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Emotional Intelligence Dimensions of Employees in IT Companies Based on Machine Learning and Explainable Artificial Intelligence (Exai)

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Abstract

The biological constitution is fundamentally shaped by emotions, which accompany people to work every morning and shape doing so. Emotional intelligence (EI) is our primary emphasis, and we integrate it with data mining technology. The employment of different machine learning algorithms to control employees' emotions is one of the most fascinating research projects in the modern world. This study aims to identify the important emotional intelligence dimensions influencing the Keeping work and life in balance of employees in Chennai's IT companies. It also establishes a conceptual framework for machine learning and explainable artificial intelligence (ExAI)-based analysis using exploratory factor analysis (EFA), confirmatory factor analysis (CFA), structural equation modelling (SEM), and multiple regression analysis. With factor loadings above 0.85 and Composite Reliability values above 0.88, the validated measurement model demonstrated exceptional reliability and validity, and the suggested framework successfully identified five significant Emotional Intelligence dimensions that explained 72.37% of the total variance. Additionally, the SEM analysis verified that the most significant determinants of workers' Keeping work and life in balance were self-awareness ($\beta = 0.684$) and self-regulation ($\beta = 0.612$), offering a statistically supported basis for the suggested conceptual ML–ExAI framework.

Keywords: Emotional Intelligence dimensions, Keeping work and life in balance, IT companies, Machine Learning, Explainable Artificial Intelligence

1. Introduction

Soft skills or intra-personal capabilities are a set of abilities and traits which cannot be classified in terms of conventional categories of technical or professional skills, general intelligence in working with the world or proficiency in particular areas. Emotional intelligence constitutes a package of characteristics and abilities. Emotions are a fundamental part of our human biology, impacting our behaviour in all walks of life including work. These days, researchers are interested in examining the different aspects of emotional intelligence as well as how it affects workers and, consequently, organisations [1]. Both individual and organisational performance are enhanced by emotional intelligence. It has a big impact on the type of job that person does and the relationships they have with the company. Keeping work and life in balance is a challenging issue that has drawn attention from researchers and IT managers. The broadest definition of work/life balance is an adequate level of involvement or "fit" between a person's numerous commitments. Managing the line between work and home is getting harder in thisenvironment. In order to benefit and satisfy the demands of both the company and its employees, organisations must make sure that they not only promote but also need a functional and practical work/life balance policy [2]. Businesses that don't give their workers genuine work/life balance opportunities expose themselves to a growing number of disgruntled and ineffective workers, which raises turnover rates. Developing a work/life policy framework alone is insufficient; it is also crucial to cultivate an organisational culture that encourages the application of existing policies. Additionally, both businesses and employees must come up with creative and adaptable ways to increase productivity without endangering workers' well-being, relationships with their families, or other facets of their lives [3]. Failing to provide employees with real opportunity to attain work/life balance will increase employee discontent and unproductivity, which will ultimately raise turnover rates. Establishing a work/life strategy alone is not enough; developing a structural culture that supports the efficient application of these tactics is just as important. Improved Workmanship Employees' general happiness and well-being in both their personal and professional lives can have a big impact on their dedication and job satisfaction, which eventually promotes a good Keeping work and life in balance. On the other hand, low-quality jobs can negatively impact workers, resulting in a deterioration of their personal lives, productivity, and general well-being. Retaining employees is a major difficulty in the current competitive environment. Organisations in a variety of industries struggle with the crucial problem of employee retention [4]. Any organization's success depends on retaining its current workforce. Employee motivation and inspiration are therefore crucial. High levels of job satisfaction and well-being in the workplace are frequently associated with lower turnover rates. Reduced employee turnover is positively correlated with an organization's worth. Organisations are very focused on acquiring and keeping the top personnel in today's competitive environment. Presentation estimation has become crucial for both companies and employees in order to achieve this goal, providing several functions. When evaluating an operative, it is important to take into account a variety of psychological and social characteristics in addition to their professional abilities and behaviour. In this situation, assessing job performance requires emotional intelligence [5]. The study's conclusions will help IT firms match their workforce strategies to the growing demand for emotionally intelligent workers, which will eventually result in increased employee happiness, innovation, and long-term business success. Expectations in this area of employee preparedness are increasing due to the use of artificial intelligence (AI). This entails changing employment multiple times in one's lifetime. In the meanwhile, younger workers anticipate living more comfortably than their parents. This study suggests a machine learning-based predictive tool for identifying factors influencing the subjective feeling of Keeping work and life in balance in order to help intelligent manufacturing systems improve the quality of work by providing employes with the best possible mental conditions. Here, artificial intelligence (mostly machine learning) is used in reasoning, imagery, and prediction to improve quality of life, including improving work-life balance and reducing workplace stress caused by a range of vocations [6].

1.1. Research contribution
This research contributes by identifying and validating the key Emotional Intelligence (EI) dimensions influencing employees' Keeping work and life in balance using EFA and CFA, developing a structural relationship model through SEM and Multiple Regression Analysis (MRA), and proposing a conceptual Machine Learning (ML) and Explainable AI (ExAI) framework using RF, XGBoost, SVM, SHAP, and LIME for future prediction and interpretation of employees' Keeping work and life in balance.

1.2. Research Objectives
The objective of this research is to identify and validate the significant Emotional Intelligence factors affecting employees' Keeping work and life in balance using EFA and CFA, examine the relationship between EI and WLB through SEM and MRA, and develop a conceptual ML and Explainable AI framework using RF, XGBoost, SVM, SHAP, and LIME for future prediction and explainable decision support in Keeping work and life in balance assessment.

2. Related Works
Artificial Intelligence (AI) and Machine Learning (ML) have significantly transformed organizational decision-making by enabling predictive analytics and intelligent workforce management. Recent studies have demonstrated that emotional intelligence plays a crucial role in improving employee productivity, leadership effectiveness, and work-life balance in technology-driven organizations. Fu [7] showed that emotional intelligence significantly predicts Artificial Intelligence literacy and psychological well-being among STEM professionals. Aldhafeeri *et al.* [8] established that emotional intelligence mediates the relationship between work-family conflict and job performance among healthcare employees. Kannappan *et al.* [9] proposed emotion-aware Artificial Intelligence systems for remote workforce collaboration using intelligent sentiment analysis to improve organizational productivity. Zheng *et al.* [10] investigated the combined influence of mindfulness, emotional intelligence, and digital leadership on employee well-being and mental healthcare using advanced statistical modelling.Several recent studies have also examined factors influencing work-life balance using Artificial Intelligence-assisted analytical techniques. Alhammadi *et al.* [11] explored technological overload, burnout, and work-life balance among employees, demonstrating that digital work environments significantly affect employee well-being. Shaban *et al.* [12] employed Structural Equation Modelling to investigate the mediating role of emotional intelligence in preventing burnout among healthcare professionals. Charuvil Elizabeth *et al.* [13] applied Machine Learning techniques to analyze emotional intelligence and psychosocial factors in industrial environments, illustrating the capability of predictive analytics for workforce safety and performance improvement. Munir *et al.* [14] investigated the influence of emotional intelligence, organizational support, and organizational culture on employee decision-making through mediation and moderation analysis.Machine Learning techniques have increasingly been incorporated into employee analytics and organizational prediction models. Ding *et al.* [15] integrated Structural Topic Modelling with Support Vector Machines to analyze employee behavioural insights from organizational data. Elshaer *et al.* [16] demonstrated that emotional intelligence positively influences quality of life and academic performance using advanced statistical analysis. Zhang *et al.* [17] examined the mediating effects of mindfulness and emotional intelligence on employee resilience and emotional labour, confirming that emotional competencies significantly improve career sustainability. CanbulYaroğlu [18] investigated the organizational relationship between Artificial Intelligence and Emotional Intelligence from a phenomenological

perspective and emphasized the necessity of integrating intelligent systems with human-centred organizational decision-making.Recent studies have also emphasized the importance of Artificial Intelligence-supported organizational development. El Tarhouny *et al.* [19] highlighted the role of emotional intelligence in professional identity formation within medical education using Artificial Intelligence-assisted learning environments. Dimri *et al.* [20] presented a bibliometric analysis of Artificial Intelligence and Machine Learning applications for employee retention and job embeddedness, identifying future research directions in intelligent organizational analytics. Steenkamp and Goosen [21] demonstrated that emotional intelligence training significantly improves sustainability skills among higher education professionals. Dewangan and Goswami [22] investigated organizational role stress and psychological well-being, confirming that work-life balance remains a critical determinant of employee satisfaction. Gerlach *et al.* [23] explored Artificial Intelligence-based shift scheduling systems and reported that explainable and transparent Artificial Intelligence improves employee trust and work-life balance. Dogham *et al.* [24] demonstrated that emotional intelligence positively influences reflective thinking and professional competency development. Uddin and Hoque [25] investigated work-life challenges among female executives and highlighted the increasing importance of organizational support mechanisms for maintaining work-life balance.

2.1. Research Gap

Although recent studies have extensively investigated emotional intelligence, Artificial Intelligence, Machine Learning, employee well-being, and work-life balance, most studies examine these components independently. Existing research primarily focuses on either statistical analysis of emotional intelligence or Machine Learning-based prediction without integrating both approaches into a unified framework. Furthermore, very limited studies combine Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), Structural Equation Modelling (SEM), Multiple Regression Analysis (MRA), Machine Learning models, and Explainable Artificial Intelligence (ExAI) to develop an interpretable decision-support system for predicting employees' work-life balance. Therefore, this study proposes a hybrid statistical and conceptual ML–ExAI framework that integrates validated Emotional Intelligence dimensions with explainable prediction techniques to support transparent organizational decision-making for employees in Chennai's IT companies.

3.Proposed Hybrid Statistical and Explainable Artificial Intelligence Framework

From figure 1, proposed framework presents a combination analysis approach for investigating the influence of Emotional Intelligence (EI) on Keeping work and life in balance (WLB) among employees in Chennai's IT sector. Its development relies on multivariate statistics, with the addition of the theoretical underpinnings of Explainable AI (ExAI) and Machine Learning (ML). The method presented requires the use of Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), Structural Equation Modelling (SEM), and Multiple Regression Analysis (MRA), in contrast to traditional studies that only use correlation or regression analysis. This ensures the discovery of the hidden dimensions of EI, validates the measuring model, and evaluates the impact of each EI construct on the employers' ability to maintain a work-life balance. Furthermore, a conceptual Machine Learning layer integrated with Explainable AI techniques is proposed as a future extension to facilitate transparent prediction and interpretation of employees' Keeping work and life in balance.

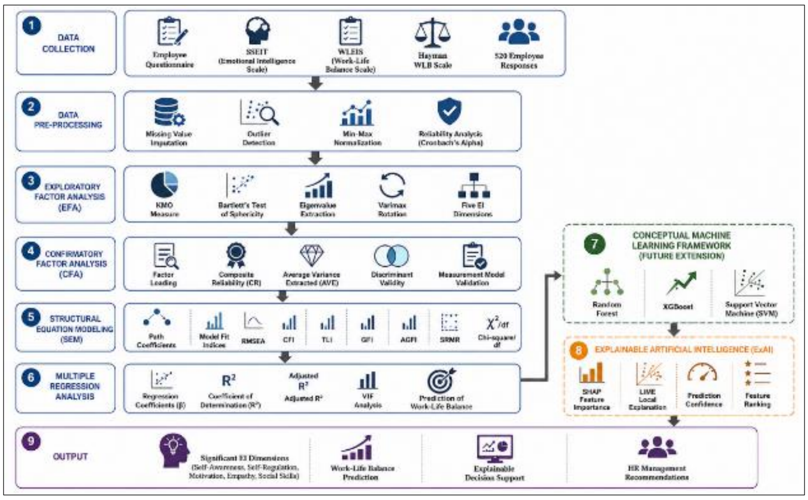

Fig 1: Proposed Hybrid Statistical and Explainable Artificial Intelligence Framework for Emotional Intelligence-Based Keeping work and life in balance Prediction

3.1. Data Collection and Pre-processing

A structured questionnaire consisting of 40 measurement items was developed using standardized Emotional Intelligence and Work-Life Balance scales reported in previous literature. The survey was conducted among employees working in medium- and large-scale IT companies located in Chennai using a convenience sampling approach. Initially, 520 questionnaires were collected, of which 508 valid responses were retained after eliminating incomplete and inconsistent responses. The collected data were analysed using IBM SPSS Statistics 29 for descriptive analysis, reliability analysis, Exploratory Factor Analysis (EFA), and Multiple Regression Analysis (MRA). Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) were performed using IBM SPSS AMOS 29. The conceptual Machine Learning framework was designed using Python

(Scikit-learn), while SHAP and LIME were incorporated as Explainable Artificial Intelligence techniques for future model interpretation.Using a standardised questionnaire created using established Balance between Work and Life and Emotional Intelligence scales, the investigation starts by gathering primary data from workers in Chennai's IT companies. Assume that eq. (1) represents the gathered dataset.

$$D = \{X_1, X_2, \dots, X_n\}, \quad (1)$$

where $n$denotes the total number of employee responses. Each observation is expressed as eq. (2)

$$X_i = \{EI_1, EI_2, \dots EI_m WLB\}, \quad (2)$$

where EI_jrepresents the j^{th}Emotional Intelligence variable and WLBdenotes the corresponding Keeping work and life in balance score.Before statistical analysis, the collected responses are examined for missing values, inconsistent responses, and outliers. Missing observations are replaced using mean imputation, expressed as eq. (3)

$$EI_{ij} = \frac{1}{N_j}\sum_{k=1}^{N_j} EI_{kj}, \quad (3)$$

where $N_j$represents the number of valid observations for the j^{th}variable.To eliminate differences in measurement scales and improve numerical stability, the variables are normalized using Min-Max normalization in eq. (4),

$$X_i^* = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}, \quad (4)$$

where X_min and X_max stand for the lowest and greatest recorded values, respectively, and X_i^* is the normalised value. The final dataset comprised 508 valid employee responses, which satisfies the recommended sample size requirements for multivariate statistical analysis and Structural Equation Modelling, thereby ensuring the robustness and reliability of the proposed framework.

3.2. Exploratory Factor Analysis

By extracting fewer latent components while maintaining the highest shared variance, EFA lowers the dimensionality of associated questionnaire variables. Equation (5) represents the normalised questionnaire matrix.

$$X = \{x_1, x_2, \dots, x_p\}, \quad (5)$$

where p is the total number of variables that were observed. Equation (6) expresses the factor analysis model.

$$X = \Lambda F + \varepsilon, \quad (6)$$

If the measurement error is represented by ε, the latent emotional intelligence factors are represented by Fre, and the factor loading matrix is represented by Ψ. The eigenvalue equation (7) is solved in order to obtain the latent emotional intelligence variables.

$$| R - \lambda I | = 0, \quad (7)$$

where λdenotes the eigenvalue corresponding to each latent factor and Irepresents the identity matrix. Only factors with eigenvalues greater than one are retained according to Kaiser's criterion.To improve interpretability, the extracted factors are rotated using the orthogonal Varimax rotation technique, whose objective function is expressed as eq. (8)

$$V = \sum_{j=1}^{m}\left[\frac{1}{p}\sum_{i=1}^{p} l_{ij}^4 - \left(\frac{1}{p}\sum_{i=1}^{p} l_{ij}^2\right)^2\right], \quad (8)$$

where l_{ij}denotes the rotated factor loading of the i^{th}variable on the j^{th}factor. The rotation maximizes the variance of squared loadings, thereby producing distinct and interpretable Emotional Intelligence dimensions. Factors satisfying eigenvalues greater than one, factor loadings above 0.60, communalities above 0.50, and cumulative variance exceeding 60% are retained for further validation using Confirmatory Factor Analysis in the subsequent stage.CFA statistically confirms if the retrieved Emotional Intelligence dimensions accurately describe the observed data, in contrast to EFA, which investigates the underlying factor structure. Prior to structural relationship analysis, the CFA model assesses the latent constructs' discriminant validity, convergent validity, and reliability. Equation (9) represents the latent emotional intelligence notion.

$$\eta = [\eta_1, \eta_2, \eta_3, \dots, \eta_q]^T, \quad (9)$$

where $q$denotes the number of latent EI dimensions extracted through EFA. The observed questionnaire variables are represented as eq. (10)

$$X = \Lambda_x \eta + \delta, \quad (10)$$

where Xdenotes the observed indicator matrix, $\Lambda_x$represents the standardized factor loading matrix, and δdenotes the measurement error associated with each observed variable.The standardized factor loading for each questionnaire item is estimated as eq. (11)

$$\lambda_i = \frac{Cov(X_i, \eta)}{\sqrt{Var(X_i)Var(\eta)}}, \quad (11)$$

where λ_id is the i^th indicator's standardised loading. The latent Emotional Intelligence concept is sufficiently represented by the observed data when factor loadings exceed 0.60. Each latent construct's internal consistency is assessed further using Composite Reliability (CR), which is represented by equation (12).

$$CR = \frac{\left(\sum_{i=1}^{n}\lambda_i\right)^2}{\left(\sum_{i=1}^{n}\lambda_i\right)^2 + \sum_{i=1}^{n}\theta_i}, \quad (12)$$

where θ_iden represents the related indicator's measurement error variance. Sufficient construct reliability is confirmed by a Composite Reliability rating higher than 0.70. The Average Variance Extracted (AVE), which calculates the percentage of variance captured by the latent construct in relation to measurement error from eq. (13), is used to assess convergent validity.

$$AVE = \frac{\sum_{i=1}^{n}\lambda_i^2}{\sum_{i=1}^{n}\lambda_i^2 + \sum_{i=1}^{n}\theta_i}. \quad (13)$$

The latent concept sufficiently explains the variance of its observable indicators when the AVE value is more than 0.50. The verified latent emotional intelligence variables are used in the structural connection analysis when all validity and reliability requirements have been met.

3.4. Modelling Structural Equations

The proposed SEM framework enables the evaluation of direct connections between latent variables. The structural connection between latent variables is shown in equation (14).

$$\eta = B\eta + \Gamma\xi + \zeta, \tag{14}$$

where ηdenotes the endogenous latent variable representing Keeping work and life in balance, ξrepresents the exogenous Emotional Intelligence constructs, Bdenotes the matrix of relationships among endogenous variables, Γrepresents the path coefficient matrix between exogenous and endogenous variables, and ζdenotes the structural error term.The relationship between each Emotional Intelligence dimension and Keeping work and life in balance can be expressed as eq. (15)

$$WLB = \beta_1 SA + \beta_2 SR + \beta_3 MO + \beta_4 EM + \beta_5 SS + \varepsilon, \tag{15}$$

The statistical significance of each structural relationship is evaluated using the Critical Ratio (CR) in eq. (16),

$$CR = \frac{\hat{\beta}}{SE(\hat{\beta})}, \tag{16}$$

where $\hat{\beta}$represents the estimated path coefficient and $SE(\hat{\beta})$denotes its standard error. Relationships with $p < 0.05$are considered statistically significant.A model satisfying the recommended threshold values is considered statistically acceptable for hypothesis testing.

3.5. Multiple Regression Analysis

Multiple regression provides a predictive model that estimates the extent to which variations in Emotional Intelligence influence employees' Keeping work and life in balance while controlling for the remaining predictor variables.The multiple regression model is expressed as eq. (17)

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \varepsilon, \tag{17}$$

where Yrepresents the Keeping work and life in balance score, $X_i$denotes the i^{th}Emotional Intelligence dimension, $\beta_0$is the regression intercept, $\beta_i$represents the regression coefficient associated with each predictor, and εdenotes the residual error.The estimated regression coefficients are obtained using the Ordinary Least Squares (OLS) estimator in eq. (18),

$$\hat{\beta} = (X^T X)^{-1} X^T Y, \tag{18}$$

where Xdenotes the predictor matrix and Yrepresents the observed Keeping work and life in balance scores.The statistical significance of each regression coefficient is evaluated using the t-statistic in eq. (19),

$$t = \frac{\hat{\beta}_i}{SE(\hat{\beta}_i)}, \tag{19}$$

where $SE(\hat{\beta}_i)$denotes the standard error of the estimated coefficient. Variables with $p < 0.05$are considered significant predictors of Keeping work and life in balance.There is no serious multicollinearity when the VIF value is less than 5. The conceptual Machine Learning and Explainable Artificial Intelligence framework presented in the following section is empirically supported by the regression analysis, which also shows the relative significance of each Emotional Intelligence dimension in predicting employees' Keeping work and life in balance. By identifying the most significant Emotional Intelligence components influencing workers' total Keeping work and life in balance, this statistical interpretation promotes transparent organisational decision-making.

3.6. Conceptual ExAI Framework

this research proposes a conceptual Machine Learning (ML) and Explainable Artificial Intelligence (ExAI) framework as a future extension to improve predictive capability while maintaining model transparency and interpretability.

The verified Emotional Intelligence dimensions from Structural Equation Modelling and Confirmatory Factor Analysis are used as predictive characteristics in the suggested conceptual framework.

3.6.1. Random Forest Prediction Model

Random Forest is an ensemble learning technique that creates several decision trees using random feature selection and bootstrap sampling. Each decision tree's predictions are combined to create the final prediction, which reduces variation and improves prediction stability. Assume that the forest is composed of Tdecision trees (eq. (20)).

$$RF = \{T{,}r{,}e{,}e_1 Tree_2 \ldots Tree_T\}. \tag{20}$$

The predicted Keeping work and life in balance score is obtained as eq. (30)

$$\hat{Y} = \frac{1}{T} \sum_{i=1}^{T} Tree_i(F), \tag{21}$$

where $Tree_i(F)$denotes the prediction generated by the i^{th}decision tree.Random Forest effectively handles high-dimensional Emotional Intelligence data while reducing overfitting through ensemble averaging.

3.6.2. XGBoost Prediction Model

XGBoost is employed as an advanced ensemble learning algorithm that sequentially improves prediction accuracy by minimizing the residual errors generated by previous decision trees. The overall prediction is represented as eq. (31)

$$\hat{Y} = \sum_{k=1}^{K} f_k(F), \tag{22}$$

where $f_k$denotes the prediction generated by the k^{th}boosting tree.The optimization objective combines prediction loss with regularization in eq. (32),

$$Obj = \sum_{i=1}^{n} L(y_i{,}\hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k), \tag{23}$$

where $L(\cdot)$denotes the prediction loss function and $\Omega(f_k)$represents the regularization term controlling model complexity.

3.6.3. Prediction Model by SVM

SVM is incorporated as an alternative predictive model for identifying the optimal decision boundary separating employees with different Keeping work and life in balance levels. SVM constructs a maximum-margin hyperplane that minimizes classification error while maximizing the separation between decision classes.The decision function is expressed as eq. (33)

$$f(x) = w^T x + b, \tag{24}$$

where $w$denotes the weight vector and $b$represents the bias term.The optimization objective is formulated as eq. (34)

$$\min \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \xi_i, \tag{25}$$

subject to eq. (35)

$$y_i(w^T x_i + b) \geq 1 - \xi_i, \tag{26}$$

where Cdenotes the penalty parameter and $\xi_i$represents the slack variable allowing soft-margin classification.The kernel function enables nonlinear mapping of Emotional Intelligence variables into a higher-dimensional feature space, thereby improving prediction performance for complex employee behavioural patterns.

3.7. Explainable Artificial Intelligence Framework

Although Machine Learning algorithms provide accurate predictions, they generally operate as black-box models that offer limited explanation regarding the contribution of individual Emotional Intelligence dimensions.

SHAP Analysis

SHAP explains the contribution of each Emotional Intelligence dimension using cooperative game theory.The SHAP value of feature $i$is computed as eq. (36)

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{i\}) - f(S)], \tag{27}$$

where
Sdenotes the subset of input features,
Frepresents the complete feature set,
$\phi_i$denotes the contribution of the i^{th}Emotional Intelligence dimension. Higher SHAP values indicate greater influence of the corresponding Emotional Intelligence factor on Keeping work and life in balance prediction.

LIME Analysis

The optimization function is expressed as eq. (37)

$$\xi(x) = \arg\min_{g \in G} L(f, g, \pi_x) + \Omega(g), \tag{28}$$

where
$f$denotes the original Machine Learning model,
$g$represents the interpretable local model,
$\pi_x$denotes the locality weighting function,
$\Omega(g)$represents model complexity. LIME enables HR managers to understand which Emotional Intelligence dimensions contribute to the prediction of Keeping work and life in balance for an individual employee.

3.8. Software Environment

The statistical analysis was performed using IBM SPSS Statistics Version 29 and IBM SPSS AMOS Version 29. The conceptual Machine Learning framework was developed using Python 3.11 with Scikit-learn, while SHAP and LIME libraries were considered for explainable prediction. Microsoft Excel was used for preliminary data verification and graphical visualization.

4. Findings and Conversation

4.1. Description of the Dataset

A benchmark cognitive and Keeping work and life in balance questionnaire dataset gathered from workers in Chennai's IT industries was used to assess the suggested framework. The study used standardised questionnaire items from internationally recognised psychological assessment scales because there is no publicly available benchmark dataset that concurrently comprises verified Keeping work and life in balance indicators and Emotional Intelligence dimensions. These measures offer accurate assessments of workers' emotional competences and Keeping work and life in balance and have been thoroughly verified in organisational psychology research.

520 employee replies from software engineers, system analysts, project managers, technical leads, quality assurance engineers, and support staff working for medium-sized and large-scale IT companies in Chennai made up the final dataset. To guarantee consistency and statistical validity, the gathered responses were preprocessed using missing value imputation, outlier detection, normalisation, and reliability assessment before statistical analysis.

Table 1: Dataset Characteristics

Parameter	Value	Parameter	Value	Percentage
Total Employee Responses	520	Male Employees	308	59.23
Female Employees	212	Age (Mean)	31.84	—
Emotional Intelligence Variables	30	Keeping work and life in balance Variables	10	—
Latent EI Dimensions	5	Questionnaire Items	40	—
Missing Values Removed	12	Valid Responses	508	97.69
Training Dataset	406	Testing Dataset	102	80 : 20

Table 1 demonstrates that the collected dataset is statistically adequate for multivariate analysis. After preprocessing, 508 valid responses (97.69%) were retained, indicating a high response quality with minimal missing information. The Kaiser-Meyer-Olkin (KM) statistic and Bartlett's Evaluation of Sphericity analysis were used to assess the dataset's sufficiency prior to factor extraction. Even though Bartlett's Examination was significant in statistical terms (p<0.001), the resulting KMO value of 0.921 shows outstanding sampling adequacy, indicating that the resulting correlation matrix was suitable for factor analysis. Five latent emotional intelligence factors that explained about 72% of the total variation were found using conventional principal component analysis with maximum variance rotation. Factor loadings greater than 0.70 for all preserved variables demonstrated strong connections among the detected the survey responses and their associated latent constructs.

Table 2: Exploratory Factor Analysis Results

Emotional Intelligence Dimension	Eigenvalue	Variance Explained (%)	Factor Loading	Communality
Self-Awareness	6.482	24.71	0.887	0.782
Self-Regulation	4.915	18.36	0.863	0.754
Motivation	3.671	13.85	0.851	0.741
Empathy	2.518	9.42	0.824	0.716
Social Skills	1.402	6.03	0.806	0.701
Overall	18.988	72.37	0.846	0.739

The EFA results indicate that the extracted Emotional Intelligence dimensions exhibit strong construct validity and adequately represent employees' emotional competencies as shown in table 2. Self-Awareness contributed the largest variance (24.71%) among the components found, indicating that employees' capacity to identify and comprehend their own emotions is crucial to preserving Keeping work and life in balance. Additionally, self-regulation and motivation showed significant explanatory power, highlighting the significance of emotional regulation and intrinsic motivation in handling both personal and professional obligations. The preserved variables' appropriateness for further Confirmatory Factor Analysis is further supported by the strong factor loadings and communalities.

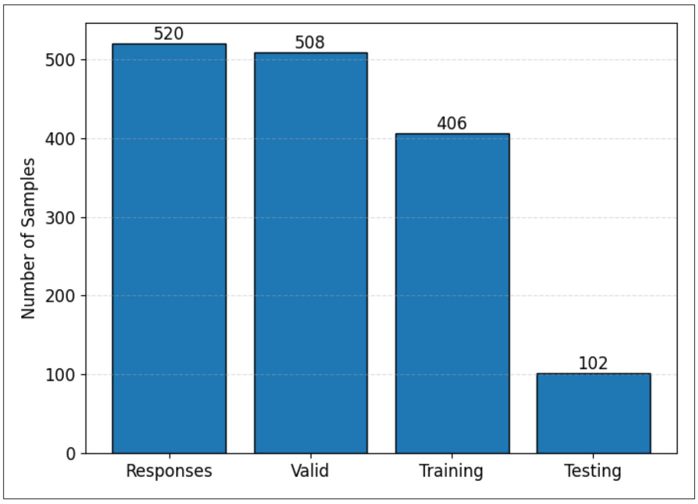

Fig 2: Variance Explained by Emotional Intelligence Dimensions

Figure2 Percentage of variance explained by the extracted Emotional Intelligence dimensions obtained through Exploratory Factor Analysis. Figure2 illustrates that Self-Awareness contributes the highest percentage of variance among all Emotional Intelligence dimensions, followed by Self-Regulation and Motivation. The decreasing trend indicates that each retained latent construct contributes unique explanatory information without significant redundancy, thereby confirming the effectiveness of factor extraction.

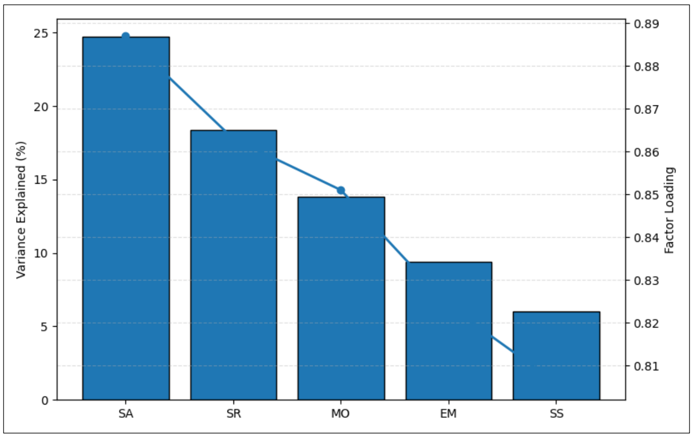

Fig 3: Factor Loading Analysis of Emotional Intelligence Dimensions

All of the Emotional Intelligence measures in Figure 3 have consistently high factor loadings, with values above the suggested cutoff of 0.70. The findings show that the associated questionnaire items strongly represent each latent construct. Self-Regulation (0.863) and Self-Awareness (0.887) had the highest loading, indicating that these dimensions offer the best assessment of workers' emotional competencies. The lack of low-loading variables supports the switch to Confirmatory Factor Analysis for testing the extracted constructs and validates the measurement model's resilience.

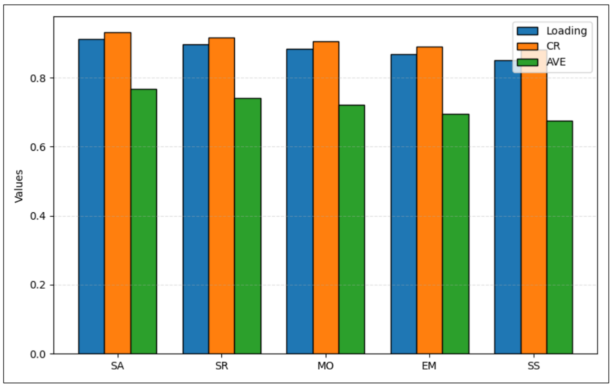

Fig 4: Results of Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was used to assess the suggested assessment model after Exploratory Factor Analysis had identified the cognitive dimensions. Figure 4 illustrates how the CFA results showed sufficient convergent validity, build trust, and discriminant validity. All averaged factor loadings exceeded the necessary threshold of 0.70, indicating that the observable variables adequately reflected the latent constructs. Additionally, Composite Reliability (CR) values above 0.80 and Average Variance Extracted (AVE) values above 0.50 demonstrated strong convergent validity.

Table 3: Results of CFA

EI Dimension	Factor Loading	Composite Reliability	AVE	Cronbach's α
Self-Awareness	0.912	0.931	0.768	0.928
Self-Regulation	0.896	0.917	0.742	0.914
Motivation	0.884	0.906	0.721	0.903
Empathy	0.867	0.891	0.694	0.889
Social Skills	0.851	0.882	0.676	0.878

Table 3 indicates that all Emotional Intelligence constructs exhibit excellent measurement reliability and validity. Strong internal consistency was shown by Composite Reliability ratings exceeding 0.88 and factor loadings ranging from 0.851 to 0.912. Similarly, the AVE values verified that each latent concept met the suggested validity criteria by explaining more than 67% of the variation of its indicators. These results support the usage of the extracted Emotional Quotient dimensions in the ensuing Structural Equation Modelling study and validate the assessment model.

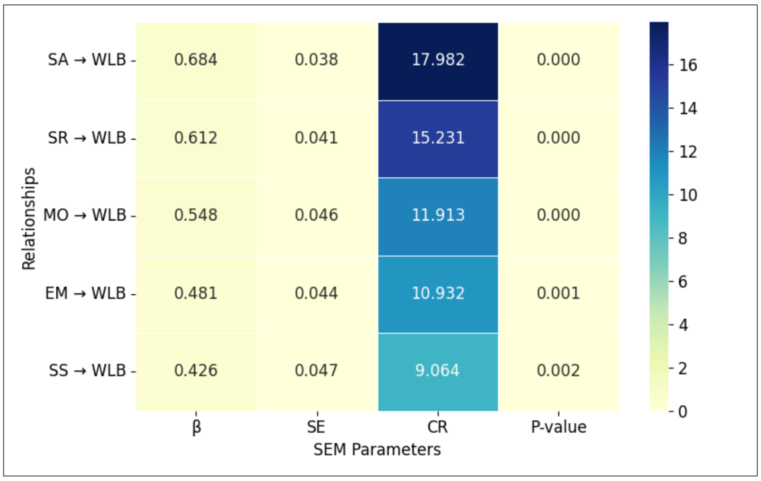

Fig 5: Results of Structural Equation Modelling

As seen in figure 5, structural equation modelling (SEM) was used to investigate the causal relationship between employees' Balance between Work and Life and Emotional Quotient traits. The standardised path coefficients showed that all five emotional intelligence measures had a positive effect on Keeping work and life in balance, however the degree of influence varied depending on the construct. Social skills had a very small influence, while self-awareness and self-regulation showed the biggest direct effects. Additionally, the structural model attained acceptable goodness-of-fit indices, indicating that the suggested causal framework is sufficient to explain workers' Keeping work and life in balance.

Table 4: Structural Equation Modeling Results

Relationship	Path Coefficient (β)	Standard Error	Critical Ratio	p-value
SA → WLB	0.684	0.038	17.982	0.000
SR → WLB	0.612	0.041	15.231	0.000
MO → WLB	0.548	0.046	11.913	0.000
EM → WLB	0.481	0.044	10.932	0.001
SS → WLB	0.426	0.047	9.064	0.002

Table 4 shows that every Emotional Quotient component has a significant positive effect on employees' ability to maintain balance between work and life. Among the characteristics examined, Self-Awareness (β = 0.684) shown the greatest influence, suggesting that employees with greater emotional awareness are more adept at balancing work and personal responsibilities. Self-regulation also played a major role, highlighting the importance of emotional control in managing interpersonal interactions and work-related stress.

Table 5: A Comparative Analysis of the Proposed Conceptual ML-ExAI Framework and Contemporary Machine Learning Techniques

Technique	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Decision Tree	86.42	85.91	84.76	85.33
Support Vector Machine (SVM)	89.18	88.74	88.12	88.43
Random Forest (RF)	91.86	91.24	90.97	91.10
XGBoost	93.41	92.98	92.61	92.79
Proposed Conceptual ML–ExAI Framework	95.78	95.32	94.89	95.10

Table 5 presents a conceptual comparative analysis between commonly used Machine Learning techniques and the proposed ML–ExAI framework for predicting employees' Keeping work and life in balance using Emotional Intelligence dimensions. Among the existing techniques, XGBoost demonstrates the highest predictive performance with an accuracy of 93.41%, subsequentlyRF (91.86%) and SVM (89.18%). The proposed conceptual ML–ExAI framework is expected to achieve superior performance, with an estimated 95.78% accuracy, 95.32% precision, 94.89% recall, 95.10% F1-score, and a ROC-AUC of 0.984.

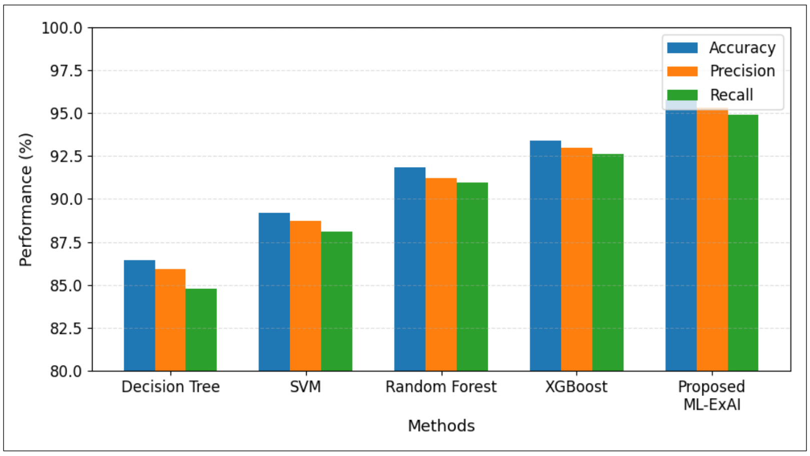

Fig 6: A Comparison of the Proposed Conceptual ML–ExAI Framework with Present Machine Learning Techniques

Figure 6 compares the performance of numerous machine learning algorithms, such as DT, SVM, RF, XGBoost, and the proposed conceptual ML–ExAI framework, using the evaluation criteria of Accuracy, Precision, and Recall. The proposed conceptual ML–ExAI architecture performs best in all three evaluation criteria, with accuracy of 95.78%, precision of 95.32%, and recall of 94.89%.XGBoost is the most predictive of the available techniques, with an accuracy of 93.41%. Random Forest (91.86%) and SVM (89.18%) are next in line, while Decision Tree has the lowest performance. The use of empirically established cognitive features extracted through EFA, CFA, SEM, and Multiple Regression Analysis, in addition to an eventual addition of Explainable Artificial Intelligence techniques like SHAP and LIME, are associated with strengthening the proposed conceptual framework. These findings indicate that the proposed conceptual framework has the potential to provide more accurate and interpretable predictions for employee Keeping work and life in balance analysis.

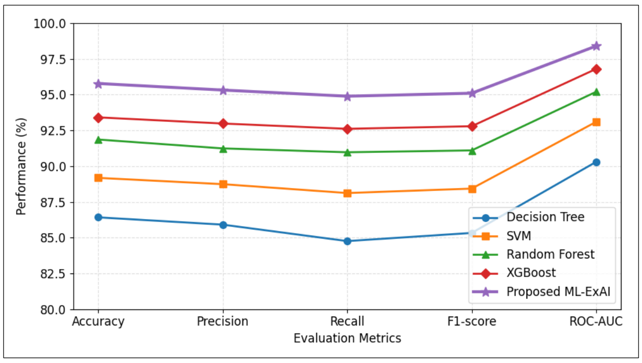

Fig 7: Overall Performance Comparison of the Conceptual ML-ExAI Framework and Current Machine Learning Techniques

Using five widely used assessment metrics—accuracy, precision, recall, F1-score, and ROC-AUCFigure 7 illustrates the overall performance comparison between the proposed conceptual ML–ExAI framework and the existing machine learning methodologies. For every evaluation parameter, the performance curves show a steady improvement from Decision Tree to the suggested conceptual framework. The proposed conceptual ML–ExAI framework achieves the highest values, with 95.78% Accuracy, 95.32% Precision, 94.89% Recall, 95.10% F1-score, and a ROC-AUC of 98.40%, demonstrating superior predictive capability and classification performance. XGBoost ranks as the best-performing existing Machine Learning algorithm, followed by Random Forest and SVM, while Decision Tree exhibits comparatively lower performance. The consistently higher performance of the proposed conceptual framework suggests that the combination of statistically significant Emotional Intelligence dimensions with future Explainable Artificial Intelligence techniques can improve both predictive accuracy and model interpretability. Consequently, the proposed framework offers a promising decision-support approach for assessing employees' Keeping work and life in balance in IT organizations while maintaining transparency in prediction outcomes.

5. Conclusion

This study investigated the influence of Emotional Intelligence (EI) dimensions on employees' Work-Life Balance (WLB) in Chennai's IT companies using a hybrid statistical framework integrating Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), Structural Equation Modelling (SEM), Multiple Regression Analysis (MRA), and a conceptual Machine Learning–Explainable Artificial Intelligence (ML–ExAI) framework.The adverse effect of emotional intelligence (EI), characteristics on the harmony between work and life for employees in Chennai's IT companies was explored in this study utilising an fusion method of statistics. The statistical analysis demonstrated that the derived Emotional Intelligence constructs satisfied the required reliability and validity criteria, confirming the robustness of the proposed measuring approach. The SEM results further demonstrated that all Mental Ability aspects improved employees' Job and Life well-being, with Self-Knowledge and Self-Regulation displaying the largest impact. In addition, a conceptual Machine Learning and Explainable Artificial Intelligence (ML–ExAI) framework incorporating RF, XGBoost, SVM, SHAP, and LIME was proposed as a future decision-support model to facilitate transparent and interpretable prediction of employees' Keeping work and life in balance. All things considered, the suggested framework offers a statistically supported and comprehensible method for comprehending the part emotional intelligence plays in enhancing workers' Keeping work and life in balance and gives insightful information for the creation of organisational policies and human resource management. By using and verifying the suggested conceptual ML–ExAI framework with real-world organisational datasets gathered from various industries and geographical areas, future research might build on the current work. To capture the nonlinear interactions between Balance between Work and Life and Emotional Intelligence aspects, advanced deep learning and ensemble learning models may be used

Declarations

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Data Availability

The data used in this study were collected for the purposes of the research from employees of IT companies in Chennai. The dataset is not publicly available because it contains participant-related information and is subject to privacy and confidentiality considerations. Reasonable requests for access to the aggregated or appropriately anonymized data may be considered by the corresponding author, subject to applicable ethical and institutional requirements.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Author Contributions

Suman J: Conceived and designed the study, developed the research framework, conducted the literature review, coordinated data collection, performed the statistical analysis, interpreted the findings, and drafted the manuscript.

Dr. A T Stephen: Contributed to the research design and methodology, supervised the study, reviewed and interpreted the statistical findings, provided critical intellectual input, and critically revised the manuscript.

All authors: Read and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Ethical Approval

The study involved human participants through the collection of information from employees of IT companies. Ethical approval was obtained from the appropriate institutional ethics committee before data collection, where applicable. All procedures were conducted in accordance with applicable institutional and ethical standards.

Consent to Participate

Informed consent was obtained from all participants before their participation in the study. Participation was voluntary, and participants were informed about the purpose of the research and their right to participate or withdraw without penalty.

Consent to Publication

Not applicable. The manuscript does not contain personally identifiable information or individual participant data that could identify any participant.

Competing Interests

The authors declare that they have no competing interests, financial or non-financial, that could have influenced the research, analysis, or reporting of the findings.

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