (Shaw, 2011; Nyberg & Ployhart, 2013). Involuntary turnover may result from probationary, low-performance, workforce reduction, no reappointment, etc. (Seung-HoAn, 2019).

Recruitment, development, and retention of talent to form the base of developing competitive advantage in many organizations (Pfeffer, 2005). (Wocke and Heymann, 2012) conducted investigation on the role of demographic variables contributing to voluntary turnover. He has identified age, level of education, gender, and race as the turnover variables to be considered in the extension turnover models. (Griffeth et al., 2000) categorized the predictors as Employee demographics, current job conditions, organization, and external environment. But no research considers the effect of different aspects together. The paper has taken into consideration about the different variables of turnover related issues to help turnover risk management by proposing an approach that will be able to predict employee turnover based on employees' attitude and mentality toward work and organization.

DATA COLLECTION AND RESEARCH METHOD

Fig. 1 illustrates the flow of feature selection. It is divided into four main steps: human resource data collection, production staff data separation & analysis, and construction of turnover prediction model. The data for this study was collected*(https://www.kaggle.com/datasets?search=human+resource)* from the Kaggle.com. Initially, human resource data were collected, and production staff was separated. The third step examines the interaction of performance score, the reason for termination, and employment status which serves as the basis in the voluntary turnover prediction process. Finally, the multilayer perceptron Model and multinomial regression model were selected to predict voluntary turnover of employees in the organization. To answer all the steps, this paper has formulated the following hypothesis:

Hypothesis 1: Workers leave manufacturing organizations due to the performance score rating.

Hypothesis 2: Different work-related reasons positively influence the employers' intention to leave the organization.

Hypothesis 3: Pay and daily error effect complaint_90_days which significantly influence employment status like the voluntary turnover decision.

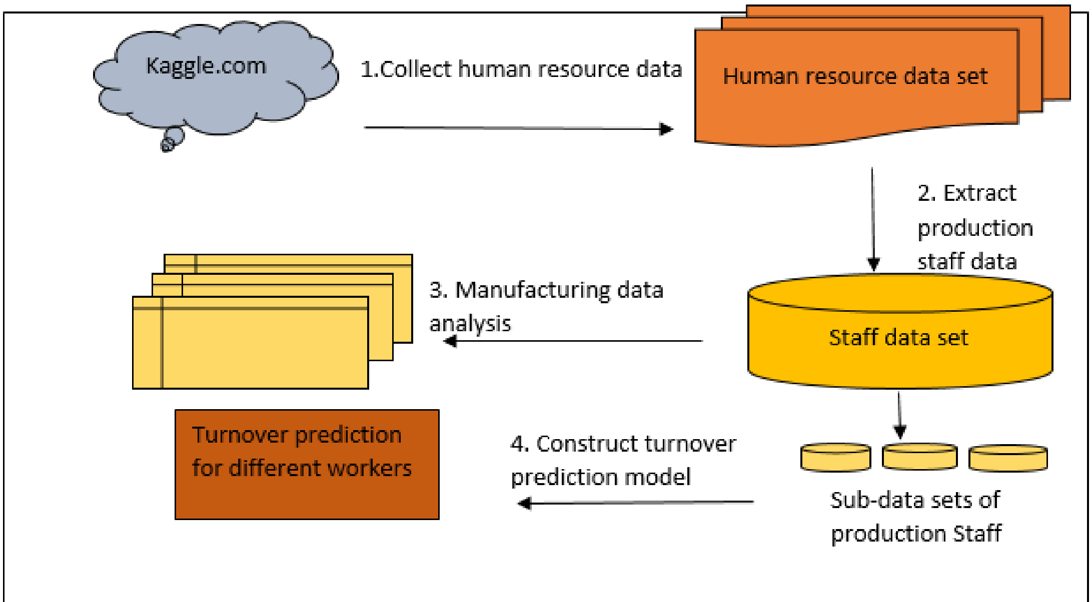

Figure 1. Flow of feature selection

The summary of dependent and independent variables in Table 1 shows 6 (six) different independent variables. Each independent variable has unique features contributing to employment status. Workers' performance is rated differently, and they get a different salary ranging from $ 14 to $55 daily. The abutment, daily error, and complaint_90_days are independent variables of the study. The dependent variable is employment status and the components of employment status are active, leave of absence, future start, terminated for cause, and voluntary termination.

Table 1. Summary of dependent and independent variables.

Dependent Variables						**Independent variable**
Performance score (ordinal)	Pay (ratio)	Abutment_ hour_week_1 (ratio)	Abutment_ hour_week_2 (ratio)	Daily error (ratio)	Complaint_ 90_days (ratio)	Employment status (nominal)
Exceptional, PIP, Needs Improvement, N/A- too early to review, Fully Meets, Exceeds, 90 days meet	Amount of pay, $ 14- $55	No. of abutment, ranges 0-19	No. of abutment, ranges 0-19	No of error, 0- 4	No of complain, 0-4	Active, leave of absence, future start, terminated for cause and voluntary termination

Data Extraction Process

A user account is opened to download the human resource data from kaggle.com (a reliable secondary data source). A complete data set of steel production firms in the USA are downloaded and production staff data is selected for the research purpose. The necessary features of the data were extracted about the production department to make research effective and apply across the production-based industry. The study considers eight features: pay, performance score, abutments/ hour week1, abutments/ hour week 2, daily error, 90-day complaints, the reason for termination, and employment status.
Before retrieving all the features from the data sets, several data filtering tasks were performed. First, this study examines the interactions among the effect of pay, error, abutments, complaints to predict employee turnover. Based on the data collected from kaggle.com, the influential variables on turnover are accommodated to fit models.

DATA MEASUREMENT AND ANALYSIS

Senior Human resource managers identified different performance-related factors, the reason for termination factors and employment status factors of workers. Each factor under different category was coded to conduct correlation analysis. Reason for termination (1= N/A - still employed, 2= attendance, 3= unhappy, 4= Another position, 5= Retiring, 6=return to school, 7=relocation out of area, 8=N/A - Has not started yet, 9=performance, 10= military, 11= no-call, no-show, 12= hours, 13= more money, 14= career change, 15= medical issues, 16= maternity leave - did not return, 17= gross misconduct), employment status (1= Active, 2= Voluntarily Terminated, 3= Terminated for Cause, 4= Leave of Absence, 5= Future Start) and performance score (1= Exceptional, 2= Exceeds, 3= Fully Meets, 4= Needs Improvement, 5= N/A- too early to review, 6= 90-day meets, 7= PIP)
SPSS software was used to construct the voluntary turnover prediction models. Two prediction techniques were applied, namely Multinomial regression analysis (MRA in SPSS) and multilayer perceptron (MLP in SPSS). Before applying two models, correlation analysis is

conducted including some descriptive analysis to help the testing hypothesis.

Multinomial regression analysis

Multinomial regression is a statistical technique that enables comparison between a set of dependent variable (s) Y and one or more predictor, dependent or outcome variable(s), X. It is an extension of the binary logistics regression model. In this research, the dependent variable is categorical which includes active, retirement, voluntary termination, leave of absence and terminated for a cause, etc. and the independent variables are both qualitative and quantitative which include qualitative data (unhappy, hours, N/A-still employed, attendance, exceeds, exceptional, fully meets and 90-day meets, etc.) and quantitative data (average salary of an employee per day, error per of an employee per day and no of complaint of an employee per 90 days, etc.). (Fullerton, 2009; Morrow-Howell, 2008) applied logistic regression in social research. (Quezada-Sarmiento et al., 2018) analyzed individual preferences of ecotourism products demand by using discrete choice models and found significant non-linear effects related to hiking and gastronomy. It also provides useful information to promote ecotourism products.

To develop a multinomial logistics regression model, Y is assumed as an outcome variable with a possible value of c (0, 1, …, c–1), and Y = 0 be the reference category. Let x = (x_1, x_2,, …,x_n) be the independent predictor variables. So, the conditional possibilities of each outcome category can be expressed as (David et. Al., 2013):

$$P\ (Y=0|x) = \frac{1}{1+e^{g1(x)+\cdots+g_{c=1}(x)}}$$

$$P\ (Y=1|x) = \frac{e^{g1(x)}}{1+e^{g1(x)+\cdots+g_{c=1}(x)}}$$

$$P\ (Y=c-1|x) = \frac{e^{gc=1^{(x)}}}{1+e^{g1(x)+\cdots+g_{c=1}(x)}} \qquad (1)$$

It follows that the logic function of category j versus the baseline category can be written (Hamzah Abdul Hamid, 2018) as:

$$g_j\ (x) = \ln\left[\frac{P(Y=j|X)}{P(Y=0|X}\right] = \beta_{j0} + \beta_{j1,}x_1 + \ldots\ldots + \beta_{jp}x_p$$

For j=1,2,…, c–1. (2)

MLP Model

MLP is feed-forward neural networks trained with the standard backpropagation algorithm. It is supervised networks, so they require a desired response to be trained. It learns how to transform input data into the desired response, so they are widely used for pattern classification. With one or two hidden layers, they can approximate virtually any input-output map. It has been shown to approximate the performance of optimal statistical classifiers in difficult problems. (Principe et al., 2000; Tseng at el., 2015). The MLP is trained with error-correction learning, which is appropriate here because the desired MLP response is the categorical result and as such known. Error correction learning works in the following way: From the system response at neuron j at iteration t, y_j(t) and the desired response d_j(t) for a given input pattern an instantaneous error e_j(t) is defined by e_j(t) = d_j(t) –y_j(t). Using the theory of gradient descent learning, each weight in the network can be adapted by correcting the present value of the weight with a term that is proportional to the present input and error at the weight:

$$w_{jk}(t+1) = w_{jk}(t) + \eta\delta_t\ (t)x_k(t) \qquad (3)$$

The h(t) is the learning rate parameter. The w_{jk}(t) is the weight connecting the output of neuron k to the input neuron j at iteration t (García-Altés at el., 2007). The local error d_j(t) can be directly computed from e_j(t) at the output neuron or can be computed as a weighted sum of errors at the internal neurons (Kurt at el., 2008).

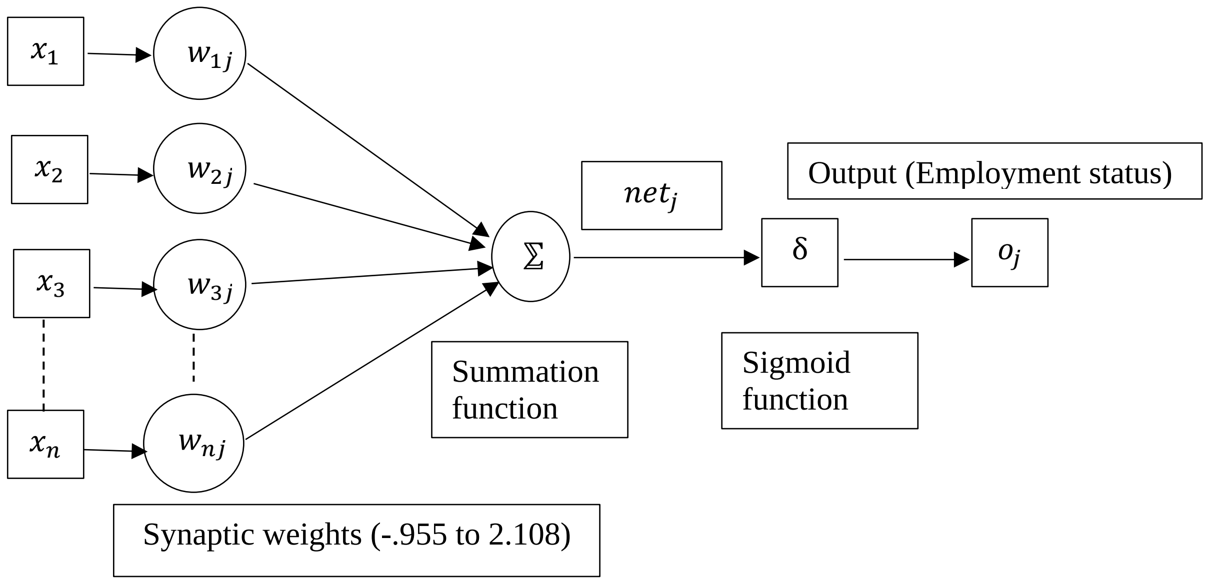

Figure 2. Multilayer perceptron network

A neural network can be thought of as a network of neurons organized in two or more layers. The predictors (or inputs) form the bottom layer, and the forecasts (or outputs) form the top layer. There may be intermediate layers containing hidden neurons. The conations between layers are associated with weights. A neuron j can be described by writing the following pair of equations:

$$net_j \sum_{i=1}^{n} w_{ij} x_i \quad (4)$$

$$o_j = \varphi(net_j) \quad (5)$$

ANALYSIS:

The analysis of data includes descriptive statistics that provide a useful idea about the structure of different information and identify category-specific causes of terminating employment from the organization. Descriptive statistics show the mean of pay, performance score, and the total percentage of voluntarily terminated workers by performance score. The correlation table displays the mean, standard deviation, and correlation of employment status with other variables.

Descriptive statistics:

Results of Table 2 show no voluntarily terminated workers and involuntarily terminated workers under the category of exceptionally performed workers. The pay structure is comparatively higher than the average pays for voluntarily terminated workers who are categorized under 90-day meets and PIP (performance improvement plan). But the average pay is higher for all workers than voluntarily terminated workers under the rest of the performance category. So, only pay can't provide any idea about voluntary termination for all types of workers.

Table 2. Descriptive statistics (mean) for the pay of production staff

Performance Score / Pay	Average	Active	Leave of Absence	Future start	Terminated for Cause	Voluntarily Terminated
90-day meets	$21.60	$19.60	$20.00	0	$15.00	$23.40
Exceeds	$24.02	$55.00	0	$25.88	$21.00	$19.14
Exceptional	$22.50	$22.50	0	0	0	0
Fully Meets	$23.25	$23.38	$19.86		$48.00	$22.76

N/A- too early to review	$21.00	$20.86	0	$22.63	$18.00	$20.48
Needs Improvement	$24.36	$31.00	0	0	$16.00	$24.00
PIP	$22.07	$20.00	0	0	$18.50	$25.33

The results of table 3 show the proportion of workers' employment status based on performance scores. The proportion is calculated by dividing the relative employment status of workers under a specific performance score category with the total number of workers under each performance score category. Thus, the equation.

$$ESP_j = \frac{\sum RES_j}{\sum_{i=1}^{n} RES_j{}^{x}i} \qquad (6)$$

The ESP_j is the employment status based on performance score? The $\sum RES_j$ is the relative employment status of total workers' under any specific performance score and the $\sum_{i=1}^{n} RES_j{}^{x}i$ is the total workers' under any performance score.

Table 3. Descriptive statistics (proportion) of workers' employment status based on the performance score

Performance Score	Active	Leave of Absence	Future start	Terminated for Cause	Voluntarily Terminated
90-day meets	0.3158	0.0526	0.0000	0.0526	**0.5789**
Exceeds	0.5909	0.0000	0.0909	0.0455	**0.2727**
Exceptional	1.0000	0.0000	0.0000	0.0000	**0.0000**
Fully Meets	0.5738	0.0820	0.0000	0.0082	**0.3361**
N/A- too early to review	0.2800	0.0000	0.2400	0.0400	**0.4400**
Needs Improvement	0.3636	0.0000	0.0000	0.2727	**0.3636**
PIP	0.4286	0.0000	0.0000	0.1429	**0.4286**

Results of table 3 show value from 0.0000 to 1.0000 which indicates the relative proportion of workers' employment status. In table 0.0000 implies none voluntarily leave under the exceptional performance score category and 0.2727 implies 27.27% of workers under exceeds the performance score category voluntarily leave the organization. 0.5789, 0.3361, 0.4400, 0.3636, and 0.4286 are some other values, imply the proportion of workers' voluntary leave organizations under different performance score categories. The value 1.0000 under the exceptional performance score category implies all active (actively involved with their organization). So, the performance score of workers can provide some idea about the tendency of workers' voluntary termination of employment. Further analysis may give some concrete ideas about the voluntary termination of workers.

Table 4. Total proportion of voluntary terminated workers for the different reason by performance score

Reason for termination	90-days Meets	Exceeds	Fully Meets	N/A- Too early to review	Needs Improvement	PIP
Another position	0.1000	0.1667	0.0244	0.2727	0.0000	0.3333
Career change	0.1000	0.0000	0.0488	0.0000	0.5000	0.3333
Hours	0.2000	0.0000	0.0488	0.1818	0.0000	0.0000
Military	0.0000	0.0000	0.0732	0.0000	0.2500	0.0000
Relocation out of area	0.1000	0.0000	0.0488	0.0000	0.0000	0.0000

Unhappy	0.4000	0.1667	0.1220	0.1818	0.2500	0.3333
More money	0.1000	0.3333	0.1707	0.0909	0.0000	0.0000
Return to School	0.0000	0.0000	0.0488	0.2727	0.0000	0.0000
Retiring	0.0000	0.1667	0.0732	0.0000	0.0000	0.0000
Attendance	0.0000	0.0000	0.0244	0.0000	0.0000	0.0000
Medical Issue	0.0000	0.0000	0.0244	0.0000	0.0000	0.0000
Maternity leave-did not return		0.1667	0.0244	0.0000	0.0000	0.0000

Table 4 explains the different causes of voluntary termination for workers who are categorized based on different performance scores. Unhappiness, career change, more money, and another position are some of the major causes of voluntary turnover. Table 4 provides a detailed scenario for the causes of the voluntary turnover of workers under a different category of the performance score. The proportion of workers shows the tendency of workers to leave the organization.

Table 5. Mean, SD and correlation.

	Mean	SD	1	2	3	4	5	6	7
(1) Employment status	1.75	1.024	1						
(2) Reason for termination	4.01	4.380	.404**	1					
(3) Performance score	3.54	1.322	.172*	.163*	1				
(4) Daily error	.90	1.077	.123	.157*	.291*	1			
(5) 90-day Complaints	.32	.706	.157*	.116	.125	.524**	1		
(6) Pay	$22.92	$8.321	.000	-.121	-.050	.035	.087	1	
(7) Abutments/Hour Wk	9.685	4.5737	-.040	.002	-.175*	-.393**	-.312**	.048	1

Correlation is significant at the 0.01 level. **, correlation is significant at the 0.05 level. *

Table 5 shows the mean, Standard deviation (SD), and correlation of the key research variables. The study includes a correlation to analyze the data and test the research hypothesis. Hypothesis 1 and 2 predicted that performance score and reason for termination are directly related to the worker's employment status. The correlation results of Table 2 show that performance score (.172) and reason for termination (.404) are positively correlated worker's voluntary turnover decisions.

Hypothesis 3 predicted that pay and daily error of workers 90_day complaints which significantly influence the employment status of workers like the voluntary turnover decision. The correlation results show 90_day complaint (.524) with pay which significantly (.157) determine workers' turnover decision. The result supports hypothesis 3 that pay is related to influence 90_day_ complaints of workers to influence the turnover intention of workers.

Multinomial regression analysis

Table 6. Model fitting criteria

Effect	Model fitting criteria	Likelihood Ratio Tests		
	B	Chi-Square	df	Sig
Intercept	3.222	.000	0	
Performance score	3.261	3.921	24	1.00
Pay	4.358	113.653	168	1.00
Abutment_hour_week	3.222	.000	0	
Daily error	3.409	18.770	16	.281
Complaint_90_days	3.391	16.877	16	.394

At 5% significance level.

In this section, the interaction of different variables influencing the voluntary turnover decision of production staffs is presented. The results of Table 6 display the significance of each of the variables in determining the turnover intentions of the workers except abutment_hour_week. The value in the significant column is the probability of obtaining the Chi-Square statistic for the true null hypothesis. The P-value in table 6 is greater than the critical value at .05 significance level. The chi-square value is less than the critical value at a specific degree of freedom (df) to declare the null hypothesis to be accepted.

The study incorporated the maximization of the likelihood function to test the overall regression model. The full model is;

=β_0+β_1Performance score + β_2Pay + β_3 Abutment_hour_week + β_4 Daily error + β_5 Complaint_90_days

And the reduced model is;

= β_0

The hypothesis test; H_0: β_1=β_2=…=β_x=0 and H_A: at least one is not zero.

The results of Table 6 shows that P-value is not zero (0). So, the test is statistically significant. The P-value for overall regression is not zero (0). So, at least one predicting variable significantly explains the intention to leave the organization. The regression analysis is based on the 2log likelihood model. Full model displays; 3.222+3.261+4.358+3.222+3.409+3.391 and the reduced model displays; 3.222. So, the null hypothesis of the study should be accepted. The alternative hypothesis performance score, reason for termination, pay and daily error do not affect employment status should be rejected.

Table 7. Predicted employment status classification (Multinomial regression)

Percentage	Predicted					
	Active	Future start	Leave of absence	Terminated for cause	Voluntary termination	Correct Percentage
Overall	.529	.091	.058	.087	.236	
Correct	.783	1.00	.636	.875	.520	.692

Preference: Voluntary termination.

The first experiment includes the complete set of independent variables in the model fitting and finding prediction results. The results of Table 7 display the predicted employment status of workers. The preference category of parameter estimation is the voluntary termination of workers. The predicted voluntary turnover is 23.6% and the predicted correct percentage of voluntary termination is 52.0%. Table 7 displays the detailed scenario of the employment status of workers under the multinomial regression model.

The model fitting criteria show the significance of 5 different variables in Table 6 where two out of the six variables are not significant, but to obtain greater insight the multilayer perceptron model is employed to conduct further analysis and validate voluntary turnover prediction. As, multilayer perceptron (MLP)-network obtains a prediction error approximately 10 times lower than the other models (Denis, 2004).

Multilayer perceptron

The second experiment is designated to study the prediction ability of voluntary turnover using a multilayer perceptron model. The model divided the total data set into a training data set and a testing data set. The purpose of the technique was to develop a parsimonious model without sacrificing much of their prediction robustness. The model has taken 140 samples (70.7%) as training data and 58 samples (29.3%) as testing data from 209 samples excluding 11 samples in the multilayer perceptron model.

The model has generated results based on the normalized importance of independent variables in the Table 9. The model has a weighted hidden layer of each of the variable automatically depending on normalized importance and produced output layer.

Table 8. Predicted employment status classification (Multilayer perceptron)

Sample	Performance	Predicted					
		Active	Future start	Leave of absence	Terminated for cause	Voluntary termination	Correct
Training	Overall	.679	.000	.000	.000	.321	
	Correct	.897	.000	.000	.000	.444	.607
Testing	Overall	.690	.000	.000	.000	.310	
	Correct	.774	.000	.000	.000	.400	.552

Preference: Voluntary termination.

Results of the table 8 shows voluntary turnover of workers as 32.1 percent for training data set and 31.1 percent for testing data set. The Table 8 also displays corrected result of voluntary turnover as 44.4 percent for training data set and 40.0 percent for testing data set. Overall correctness of training result is 60.7 percent and testing result is 55.2 percent.

Table 9 Independent variable importance

Term	Pay	Performance score	Abutments/Hour Wk1	Abutments/Hour Wk2	Daily error	Complaint 90 days
Importance	.193	.252	.179	.140	.145	.092
Normalized Importance	.766	1.00	.709	.556	.578	.364

Predictability of the recommended model

The third experiment is designated to find the predictability of two different models. Figure 4 displays the relative accuracy of prediction of voluntary termination. The preference category is voluntary termination prediction. Multilayer perceptron network makes prediction more accurately than other models. The actual terminated workers are 35.9% and multilayer perceptron network's predicted result is 32.1%.

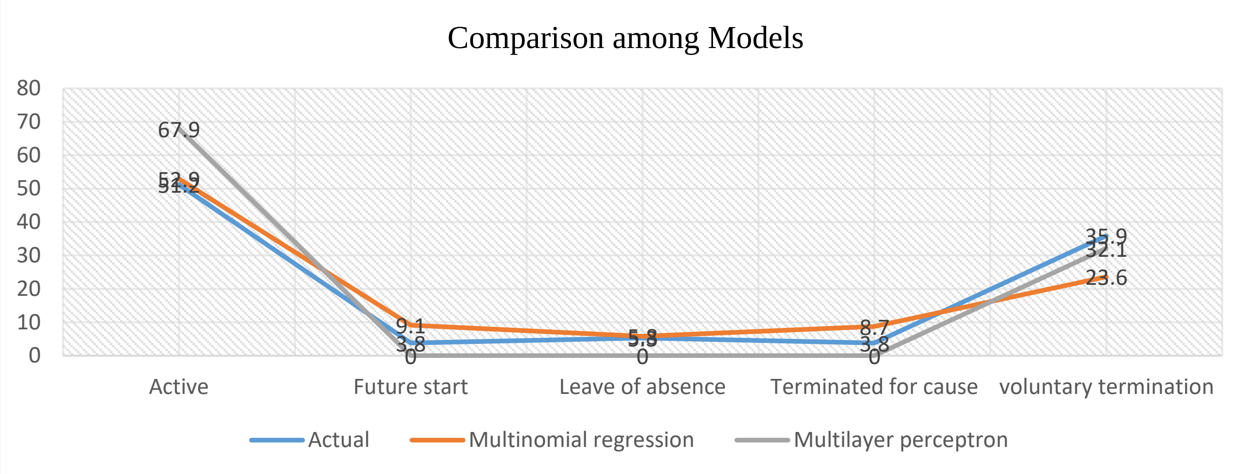

Figure. 4 Comparison among different Models

It can be seen from the figure that considering only the multilayer perceptron model does not provide satisfactory results, where the multinomial regression model provides a better probability of different employment status than a multilayer perceptron. The comparison of employment status in Fig.4 shows a very close relationship between actual results and predicted results of the multinomial regression model. But the Comparison is showing anomalies to some aspects of employment status between actual results and predicted results of the multilayer perceptron model. But the multilayer perceptron model meets the specific requirement of the study which is finding voluntary turnover which is very close to actual findings.

DISCUSSION:

Identification of key predictors of turnover has attracted much interest to the researchers and academicians, but key insights may remain obscured if some influential variables are not included in experiments considering interactions among variables. Besides, the role of pay, performance score, error, etc. dominate the academic literature, but they may not be applicable for or generalizable to all situations. Therefore, the main purpose of the study is to assess how prediction models accurately forecast voluntary employee turnover in the production organization. The results of the empirical study provide real-life evidence of the factors that significantly help in determining intentions to maintain employment in the organization.

Results of Table 2 and Table 3 display that the employees whose performance scores are in the category of PIP (performance improvement plan) and 90-days meets are comparatively more interested to leave the organization voluntarily than other categories of workers. This alone helps to clarify the debate on which workers may voluntarily leave the organization. Table 4 shows the specific reason for the voluntary turnover of employees in the production firm. Most of the workers leave the organization voluntarily due to unhappiness which supports Hypothesis 1. Despite different interacting independent variables contributing to voluntary turnover, turnover may be low if workers realize that their job is useful (Pines & Keinan 2005).

The study also considers different work-related factors like pay, error, complaints, etc. to contribute to voluntary turnover intentions. In addition, table 4 displays different turnover related factor which supports Hypothesis 2 of the study. The predicted result of a multilayer perceptron is based on the normalized importance of independent variables in Table 9, whereas the performance score gets maximum priority in forecasting voluntary turnover in the production organization. The multinomial regression analysis shows more than 69% forecasting accuracy, whereas the multilayer perceptron model represented 60.7% prediction accuracy in training set data and 55.2 % prediction accuracy in the testing data set. Fig.3 shows the relative comparison among actual, multinomial regression analysis and multilayer perceptron network results. The target category of analysis in the study is to assess the capability of the prediction model to accurately forecast voluntary turnover. The experiments show the accuracy of the multilayer perceptron model's forecasting capability (Denis, 2004) of voluntary turnover than the multinomial regression model. But the multinomial regression model forecasts each category of employment status.

Regarding Hypothesis 3, pay and daily error effects 90_day_ complaints which ultimately affect intentions to employment status in the organization. Results of the Table 6 demonstrate that effective use of the model can help in accurate turnover prediction which will help the organization to identify causes of turnover and take necessary steps to minimize voluntary turnover or take steps to fill up the vacant position by recruiting the required number of workers based on employees' perceptions, immigrant information technology, and access positions in the labour market to match their skills and qualifications (Shamika et al., 2015).

Previous researches have shown the causes leading to voluntary turnover like the role of physical contract, (Clinton & Guest, 2014) moral stress, (DeTienne, et al., 2012), the cognitive ability of employees, (Maltarich et al., 2010), and ongoing cycle of job search to remain active in a volatile economy (Direnzo & Greenhaus, 2011). This study has added literature the pay, performance score, daily error and complaint are the causes of voluntary turnover. The research variables in this study were collected from single-source data, namely from kaggle.com. I believe that due to the nature of variables (pay, performance score, daily error, 90-day complaints, abutments) subjective reports would be the most appropriate. However, researchers and practitioners will find it important to understand the value of quality-enhancing variables and find a way to develop prediction models.

CONCLUSION AND LIMITATIONS:

This paper explores the predictability of two different models that can be used by steel production firms to predict voluntary turnover of production staffs. Based on the findings, the main conclusions are:

1. Organizations often identify different factors of turnover (pay, performance, error, complaints, etc.). Although all variables related to identifying turnover are important, making predictions and taking necessary actions are the most relevant, since they imply the ability to know how many staffs to be recruited to meet the gap between the required human resources and existing human resources in the organization.
2. The paper focuses on voluntary turnover models, using a triangulation method to assess the applicability of different methods (MRA and MLP) to forecast voluntary turnover. We hypothesize that organizations normally using "descriptive statistics" can use "MRA and MLP" methods while "unexpected vacancies" will be removed. (Rahman et al., 2019) have suggested considering both intrinsic and extrinsic factors to increase motivation and job satisfaction workers to accelerate productivity which may reduce turnover. The reason for termination explains different intrinsic and extrinsic factors of employment status.

3. The key point is now to determine the level of voluntary using the most suitable methods. For that reason, two different methods are proposed to predict the level of voluntary turnover using different independent variables namely pay, performance score, error, complaints, etc. The results undoubtedly support three hypotheses. If we take into consideration the fulfilment of unexpected vacancies, the predictability of the models will help to identify the number of vacancies to fill the unexpected vacancies.

The use of prediction models has implied flexibility and reduced costs identifying the factors contributing to voluntary turnover, so it appears that this prediction model will persist, suggesting that sufficient human resources will exist.

Employee turnover and its related variables have become of interest to researchers for many disciplines. In addition to studying the impact of different variables leading to voluntary turnover, the researchers are interested to know what the symptoms of voluntary turnover are along with causes of voluntary turnover. Two models of employee turnover prediction will help the organization to predict employee's turnover depending on the turnover related factors which may motivate works to leave the organizations as the variables used in the study has predicted turnover. The hypothesis of the study has also proved, and the predictability of the models is also assessed. So, all the organizations can use any or both models to predict the possible employees' turnover in a specific period and take necessary steps to recruit new employees or retain the existing employees considering pay, performance score, error, complaints, etc.

LIMITATIONS:

Every research has some limitations due to a lack of time or resources. This study is not without limitations. First, the analysis is restricted to data collected from a steel production industry which may not be generalized to the entire production industry across the world. Second, all the study variables were examined concurrently missing long-term investigation because voluntary turnover changes over one's one employment period to another (Dunford et al., 2012). The study also does not consider situational variables and individual differences which may distort the prediction and decision of workers.

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