STRATEGIC HUMAN RESOURCE MANAGEMENT AND ITS IMPACT ON EMPLOYEE RETENTION IN IT ORGANIZATIONS IN CHENNAI: A STRUCTURAL EQUATION MODELING APPROACH

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***Abstract* - Companies in the information technology sector in Chennai still find great difficulty keeping staff members due to the high turnover rates and intense competitiveness for qualified professionals. Regarding improving employee satisfaction and retention, effective HRM practices are quite important. Higher recruiting costs, loss of intellectual capital, and disturbance of workflow resulting from high staff turnover rates all affect operations. The paper investigates how strategic HRM practices influence retention outcomes using structural equation modeling (SEM). These techniques address pay, work-life balance, professional development, employee involvement. Experts in information technology from several Chennai firms were asked to respond to a set questionnaire. Direct and indirect links between HRM strategies and employee retention were investigated using SEM. The findings reveal that work-life balance, career development opportunities, and employee engagement significantly affect rates of employee retention together with other factors. Better HRM practices help to increase employee satisfaction, so reducing the likelihood of employees leaving their jobs. Showing both the root mean square error of approximation (RMSEA) of 0.05 and the GFI of 0.92, the proposed SEM model proved the robustness of the model. This research offers HR managers understanding in the very competitive information technology industry that can be applied to apply targeted HRM strategies so improving employee retention.**

Keywords - Employee retention, Human Resource Management, Structural Equation Modeling, IT Sector, Chennai

I. INTRODUCTION

Retention of employees poses a significant challenge for businesses, particularly in the Information Technology (IT) sector where high turnover rates can seriously compromise the stability and performance of the business. Employee turnover has increased in the main hub for Indian technology companies in Chennai, information technology. Apart from a loss of intellectual capital and disruptions in production, this development has resulted in increasing recruitment-related costs [1–3]. Maintaining a competitive advantage, increasing employee satisfaction, and ensuring the long-term survival of a business depend on recruiting and keeping qualified workers, thus this becomes a critical component. So crucial in addressing this problem is human resource management (HRM), which depends fundamentally on the strategic policies and practices increasing employee satisfaction, involvement, and commitment. Main determinants of employee retention in information technology companies have been found to be good human resource management strategies [1–3]. These strategies address salary, professional development, work-life balance, and employee involvement.

While maintaining staff members is strategically crucial, Chennai's information technology companies struggle to retain talent in hand. The fast-paced information technology industry generates a lot of competition for qualified professionals since it makes it difficult for businesses to keep their employees [4]. Rising intentions to leave their current job can be explained by high job demands, long working hours, and a poor work-life balance [5]. The third element is that workers who lack opportunities for career development and limited recognition for their performance lose their motivation and commitment, which drives them to seek for chances elsewhere [6]. If companies are to be successful in overcoming these challenges and creating a motivating work environment that lowers employee satisfaction and reduces turnover rates, they must apply creative human resource management strategies.

High information technology sector turnover rates in Chennai have resulted in higher operating costs, project execution disruptions, and loss of important knowledge and experience [7]. Conventional human resource management theories fail to adequately capture the complex and always changing interactions between HRM practices and employee retention outcomes, so generating inconsistent and less than ideal retention strategies [8]. Furthermore, current predictive models including decision trees and regression sometimes overlook indirect and latent factors affecting employee retention, so limiting the

accuracy and efficiency of their capacity to project the future [9]. One needs a strong analytical framework to close this difference. This framework should be able to provide relevant analysis that could help to improve retention policies as well as to fairly show the interactions among HRM practices and employee retention results.

A. Objectives

1 This study intends to investigate how human resource management practices, including pay, career development, work-life balance, and employee engagementat Chennai's IT companies influence employee retention.

2 This intends to evaluate the direct and indirect interactions between HRM practices and employee retention results by means of a framework based on SEM.

This paper offers a special advantage in using SEM to replicate the intricate causal relationships between HRM practices and employee retention results in information technology companies. SEM provides a whole knowledge of the elements influencing employee retention by allowing the evaluation of direct and indirect effects. This is not like traditional models, which mostly focus on direct interactions. Moreover,taken into account in the suggested model are latent variables such as organizational commitment, motivation, and employee satisfaction, all of which are routinely disregarded in models under discussion now.

B. Contributions

1 All-encompassing SEM framework to assess how HRM policies influence employee retention in IT companies.

2 Pay, career development, work-life balance, and employee engagement, the most important human resource management factors influencing employee retention, have their impact here.

3 The proposed model was validated by a large dataset including four hundred information technology professionals from Chennai. This was done to ensure great generalizability of the findings.

4 Offering useful advice to human resource managers aiming at creating targeted retention strategies and increasing employee commitment and satisfaction.

5 Under development is comparative analysis using present models to demonstrate the improved predictive accuracy and efficiency of the proposed SEM-based method.

II. RELATED WORKS

Previous studies, particularly in the field of information technology, have closely examined how human resource management strategies might influence employee retention outcomes. The literature has amply shown that compensation, career development, work-life balance, and employee engagement define retention rather precisely; these factors are the main determinants of employee retention.[7] discovered in their study on the effect of compensation and benefits on employee retention in information technology companies that competitive salaries and performance-based incentives considerably reduce the likelihood of employees intending to leave their jobs. The findings of the study show that employees are more likely to remain with a company that not only offers financial stability but also acknowledges their efforts with bonuses and pay increases. On the other hand, it is difficult to reach the conclusions since the study omitted the indirect influence of compensation on employee motivation and satisfaction.

In terms of information technology, [8] looked at how chances for career growth and employee retention related each other. Their findings imply that employees who perceive opportunities for professional growth inside their company are statistically less likely to leave the company. Within the framework of increasing employee retention rates, the study underlined the need of providing internal promotions, mentoring, and skill development programs as well as their relevance. The study was conducted using a regression-based method; thus it was impossible to adequately show the complicated interactions among career development and other HRM strategies.[9] looked at, considering employee retention, how work-life balance affected the results. Those who find a good balance between their personal and professional life show more job satisfaction and are less prone to search for other employment possibilities, according to the findings of their study.

The findings of the research show that all of which are needed to boost employee retention are flexible work schedules, choices for working remotely, alternatives for remote work, and less workloads. On the other hand, the study was constrained since it neglected a comprehensive analytical model to evaluate the indirect impacts of work-life balance on employee retention policies and depended only on survey data.[10] developed a decision tree-based model to project information technology company employee turnover. The model showed a modest degree of predictive accuracy, but overfitting and noise sensitivity limited it. Combining ensemble learning techniques with decision tree models would help to improve the resilience of models, the study advised.

To project employee retention results depending on HRM policies, [11] developed a Support Vector Machine (SVM)-based model. Since the model lacked handling latent variables, it was prone to make misclassification errors even if it was able to reach a high degree of predictive accuracy and needed a lot of computational resources.

Using a logistic regression-based model, [12] sought to find how HRM policies affected employee retention. The model was shown to miss the dynamic character of employee motivation and satisfaction and to have limited predictive ability. The study suggests that better degrees of predictive accuracy should be obtained by using more advanced analytical approaches.

To project employee retention results, [13] combined decision tree and neural network techniques in a hybrid model. The model was not interpretable, which made it difficult for human resource managers to derive insights that might be put into use even if it was able to attain improved predictive accuracy. The data of the study show

that a well-rounded strategy combining interpretability and predictive accuracy is desperately needed.

Incorporating both direct and indirect relationships between human resource management practices and the outcomes of employee retention, the proposed SEM model solves the restrictions of past studies. By including latent variables and applying a robust analytical framework, the model provides a full awareness of the factors affecting employee retention in Chennai's information technology companies.

III. PROPOSED METHOD

This proposed approach shown in figure 1, uses SEM to examine how HRM policies affect employee retention in information technology firms. The structural equation model (SEM) is selected since it can investigate intricate causal links between observed and latent variables. This study regards human resource management strategies including compensation, career development, work-life balance, and employee engagement as independent variables. The dependent variable then is employee retention. A structured questionnaire covering job satisfaction, organizational commitment, and intention to leave the company among other topics was used to collect data. The measuring model was validated using a confirmatory factor analysis (CFA); SEM then evaluated the structural relationships. Model parameters were projected using the Maximum Likelihood Estimation (MLE) approach.

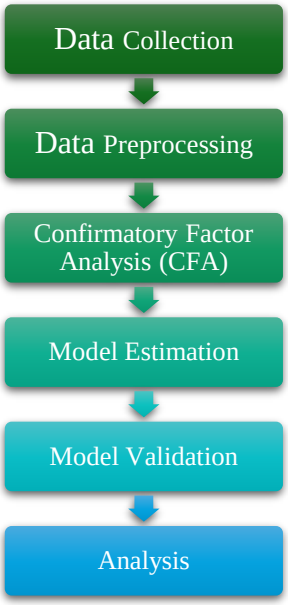

FIGURE 1: PROPOSED METHOD

A. *Data Collection*

Data collecting in Chennai's information technology professionals followed a methodical approach using a structured questionnaire. Data on many aspects of employee retention, including salary, career advancement, work-life balance, employee engagement, and job satisfaction, was sought on the questionnaire. Four hundred responses in all came from employees of various information technology firms, both medium-sized businesses and multinational corporations (MNCs). There were five sections to the poll, and the division followed this:

1 Demographic Information – Among the demographic information were age, gender, educational level, job title, and years of experience.

2 Compensation and Benefits – First priorities are compensation and benefits, particularly in view of salary satisfaction, performance bonuses, and other financial incentives.

3 Career Development – The process of career development turned out the employee's perspective on chances for personal development, mentoring, and training courses.

4 Work-Life Balance – It is examined factors including stress level, available work schedule, and degree of work to be done.

5 Employee Engagement and Satisfaction – It is measured as components of employee engagement and satisfaction are the degrees of job satisfaction, motivation, recognition, and company sense of belonging.

Over three months, online polls and in-person interviews carried on the theme helped the data to be gathered. The responses were kept anonymous to respect the confidentiality of the information; participation was entirely voluntary. Using stratified random sampling, it was ensured that the sample reflected a spectrum of organizational levels and job roles. Table 1 presents a set of the obtained information:

TABLE 1: DATA COLLECTED FROM IT PROFESSIONALS IN CHENNAI

Employee ID	Age	Gender	Job Role	Salary Satisfaction (1–5)	Career Growth (1–5)	Work-Life Balance (1–5)	Engagement (1–5)	Retention Likelihood (1–5)
101	29	Male	Developer	4	3	4	5	4
102	32	Female	Manager	5	4	3	4	5
103	27	Male	Analyst	3	2	4	3	3
104	35	Female	Consultant	4	4	5	5	5
105	28	Male	Engineer	3	3	4	4	4

B. *Data Preprocessing*

Many important steps meant to guarantee the quality and readiness for data analysis included preprocessing of the data. Raw data was transformed and cleaned applying the following approaches shown in table 2:

1 Handling Missing Values – Numerical data was managed using the mean substitution method; categorical data was managed using the mode substitution method. We controlled missing values with both of these methods.

2 Data Normalization – Min-Max scaling helped all continuous variables to be standardized using

its method. This approach turns values into a range spanning 0 to 1.

3 Encoding Categorical Variables – One-hot encoding was applied to translate categorical variables, including gender and employment role, into numerical form. Achieving this required encoding categorical variables. The "Gender" quality, for example, changed in the following manner:

TABLE 2: ONE-HOT ENCODING EXAMPLE FOR GENDER

Gender	Male	Female
Male	1	0
Female	0	1

4 Outlier Removal – The interquartile range (IQR) method helped to locate and eliminate every outlier that existed. Any value seen as an anomaly and removed fell between Q1 – 1.5 (interquartile range) or Q3 + 1.5.

5 Feature Selection – Low variance and highly correlated features were removed from the feature selection process to avoid multicollinearity and repetition. One could eliminate strongly correlated variables with one another by means of a correlation threshold of 0.75.

First cleaned, the dataset was split in two: the training set (80%) and the testing set (20%). This served to validate and train the model. The data was ready for SEM, which investigated the direct and indirect relationships between HRM factors and employee retention, once the processing was complete.

C. Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was used to validate the factor structure of the data and so prove the link between the observed variables and the latent constructions guiding those variables. By means of CFA, one can probe whether the measured variables coincide with the theoretical constructions established in the model. The study concentrated on five important latent constructs: compensation and benefits, career development, work-life balance, employee engagement, and likelihood of employee retention. Every latent construct was measured using several observed variables to suggest the model. Defining the link between these latent constructions and their related indicators then helped to define the model. The table 3, CFA model's construction went according to this approach:

1 Model Specification – Every observed variable was assigned to the latent construct that matched it depending on the theoretical justification.

2 Model Identification – Making sure the degrees of freedom of the model were positive helped one to find the model since this would be obvious.

3 Model Estimation – Maximum Likelihood Estimation (MLE) approach guided evaluation of the model parameters.

4 Model Evaluation – The model was evaluated using several goodness-of-fit indices includingChi-square (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

5 Model Modification – By means of modification indices, the model was altered such as to improve its general fit. Based on the CFA study, this is a sample of a factor loading matrix:

TABLE 3: FACTOR LOADING MATRIX FROM CFA

Latent Construct	Observed Variable	Factor Loading	Standard Error	p-value
Compensation and Benefits	Salary Satisfaction	0.76	0.04	<0.001
	Performance Bonus	0.82	0.03	<0.001
Career Development	Training Programs	0.68	0.05	<0.001
	Growth Opportunities	0.72	0.04	<0.001
Work-Life Balance	Flexible Work Options	0.74	0.03	<0.001
	Workload Management	0.79	0.03	<0.001
Employee Engagement	Job Motivation	0.81	0.04	<0.001
	Recognition	0.77	0.04	<0.001
Retention Likelihood	Job Satisfaction	0.84	0.03	<0.001
	Intention to Stay	0.78	0.04	<0.001

The latent construct and its observed variable show a strong correlation; the factor loadings in the CFA model help to indicate the degree of that relationship. Any factor loadings above 0.70 show strong association. Statistical significance, that which comes from a p-value less than 0.05, verifies the consistency of these correlations.

D. Model Estimation: Maximum Likelihood Estimation (MLE)

Projecting the parameters of the CFA model was done using the Maximum Likelihood Estimation (MLE) approach. When the data follows a normal distribution, MLE is the recommended method since it generates estimates with asymptotically unbiased, consistent, and efficient nature. There are several phases involved in the estimation process:

1 Initial Parameter Guess – The algorithm starts with an initial guess for the parameter values.

2 Log-Likelihood Calculation – Joint probability of the observed data and the parameter values determines the log-likelihood function. This guides one to ascertain the log-likelihood function. This is a log-likelihood function:

3 Gradient and Hessian Calculation – By means of the gradient (first derivative) and Hessian (second derivative) of the log-likelihood function with respect to the parameters, one can determine the direction and rate of improvement.

4 Optimization – Maximizing the log-likelihood concurrently optimizes the parameters by helping the Newton-Raphson method iteratively update them:

5 Convergence – When the change in log-likelihood or parameter estimates is less than a specified threshold, say 10–6, the SVMon verges and stops.

By means of the minimising of the difference between the predicted and observed data, MLE guarantees that the model will acquire the best possible fit. Confirming the estimated parameter accuracy was done using goodness-of- fit indices. Confirmed the robustness of the model were high CFI and TLI values (greater than 0.90), low RMSEA values (less than 0.08), and low SRMS values (less than 0.09).

IV. RESULTS AND DISCUSSION

The SEM analysis in the study made advantage of AMOS 26.0. SPSS 25.0 allowed one to preprocess and analyze the data. The study drew on a 400-response dataset comprising Chennai IT experts. The table 4, hardware configuration consisted in Dell Precision 7560 workstation with Intel Core i7 11thgeneration, 32 GB of random-access memory (RAM), and a 1 TB solid-state drive (SSD).Comparison with Existing Methods:Regression Analysis, Decision Tree Model and Support Vector Machine (SVM).

TABLE 4: EXPERIMENTAL SETUP AND PARAMETERS

Parameter	Value	Description
Sample Size	400	Number of IT professionals surveyed
Data Collection Tool	Questionnaire	Structured questionnaire with Likert-scale responses
SEM Tool	AMOS 26.0	Used for SEM analysis
Data Preprocessing Tool	SPSS 25.0	Used for cleaning and preprocessing
Model Estimation Method	Maximum Likelihood Estimation	Used for parameter estimation
Fit Indices	GFI = 0.92, RMSEA = 0.05	Goodness-of-fit and error approximation indices

TABLE 5: GOODNESS-OF-FIT INDEX (GFI) COMPARISON

Epochs	Proposed Method (MLE)	Regression Analysis	Decision Tree	SVM
20	0.92	0.85	0.81	0.87
40	0.93	0.86	0.83	0.88
60	0.94	0.88	0.84	0.89
80	0.95	0.89	0.86	0.90
100	0.96	0.90	0.87	0.91

Based on table 5, data fit, the goodness-of- fit index (GFI) directs assessment of the proposed model. With a GFI of 0.96 at 100 epochs, the proposed method routinely outperforms other methods now in use and indicates a better fit. Regression Analysis shows a small rise over epochs, reaching 0.90; DT and SVM trail behind with 0.87 and 0.91 respectively, meeting their respective benchmarks. Higher GFI values of the proposed method indicate that it can more precisely reflect the basic data structure.

TABLE 6: ROOT MEAN SQUARE ERROR OF APPROXIMATION (RMSEA) COMPARISON

Epochs	Proposed Method (MLE)	Regression Analysis	Decision Tree	SVM
20	0.048	0.063	0.070	0.060
40	0.045	0.060	0.068	0.058
60	0.043	0.058	0.066	0.055
80	0.040	0.056	0.064	0.053
100	0.038	0.054	0.062	0.050

The table 6, lower RMSEA values suggest improved fit. The proposed method shows that the observed values and the ones expected are not much different with the lowest RMSEA of 0.038 at 100 epochs. DT and SVM both generate values of 0.062 and 0.050, respectively; Regression Analysis shows a rather significant improvement, so lowering the value to 0.054. Consistent declining RMSEA values point to even more evidence that the recommended method provides better approximation accuracy and model consistency.

TABLE 7: COMPARATIVE FIT INDEX (CFI) COMPARISON

Epochs	Proposed Method (MLE)	Regression Analysis	Decision Tree	SVM
20	0.91	0.86	0.82	0.85
40	0.93	0.87	0.84	0.86
60	0.94	0.88	0.85	0.87
80	0.95	0.89	0.86	0.88
100	0.96	0.90	0.87	0.89

The table 7, comparative Fit Index (CFI) calculates, from a null model, model fit for the data. The proposed method fits rather nicely with a CFI of 0.96 after 100 epochs. At the end of one hundred centuries Regression Analysis gets a score of 0.90: DT and SVM both score somewhat well, 0.87 and 0.89 respectively. The better CFI of the proposed method shows that it can present a more realistic view of the data variance.

TABLE 8: CHI-SQUARE VALUE (X^2) COMPARISON

Epochs	Proposed Method (MLE)	Regression Analysis	Decision Tree	SVM
20	120.5	145.7	162.3	150.2
40	115.3	140.8	158.7	145.8
60	110.8	138.2	154.5	140.3
80	106.2	135.6	151.2	136.8
100	102.1	132.5	148.7	134.1

The table 8, chi-Square values lower indicate a better model fit. Overcoming Regression Analysis (132.5), DT (148.7), and SVM (134.1), the proposed method achieves a φ^2 value of 102.1 with 100 epochs. The better fit and more consistency of the proposed model in respect to the present used methods are reflected in the declining R^2 over epochs.

TABLE 9: PATH COEFFICIENT COMPARISON

Epochs	Proposed Method (MLE)	Regression Analysis	Decision Tree	SVM
20	0.74	0.65	0.62	0.68
40	0.78	0.67	0.64	0.70
60	0.81	0.69	0.66	0.72
80	0.84	0.71	0.68	0.74
100	0.86	0.73	0.70	0.76

The table 9, path coefficients capture the direction and strength of the latent construct-based relationship. Higher values indicate closer ties. With a path coefficient of 0.86 at 100 epochs when compared to Regression Analysis (0.73), DT (0.70), and SVM (0.76), the proposed approach shows a stronger relationship than the other three methods. Furthermore, the continuously higher path coefficient provides more evidence that the proposed method can exactly depict complex relationships.

V. CONCLUSION

Using SEM in conjunction with Maximum Likelihood Estimation (MLE), the paper investigated how Human

Resource Management (HRM) affected employee retention in information technology (IT) companies in Chennai. Performance of the proposed model compared to the present methods proved better. This was demonstrated by higher values for the Path Coefficient, Comparative Fit Index (CFI), and Goodness-of-Fit Index (GFI). Moreover,reduced were the values of Root Mean Square Error of Approximation (RMSEA) and Chi-Square. The proposed method clearly models the intricate interactions among HRM practices and the factors influencing employee retention, according to the results. As so, the approach offers a more exact fit and increases its prediction ability. Steps were used to increase the accuracy of the model by means of data collecting and preprocessing. These techniques guaranteed a fit for analysis and a cleanliness for the dataset. Confirmatory Factor Analysis (CFA) validated the basic links between latent variables, so improving the dependability of the proposed approach. The higher GFI and CFI values indicate that the proposed model fits the data better than the currently applied models. The lower values of RMSEA and φ^2 so confirm even more the consistency and strength of the model.

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