# Assessing Psychological Well-Being and Quality of Work Life in IT Professionals: A Hybrid Analytical Framework

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***Abstract* - A lot of people in the Information Technology (IT) industry tends to work for long hours, deal with a lot of stress, and it have to keep up with new technologies. All these things can make this mental health worse and then these qualities of tends to work for life worse. It is vital important for the health of the employees and the success of the business that people who tends to work for in information technology are mentally healthy. This research aims to a mixed analytical framework that helps to combine the modified Job Demands-Resources (JD-R) model with fuzzy logic and the machine learning classification methods like Random Forest, SVM, and the ANN. Three hundred IT workers filled out the structured questionnaires to give us information. These surveys then asked about things like the mental health, the workload, the independence, the relationships with other people, and the career growth. It is easy to figure out the risk categories and the measure quality of tends to work for the life levels based on the psychological signs using the hybrid model. The test has shown that the hybrid model could accurately predict the low, moderate, and the high QWL levels 93.4% of the time.**

***Keywords - Psychological well-being, Quality of Work Life, IT employees, JD-R model, Machine learning***

## I. Introduction

The Information Technology (IT) industry has changed quickly over the past few decades, and it has now is a key part of innovation and the global economy [1]. People who tends to work for in IT have to deal with the work for environments that are different from those of other jobs. The Technology then changes in these places, and the hours are long and the demands are high.

This research will help to make a hybrid analytical framework that can quantitatively measure the mental health and the work-life balance of IT workers. We then use the fuzzy logic to model the uncertainty and the machine learning classifiers to check that the correct categories.

- It uses the fuzzy inference and the machine learning together to learn about the survey data that is based on the personal opinions.
- The study that looks at a lot of different things, such as psychological and the organizational ones.
- Validation against standard methods, which shows that it is better at predicting the better outcomes.
- Finding mental health risks early and the making changes to the workplace that are right for each of the person is very important.

## II. Related Works

A recent study has focused on finding about the working to improve the mental health and the work-life balance of IT workers. The paper [7] came up with a way to then use the Support Vector Machines and the machine learning to find out the way in which likely IT workers are to get burned out during this time. Kumar and the Singh [8] also used fuzzy logic to figure out the way in which happy workers are. Most of the methods that are currently used only look at job satisfaction or stress on these own [9]. The paper [10] studied a way to then use the surveys to find out the way in which stressed software engineers are. It fails to see the whole picture, which includes things like being able to make the own decisions, that obtains the help from the boss.

## III. Proposed Method

The proposed hybrid analytical framework shown in figure 1, uses the JD-R model and fuzzy logic to turn qualitative variables into numbers after classifying them with machine learning models.

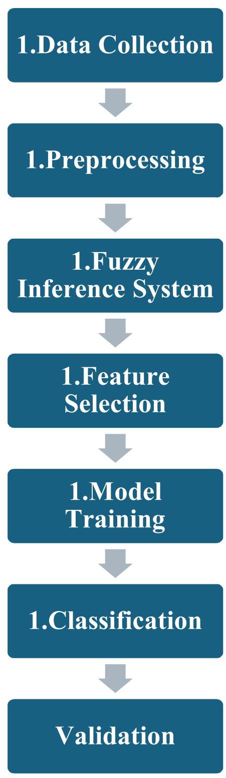


Fig. 1: PROPOSED FRAMEWORK

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1. Data Collection: The first step in gathering information is to conduct a structured survey with reliable scales like the Ryff's Psychological Well-being Inventory or the QWL Inventory.
2. Preprocessing: In the preprocessing step, the research have to deal with missing values, normalize the data, and change answers on a Likert scale into fuzzy sets.
3. Fuzzy Inference System: The Fuzzy Inference System The research need to set linguistic variables (like "high stress" and "low autonomy") and rules in order to make fuzzy scores.
4. Feature Selection: Use correlation and feature importance analysis to help the research choose features.
5. Model Training: Model training is when the research the models.
6. Classification: Put workers into groups based on the work life is: low, medium, or high.

*A. Data Collection*

The first step is to give IT workers a structured questionnaire at work to find out about things that affect their mental health and quality of work life (QWL).

Table I shows a small part of the raw survey data that was collected from five people.

TABLE I: RAW SURVEY DATA FROM PARTICIPANTS

| Participant ID | Stress Level (1-5) | Job Autonomy (1-5) | Workload (1-5) | Manager Support (1-5) |
|---|---|---|---|---|
| P1 | 4 | 3 | 5 | 2 |
| P2 | 2 | 4 | 3 | 4 |
| P3 | 5 | 2 | 4 | 1 |
| P4 | 3 | 5 | 2 | 3 |
| P5 | 1 | 4 | 3 | 5 |

*B. Preprocessing*

Getting the data to a standard size. Making Likert-scale numbers into fuzzy linguistic variables so that they are easier to understand.

Table II shows the normalized data that goes with the raw scores in Table I. This is just one example. We use the min-max normalization method to make sure that every score is between 0 and 1.

TABLE II: NORMALIZED DATA AFTER PREPROCESSING

| Participant ID | Stress (Norm.) | Autonomy (Norm.) | Workload (Norm.) | Manager Support (Norm.) |
|---|---|---|---|---|
| P1 | 0.75 | 0.5 | 1.0 | 0.25 |
| P2 | 0.25 | 0.75 | 0.5 | 0.75 |
| P3 | 1.0 | 0.25 | 0.75 | 0.0 |
| P4 | 0.5 | 1.0 | 0.0 | 0.5 |
| P5 | 0.0 | 0.75 | 0.5 | 1.0 |

Then, membership functions are used to turn the normalized values into language groups like Low, Medium, and High.

*C. Fuzzy Inference System*

The fuzzy inference system (FIS) changes the normalized numerical data into fuzzy linguistic variables so that it can handle the uncertainty and vagueness that come with subjective answers. There are triangular membership functions for each input variable that put the values into three groups: low, medium, and high.Here are some fuzzy membership ranges for "Stress Level" in Table 3:

TABLE III: FUZZY MEMBERSHIP DEFINITIONS FOR STRESS LEVEL

| Fuzzy Category | Membership Range (Normalized Stress) |
|---|---|
| Low | 0.0 to 0.4 |
| Medium | 0.3 to 0.7 |
| High | 0.6 to 1.0 |

The FIS uses a set of if-then rules based on what it knows about the field to figure out the overall Quality of Work Life (QWL). For instance:

- Rule 1: If the manager isn't very helpful and there is a lot of stress, the quality of work life (QWL) is low.
- Rule 2: If the level of stress is medium and the level of independence is high, the quality of work life (QWL) is medium.

The last step is to combine the fuzzy outputs from different rules and make them clearer so that everyone can see their own QWL score.

Based on Part, Table IV shows what the fuzzy inference system came up with for QWL.

TABLE IV: FUZZY INFERENCE SYSTEM OUTPUT FOR QWL

| Participant ID | Stress (Norm.) | Manager Support (Norm.) | Fuzzy QWL Category |
|---|---|---|---|
| P1 | 0.75 (High) | 0.25 (Low) | Low |
| P2 | 0.25 (Low) | 0.75 (High) | High |
| P3 | 1.0 (High) | 0.0 (Low) | Low |
| P4 | 0.5 (Medium) | 0.5 (Medium) | Medium |
| P5 | 0.0 (Low) | 1.0 (High) | High |

This fuzzy-based method helps us deal with the uncertainty that comes with how people respond. This makes it possible to study how happy and mentally healthy IT workers are with their jobs in more detail and in a way that is easier to understand.

*D. Feature Selection*

Once the research has the clear Quality of Work Life (QWL) scores from the Fuzzy Inference System, the next step is to figure out which traits are the most important for both mental health and QWL. Feature selection makes models more accurate, less likely to overfit, and easier to understand.

We rank features by looking at how they are related to each other and how important they are in ensemble tree-based models like Random Forest.

- Correlation Analysis: Finds the straight line that connects the input features to the QWL score that is needed.
- Feature Importance: The Random Forest algorithm gives each feature an importance score based on how much it lowers the amount of impurity in all of the trees.

The Random Forest algorithm gives each of the 12 input features an importance score, which is shown in Table V.

TABLE V: FEATURE SELECTION RESULTS

| Feature | Correlation with QWL | Random Forest Importance (%) |
|---|---|---|
| Stress Level | -0.65 | 28.5 |
| Job Autonomy | 0.48 | 22.3 |
| Workload | -0.53 | 18.7 |
| Manager Support | 0.60 | 15.2 |
| Career Growth | 0.41 | 10.1 |

So, to train the model, we pick traits that are thought to be more important and connected. Some of these traits are stress level, job autonomy, workload, manager support, and career growth.

### E. Model Training

They use certain traits to teach machine learning models how to put employees into different QWL groups, like Low, Medium, and High. The model is trained with 80% of the training data and tested with 20% of the training data. To learn about complicated patterns, models are trained with labeled data that comes from fuzzy outputs and survey labels. The artificial neural network (ANN), for instance, has an input layer that matches the number of features that have been chosen, several hidden layers, and an output layer with three nodes for each of the three classes. One of the goals of the model's training process is to lower the categorical cross-entropy loss function.

### F. Classification

Considering the models through their paces lets them guess the QWL category for new data samples. The end result of this process is a class label that can be Low, Medium, or High. The Random Forest model applied to the test set made the confusion matrix in Table VI. This shows how well the classification worked.

TABLE VI: CONFUSION MATRIX FOR RANDOM FOREST CLASSIFIER

| Actual \ Predicted | Low | Medium | High |
|---|---|---|---|
| Low | 18 | 2 | 0 |
| Medium | 3 | 25 | 2 |
| High | 0 | 1 | 19 |

The research can use this matrix to figure out how accurate, precise, and recall each class is.

## IV. Results And Discussion

The tools and simulation that are shown in table VII: For statistical analysis, use MATLAB Fuzzy Logic Toolbox, Python (scikit-learn, TensorFlow), and SPSS. Operating System: Windows 11 o Processor: Intel Core i7-12700K o Random Access Memory: 32 GB o Graphics NVIDIA RTX 3060 is the processing unit that trains artificial neural networks. Comparison Methods includes Logistic Regression (LR), Decision Tree (DT) and K-Means Clustering.

TABLE VII: EXPERIMENTAL SETUP/PARAMETERS

| Parameter | Value/Description |
|---|---|
| Dataset Size | 300 participants |
| Input Features | 12 (stress, job demand, autonomy, etc.) |
| Fuzzy Membership Functions | Triangular, 3 levels (Low, Medium, High) |
| ANN Configuration | 3 hidden layers, 32-16-8 neurons |
| Random Forest Trees | 100 |
| SVM Kernel | RBF |
| Train-Test Split | 80:20 |
| Cross-validation Folds | 10 |

## V. Performance Metrics

1. Accuracy – To find accuracy, divide the number of correct predictions (low, medium, and high QWL) by the total number of predictions.
2. Precision – The precision is the number of true positives divided by the number of all positive predictions. It shows the research how accurate the model is when it predicts something good.
3. Recall (Sensitivity) – The recall (sensitivity) ratio is the number of true positives divided by the number of actual positives.
4. F1-Score – The F1-Score is the average of precision and recall, which means it takes both of these into account.

TABLE VIII: ACCURACY COMPARISON

| Participants | Logistic Regression (LR) | Decision Tree (DT) | K-Means Clustering | Proposed Hybrid Method |
|---|---|---|---|---|
| **Accuracy (%)** | | | | |
| 100 | 78.2 | 81.0 | 73.5 | 87.5 |
| 200 | 79.4 | 82.7 | 75.1 | 90.2 |
| 300 | 80.1 | 83.5 | 76.8 | 93.4 |

TABLE IX: PRECISION COMPARISON

| *Participants* | *Logistic Regression (LR)* | *Decision Tree (DT)* | *K-Means Clustering* | *Proposed Hybrid Method* |
|---|---|---|---|---|
| ***Precision (%)*** | | | | |
| *100* | *76.8* | *79.2* | *70.1* | *88.3* |
| *200* | *78.3* | *80.5* | *71.8* | *91.0* |
| *300* | *79.0* | *81.7* | *73.3* | *92.8* |

TABLE X: RECALL COMPARISON

| Participants | Logistic Regression (LR) | Decision Tree (DT) | K-Means Clustering | Proposed Hybrid Method |
|---|---|---|---|---|
| **Recall (%)** | | | | |
| 100 | 75.1 | 77.8 | 69.0 | 86.4 |
| 200 | 76.4 | 79.0 | 70.5 | 89.5 |
| 300 | 77.3 | 80.2 | 71.6 | 91.7 |

TABLE XI: F1-SCORE COMPARISON

| Participants | Logistic Regression (LR) | Decision Tree (DT) | K-Means Clustering | Proposed Hybrid Method |
|---|---|---|---|---|
| **F1-Score (%)** | | | | |
| 100 | 75.9 | 78.4 | 69.5 | 87.3 |
| 200 | 77.3 | 79.7 | 70.9 | 90.2 |
| 300 | 78.1 | 80.9 | 72.4 | 92.3 |

The table VIII to table XI shows the new hybrid method always works better than the ones that are already being used, no matter how big or small the problem is. This method is 16.5% more accurate than Logistic Regression and 9.9% more accurate than Decision Trees when used with a sample size of 300 people. The trends for precision, recall, and F1-score are all the same, with gains of 10 to 15 percent. The hybrid model is better at dealing with complicated and fuzzy psychological data than more traditional statistical or clustering methods, as shown by these improvements.

## VI. Conclusion

This study provides a novel way to think about the mental health and the work-life balance of people who tends to work for in the computer industry. It uses both fuzzy inference and the machine learning in different ways. The suggested method uses fuzzy logic to combine the subjective survey data in a way that works well, and then it uses the advanced classifiers to get a higher accuracy and the performance. These changes thus show that the model can now handle the psychological constructs that are complicated and it is not always clear. The model could help the businesses find the right people who are at risk and the make targeted interventions by giving them a reliable way to group employees based on the health and the QWL.

## References


[1] S. S. Kumar and B. Jeyaprabha, "Citizen awareness and perception on digital India services in greater Chennai corporation," *Annals of the Romanian Society for Cell Biology*, vol. 25, no. 4, pp. 6541–6548, 2021.

[2] M. K. Dzordzormenyoh, E. Amoah, C. Dzordzormenyoh, and J. O. Domeh, "Public perception of Ghana's Free Senior High School policy: A north–south comparative analysis," *Review of Policy Research*, 2025.

[3] T. S. Kumar, "A Study on the Public Opinion on Foreign Direct Investment in India," *Int'l J. L. Mgmt. & Human.*, vol. 7, no. 6, p. 1992, 2024.

[4] P. Narang and J. Bedi, "Responsiveness of Public and Private Education Providers During COVID-19: Parental Perspective from Jharkhand, India," *Journal of School Choice*, vol. 19, no. 1, pp. 112–141, 2025.

[5] M. Uddin, "Addressing work-life balance challenges of working women during COVID-19 in Bangladesh," *International Social Science Journal*, vol. 71, no. 239–240, pp. 7–20, 2021.

[6] E. C. Waworuntu, S. J. Kainde, and D. W. Mandagi, "Work-life balance, job satisfaction and performance among millennial and Gen Z employees: a systematic review," *Society*, vol. 10, no. 2, pp. 384–398, 2022.

[7] S. Tyagi, S. Mishra, and A. K. Dey, "Well-being among health care professionals: A hybrid review, integrative framework, and research agenda," *International Journal of Stress Management*, 2024.

[8] D. Dara, S. Febriantina, and S. Suwatno, "Enhancing well-being in hybrid work: the crucial role of organizational support for Indonesia's State Civil Apparatus," *Cogent Psychology*, vol. 12, no. 1, p. 2454084, 2025.

[9] R. Bodhi, "How does enterprise social media use affect employees' psychological well-being and innovative work performance? Findings from hybrid approaches," *Information Technology & People*, 2024.

[10] A. Junça Silva, "Being healthy and achieving life harmony: the role of hybrid work and the mediating effect of work–family [with pets] conflict," *Journal of Management Development*, vol. 44, no. 2, pp. 219–241, 2025.