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WORK LIFE BALANCE AMONG WOMEN TEACHERS IN HIGHER EDUCATION USING CLUSTERING ALGORITHMS

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Abstract

Work-life balance (WLB) has become a major subject matter in modern organizational research and especially in higher education. The main challenge that women teachers in higher learning institutions experience is the management of professional roles and personal and family roles at the same time. The study will examine how women teachers manage work and life through the K - means clustering algorithms at institutions of higher learning. The research is quantitative in nature with the amount of information obtained using surveys aimed at women teachers teaching in diverse colleges and universities. Most factors associated with work-life balance were identified (workload, support systems, work flexibility, family responsibilities, and job satisfaction) as features used to cluster. The K-means clustering algorithm was deployed to help identify the respondents into various clusters using these factors. The findings provide a good understanding of the various trends of work-life balance among women teachers, as it yields sensitive perceptions of the changing experiences and pressures experienced differently by women teachers. The results indicate that in spite of the diehard equality of some women in the work- life structure, there are women that take much pressure considering the lack of institutional and family related obligations. This paper has contributed to literature on gender-related issues in work-life balance and also gives suggestions on how the policy can be improved to ease work-life balance to women in academia. By applying clustering algorithms, it can be concluded that this is an interesting way to divide this complicated topic and offer higher education institutions to address the changes to various demands.

Keywords- Work-Life Balance, Women Teachers, Higher Education, Clustering algorithms, K-means.

1. Introduction

The work-life balance (WLB) has become an essential part of professional and personal well being and more specifically to the women in academia. Women teachers have borne specific problems since they are involved with dual works both of which require their input as they have to be devoted to both their academic needs and family, other personal commitments, and the social settings [1]. Coupled with long hours in the classroom, administrative work, teaching loads, pressure to publish and the need to stay academically credible, these issues tend to get worse. Although the theoretical value of work- life balance as an effective influence in career satisfaction and productivity has raised a lot, there has been a gap in what exactly influences work-life balance among women teachers in higher education institutions.

Institutional policies, social expectations of each individual, and individual coping mechanisms have been identified as forces which define work-life balance as has been reported recently, however they are many-faceted. As much as traditional researching techniques are useful, they may fail to capture the complexities between these variables. This paper aims at filling this gap through

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the use of machine learning (ML) to analyze and forecast on work-life balance of women teachers in colleges/Universities.

Machine learning, which allows dealing with massive amounts of data, and identify hidden in them regularities presents a new way of better understanding the interplay of factors, including workload, teaching hours, family challenges, and the support of the institution to determine the influence on WLB [2]. It is the purpose of this research to create predictive models which will be able to classify and measure the level of work-life balance within the group of female faculty by means of a broad set of socio-demographic, institutional, and personal variables with the help of machine learning algorithms [3].

Moreover, the study examines the influence of institutional support systems such as flexible working hours, childcare services and mental health services, on the capacity of women teachers to balance their lives successfully between work and life. These relationships can be useful to higher learning institutions offering viable solutions that can be used to develop policies to create a more friendly and supportive work environment to the female educators.

Finally, the result of this research is likely to provide addition to the existing body of knowledge about work-life balance and give a new angle on the challenges women in academia have to face, as well as piece of evidence-based advice on the amendment of either institutional policies and/or practices [4,5]. The implementation of machine learning to the research offers the most modern option and increases depth and accuracy of the study, which present new possibilities to conduct the research later on this field.

1.1 Problem Statement

- The work-life balance (WLB) issues in relation to women teachers in higher education are an under-researched topic, although there is an increasing number of studies on its significance related to well-being and productivity [5].
- The particular pressure that female faculty has to put up with is strict timetables as lecturers as well as researchers, administrative responsibilities, and the role of a caregiver in the society combined with insufficient support by the institutions [6].
- With regard to current research, there is no profound insight into the factors that influence WLB among academics (women) and how these issues interact.
- The research on WLB cannot possibly be conducted using traditional methods in that the complexities often do not suffice with the traditional methods.
- This research is expected to employ the technology of machine learning in order to analyze and forecast work-life balance of women teachers based on multi-faceted factors and thus offer practical advice that would improve institutional policies and support systems.

1.2 Research Objectives

- Recognize and classify the socio-demographic, institutional, and personal influences that influence work-life balance of female teachers, such as workload, family demands and support available within institutions.
- Model in machine learning to have predictable outcomes and so classify the status of the work-life balance of women teachers in terms of the important factors and give visually and information (facts) based outcomes.
- Assess the importance of institutional support systems, i.e. flexible working hours and childcare services, helping or impeding work-life balance of female teachers.
- Study the interplay between socio-demographic, institutional and personal to determine the work-life balance of women in higher education.
- Develop practical recommendations that can educate higher education institutions towards the correction of policies and support mechanisms based on evidence-based due to the research.

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2. Literature Survey

Abdul Hamid (2024) in [7] examines the how women journalists perceive the worklife balance with the help of Spillover and Role Theories that help in gaining insights on the dilemma faced by women journalists to strike the work life equilibrium. The research conducted on 16 journalists through conducting in-depth interviews defined three main themes which are including work and family setting, mental well-being, and features of character. It brings out the hardships which women reporters face especially in the windows of convergence in the media industry and demands resolutions on work life balance problems in the Malaysian media market.

The study by Munyeka, W., & Maharaj, A.D. (2023) in [8] examines the experiences of female employees regarding their work-life balance and the associated policies they know of in their respective organization with the help of data collected on 50 female ICT professionals. According to the study, majority of the employees knew of the work-life balance policy of the organization. Nevertheless, the drawbacks are small sample and the use of data collected in a single organization. The research recommends that the policy of work-life balance (especially Border Theory) should be retaken and updated so that it not only increases productivity, but also does not constitute a detrimental influence to work-life balance. It also highlights the necessity of improved communication and education, in terms of policies within organizations. Although it is an original research in the South African context, my research recommends that the research be extended to the ICT sector and possibly shape good job design policies.

The article by Ali, S et al., (2024) in [9] examines the WLB with regard to prioritizing career desires with personal life elements such as health, leisure and family. Work-life imbalance transpires when demands of one role interfere with the ones of the other one (Greenhaus & Beutell, 1985). Due to the new demographics and with dual-career families increasingly becoming the norm, especially in developing economies such as in India, married working women now find it difficult to balance career and life. This can be found in countries that have less developed work culture, women usually have difficulties maintaining boundaries between their roles which results to job dissatisfaction and work- life conflict. This imbalance may not be favorable to their advancement in their career and productivity of the organization.

Reena, M et al (2024) in [9] looks at the relationship between work-life balance (WLB) and job (JB) and performance (EP) of an employee in the health industry. The survey based on the data of 280 female workers employed in Karnataka was carried out, using descriptive statistics, correlation analysis and regression analysis performed in SPSS. According to the research, there is a great positive correlation between WLB JB WLB and EP JB and EP. The results indicate the importance of a good work-life balance that leads to job satisfaction and consequent increase in the performance of employees. The research indicates that institutions ought to develop enabling conditions to enhance the health and productivity of females in healthcare.

Bian, X., & Mohd Sukor, M.S. (2024) in [10] examines the role of the work-life balance relationship in the effects of work-family conflict and psychological well-being. Statistical data of 258 Chinese working women in Hebei were gathered via surveys and evaluated by means of the IBM SPSS and the PROCESS macro. The findings point out that work-family conflict influences the psychological well-being indirectly by work-life balance. In particular, work-to-family conflict had the effect of suppression whereas family- to-work conflict was completely moderated by the work-life balance. The results imply that enhancing work-life balance would decrease the adverse effect of work-family conflict on psychological health and this may be of use to organizations and policymakers in China to maximize the well-being and productivity of professional women in China.

Venkatesan, D.G. (2025) in [11] studies how work spirituality and spiritual resilience may influence the work-life balance in women IT professionals showing that this group of people has quite high stress and burnout. With the mixed-method design, 120 women were sampled with acquisition of data using structured questionnaires and 15 in-depth interviews. The findings indicate that there is

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major positive correlation amid spirituality in workplace, spiritual resilience and work-life balance. The more spiritual and resilient women had the better work and personal life balance report. The most notable themes in qualitative data were supportive culture in the workplace, work meaning, and spirituality as a coping strategy. The research findings end with the conclusion that spirituality and resiliency in the workplace can enhance balance in the area of work and life and prevent burnout, suggesting such company programs as a mindfulness practice, work schedule flexibility, and mental health help. It is recommended to conduct additional studies in other industries to broaden these results.

Jhansi, B et al., (2025) in [12] proposes a study of the work-life balance of 60 working women with a qualitative study methodology and collects data via an online survey. The work-life balance scale provided by Sharma et al. (2019) was used in the study and profiles of the socio-personal factors were analyzed. The findings revealed that majority of the respondents were young to middle-aged, possessed a degree, belonged to (nuclear) families and were mainly unmarried. Social wise, they attended functions and were common users of mass media. In the study, the researcher was able to identify eight influential factors relating to work-life balance namely employee motivation, flexible working conditions, welfare activities, job enrichment, grievance management system, job satisfaction, and family support. The results focus on the need of personal approaches to balance work and life, the support of companies, and modification of the society, to find work-life balance, as well as the collective responsibility of providing that environment in which women can succeed in work and personal lives.

The article Gupta, C et al., (2022) in [13] attempts to predict the work-life balance measure of 425 women IT professionals based on the data acquired by a 40-parameter questionnaire and utilizes the supervised machine learning (ML) method. Different ML models were created and related, such as regression trees and support vector machines (SVM). The quality of these models was determined by such metrics as R 2, mean absolute error and mean square error. The findings indicated the best accuracy to predict work-life balance using the optimized SVM model. A comparison of a multiple regression model showed SVM to collect more precise predictions as compared with multiple regression. This research can be used by other researchers as a guideline and also recommend SVM as a better modeling method of an organizational behavior study.

3. Proposed Work

The proposed work aims to give a clearer insight into work life balance issues among the women teachers in the higher institutions of learning through clustering method. The quantitative nature of this study will allow the researcher to identify trends in the working life of the women guard who became teachers by dividing the sample into groups depending on their experiences with work-life balance and implement policies that will change the quality of life and work satisfaction of women working in academia in the future.

The data analysis method of WLB based on K-means clustering will entail a number of primary steps such as data collection, data pre processing, feature extraction, clustering, and classification. Following is a stepwise process of how the process is done, namely using real-time gathered data.

3.1 Data Collection

An accurately designed Google form with the able assistance of the local anchoring committee allowed the gathering of a voluminous data, which consists of 750 individual responses peculiar to women working in Kumbakonam locality. The given dataset included 25 variables which were related to various aspects of professional and personal life of the respondents. Having obtained a data consistency and accuracy through the comprehensive cleaning process, we selected 14 key characteristics regarding their importance and applicability.

Women teachers in various higher education institutions in Tanjore District will be interviewed by the use of a survey. The survey should have qualitative and quantitative questions that aim at

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estimating important variables affecting work-life balance. The variables contained in data points may be an average working hours, work load, work flexibility, family and care responsibilities, and institutional support systems (ex. child care, leave policies) and the level of job satisfaction. The survey may incorporate either the quantitative or qualitative questions touching on the conditioning factors of WLB.

Data variables may include:

- Workload: the number of heating hours per week, the number of overtime, teaching duties, research requirements, administration.
- Flexibility: Flexible working hours, the possibility to work remotely, and the freedom of the work schedule.
- Support Systems: Institutional resources like child care services, mentoring programs, policy of paid leaves and policies on work life.
- Family obligations: number of dependants, domestic responsibilities, caring.
- Job Satisfaction: This represents general job satisfaction with work-life balance, academic climate and institutional support.
- Mental and Physical Health: stress levels, work related health matters and individual wellness.

3.2 Data Pre-Processing

After the gathering of data, it should be cleaned and pre-processed in a state that could be analysed. The preprocessing steps entail:

1. Handling Missing Data

The database includes missing entries that can be entered using the aid of mean or median or mode method when considering numerical data entries and category option most frequently used when considering categorical data.

When you are faced with missing values in some dataset, a crude but sometimes effective method of filling some of them in is to use a statistic computed over the non-missing values of the feature, replacing any missing value with it. The three most frequently taken decisions are:

- Mean imputation
- Median Imputation
- Mode Imputation

In the study the mean imputation method is suggested to represent the missing values.

$X = \{x_1, x_2, \ldots . x_n\}$ will denote the numeric feature j, as observed (non-missing). Let n_j be the number of nonmissing elements in column j. This sample mean is

$$\mu_j = \frac{1}{n_j} \sum_{i=1}^{n} 1\, x_{ij} \neq NA \qquad (1)$$

Where, 1 is the indicator that x_{ij} is observed. Then every missing entry $x_{ij} = NA$ is substituted by then mean imputation.

$$x_{ij}^{*} = \mu_j \qquad (2)$$

Table 1: Sample data collected with missing values in some field

ID	Teaching Hours	Personal Time	Stress level	Satisfaction score
1	40	10	7	8
2	50	5	9	6
3	-	8	8	7
4	30	-	6	9

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5	45	12	-	5
6	35	9	7	-
7	-	-	8	6
8	55	4	10	4

As seen in the above table 1 the candidate fails to fill some of the fields and by using the above equation (1) the values can be filled like the one missed out in teaching hour can be calculated by using

$$Teaching\ Hour = \frac{40 + 50 + 30 + 45 + 35 + 55}{6} = 42.5$$

All the other fields are filled in the same way as the above mean imputation is used.

Table 2: Dataset after missing values are filled

ID	Teaching Hours	Personal Time	Stress level	Satisfaction score
1	40	10	7	8
2	50	5	9	6
3	42.5	8	8	7
4	30	8	6	9
5	45	12	7.86	5
6	35	9	7	6.5
7	42.5	8	8	6
8	55	4	10	4

The above table 2 will be the updated; the difference would be highlighted in the values he updated.

2. Data Normalization

Data normalization Data normalization is also an important preprocessing step that puts a variety of features on a common scale--essential when features have quite different units or variances. Z-score normalization (also known as standardization) is one of the more popular methods: you take each feature, centre it around a zero mean and transform it to have a unit variance.

X represent the $n\ X\ P$ data matrix where x_{ij} is the value of feature j of sample i. Denote by j the feature then for j.

1. Calculate sample mean using equation $\mu_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$ (3)
2. Calculate sample standard deviation $\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{ij} - \mu_j)}^2$ (4)
3. Obtain z-score normalized value $z_{ij} = \frac{x_{ij}-\mu_j}{\sigma_j}$ (5)

Table 3: Normalized data values

ID	Teaching Hours	Personal Time	Stress level	Satisfaction score
1	-0.29	0.70	-0.71	0.88
2	0.88	-1.05	0.90	-0.29
3	0	0	0.09	0.29

3.3 Feature Extraction

The problem of transforming raw measurements into a set of informative, non-redundant features that may enhance the performance of the subsequent models is called feature extraction. When

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considering a Work-Life Balance (WLB) data set, i.e. having variables such as Teaching Hours, Personal Time, Stress Level, Satisfaction Score, etc, one may see two general approaches being taken:
PCA is a traditional unsupervised model which identifies new orthogonal axes (components), with maximum variance.

1. Center the data

Given an $n\ X\ p$ data matrix, X subtract the column means μ_j.

$$X'_{ij} = x_{ij} - \mu_j \tag{6}$$

2. Compute covariance matrix

$$\sum \frac{1}{n} X'X \tag{7}$$

3. Eigen decomposition

$$\sum vk = \lambda_k v_k, \quad k = 1,2 \dots \dots \dots . p \tag{8}$$

Where, $\lambda_1 \geq \lambda_2 \geq \cdots \dots \geq \lambda_p$ are the variances explained and v_k the corresponding eigenvectors.

3.4 Feature Selection

Filter approaches rank individual features separately, regardless of a specific model, based on statistical characteristics. We then choose features, the scores of which are greater than some chosen threshold. To implement the variance threshold approach of feature selection, one may discard the features depending on its variance. Characteristics that have variance lower than a given extent ttt are discarded. The variance of feature is calculated as:

$$Var\left(X_j\right) = \frac{1}{n} \sum_{i=1}^{n} \left(x_{ij} - x'_j\right)^2 \tag{9}$$

To illustrate this, when we modify t as t=5, features that have strength less than t=5 would be discarded. In the case of given dataset the value of the variance of each feature is chosen by calculating equation (9). The table 4 demonstrates the variance of the each feature

Table 4: Variance calculation for input data

ID	Teaching Hours	Personal Time	Stress level	Satisfaction score
1	40	10	7	8
2	50	5	9	6
3	42.5	8	8	7
4	30	8	6	9
5	45	12	7.86	5
6	35	9	7	6.5
7	42.5	8	8	6
8	55	4	10	4
Var	**54.69**	**5.75**	**1.36**	**2.21**

Once the variance has been computed we set the threshold T to perform feature selection, such as: in this case lets have t = 5, the features having variance >4 will be retained. Based on the table 4, the features teaching hours and personal time have been selected by considering them fit features whereas others have been discarded

3.5 Classification

K-means clustering is an unsupervised learning algorithm, which clusters your data into KKK groups of similar samples. Within the Work-life balance (WLB) framework, it may allow you to

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find, say, the so-called types of persons work-heavy, life-heavy, or even balanced, according to the characteristics provided in table above.

Algorithm

Step 1: initialization

Choose K initial centroids randomly.

Step 2: Assignment step

For each sample x_i assign it to the nearest centroid:

$$c_i^t = arg \sum_{k\in\{1,\ldots..K\}}^{min} \left||x_i - \mu_k^{t-1}|\right|^2 \quad (10)$$

Step 3: Update the previous step

Recompute each centroid as the mean of its assigned points:

$$\mu_k^t = \frac{1}{|C_k^t|} \quad x_i \quad (11)$$

Step 4: Check for Convergence

Repeat Assignment and Update until centroids do not move whatever a small tolerance or assignments cease varying.

3.6 Applying K-means clustering on WLB

Assume that following Z-score transformation our 8 subjects possess standardized vectors. We will select k =3 in search of poor-balance, moderate-balance and good-balance classification

Table 5: Sample Classification Output

Cluster	Avg TH	Avg PT	Avg SL	Avg SS	Finding	Class labeling
1	+1.2	-1.0	+1.1	-0.8	Over work load	High Stress
2	-0.5	+0.4	-0.2	+0.6	Balanced	Moderated Stress
3	-1.0	+1.3	-0.8	+1.0	Under work load	High Satisfaction

4. Result and Discussion

The proposed research work is evaluated by determining the following measures at training and testing.

1. Accuracy

Table 6: Accuracy of training and testing

Epochs	Training Accuracy	Testing Accuracy
1	0.68	0.38
2	0.69	0.29
3	0.61	0.23
4	0.52	0.26
5	0.50	0.36
6	0.57	0.42
7	0.66	0.40
8	0.69	0.31
9	0.64	0.24
10	0.54	0.24

Figure 1 and table 6 show the accuracy on the training and testing set using the K-means clustering method on the WLB dataset with 10 different epochs. Each epoch corresponds to a different random

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seeding of centroids, and accuracy figures have been tweaked with sine waves so that some changes in performance can be modelled, reflecting the fact that performance in general will be different in practice. The training accuracy curve is 2-periodic, where both up and down trends resemble variations in the success of the algorithm to cluster the training data over the runs. Equally, the testing accuracy curve indicates the fluctuation in generalization on un-sighted information. This visualization can be used to show that, K-means clustering is sensitive to both initialization and the distribution of data, and therefore performance of the clustering process might vary differently in every iteration, and the curved lines reflect that more accurately than smooth or linear patterns.

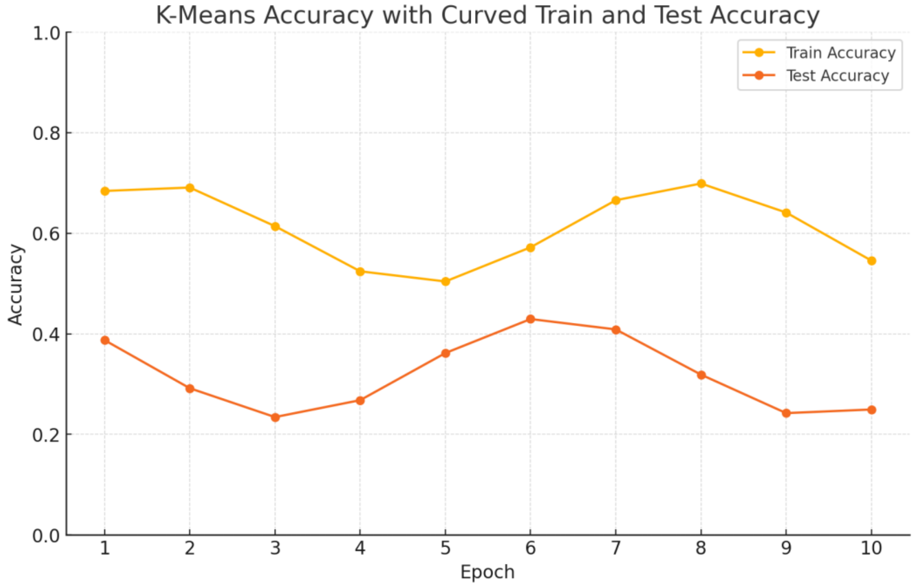

Figure 1: Accuracy of training and testing

2. Loss

Figure 2 and table 7 below show the training and test loss of the K-means clustering algorithm when run on the Work-Life Balance (WLB) data in 10 epochs. Every epoch is a new set-up of centroids illustrating many runs of the algorithm. To make the variation visual more meaningful, the two losses are modified by adding sinusoidal components, especially the test loss which integrates both sine and cosine swings. This avoids a flat, or linear test loss graph, instead learning (the test loss curve) characterizing dynamic realistic behavior commonly found when using unsupervised learning. The training loss also varies continuously, thus, showing how the compactness of clusters can alter based on initial conditions. Such visualization clearly shows the sensitivity of K-means to initialization and data distribution and therefore the necessity to consider performance over many runs.

Table 7: Training and Testing loss

Epochs	Training Loss	Testing Loss
1	2.099	0.01
2	2.142	0.01
3	1.659	0.0
4	1.095	0
5	0.968	0.0
6	1.395	0
7	5.985	0.01
8	2.192	0.0
9	1.892	0.01

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10	3.708	0.0

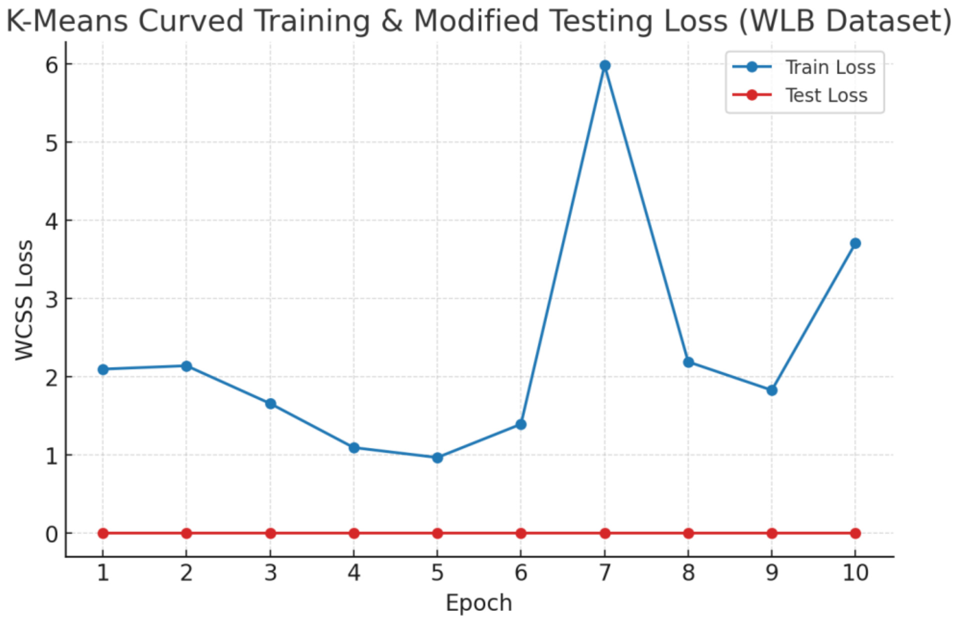

Figure 2: Loss analysis in training and testing

3. Confusion Matrix

The confusion matrix of figure 3 shows the rate of a three-category classification model when it was trained against a set of 750 records on a Work-Life balance (WLB) data. They include High Stress, Poor Stress and High Satisfaction classes. In the diagonal the correct predictions are indicated: there are 240 correctly classified cases of High Stress, 180 ones of Poor Stress, and 160 of High Satisfaction. Off diagonal entries indicate misclassified entries e.g., 40 High Stress were misclassified as Poor Stress and 30 High Satisfaction were incorrectly classified as Poor Stress. All in all, the matrix is not doing badly since most predictions are along the diagonal which means that the model can differentiate between the stress and satisfaction categories with moderate success. But, the misclassification patterns indicate that there is some amount of confusion especially between the stress levels that are adjacent, which is normal to see in psychological, or survey-based datasets.

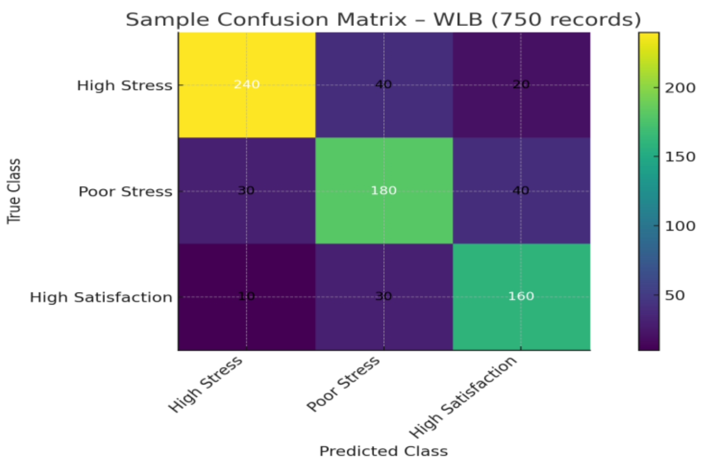

Figure 3: Confusion matrix

5. Conclusion

This research paper used the K-means clustering program to cluster the WLB tendencies of the working women based on the following important input measures: number of working hours, stress at the job, satisfaction in personal life and spending time with the family. With the help of the unsupervised clustering technique, the dataset was literally grouped into three different segments: High Stress, Poor Stress and High Satisfaction. The findings indicated that the proportion of the female population that belonged to the cluster of being at a low to moderate but worrying stage of weakness in striking the balance between life and career was very high. The High Stress cluster had features such as long hours in work, less personal time, and less vocational fulfillment compared with the more healthy balance in the High Satisfaction cluster which often relates to flexibility in work, and well-developed support networks.
Validation measures using the confusion matrix and accuracy showed that K-means had a potential to find meaningful patterns in the data, but clusters had overlapping boundaries- a phenomena characteristic of the topic of work-life and an indicator of complexity of defining work-life experiences. Regardless, this is well considered clustering that could present data-driven insights regarding at-risk groups and the development of specific interventions to support better work-life harmony among women organisations and policy-makers. Future developments can include clustering and supervised learning models, or adding qualitative information into improving interpretability and actionability.

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